

ARTIFICIAL INTELLIGENCE-BASED MEDICATION RECOMMENDATION METHOD AND APPARATUS, DEVICE, AND STORAGE MEDIUM

CROSS-REFERENCE TO RELATED APPLICATION(S)

[1] This application claims priority to a Chinese Patent Application No. 202010475961.3 filed on May 29, 2020, and entitled “ARTIFICIAL INTELLIGENCE-BASED MEDICATION RECOMMENDATION METHOD AND APPARATUS, DEVICE, AND STORAGE MEDIUM”, the present disclosure of which is hereby incorporated by reference in its entirety.

TECHNICAL FIELD

[2] This disclosure relates to the technical field of artificial intelligence (AI), and more particularly, to an AI-based medication recommendation method and apparatus, a device, and a storage medium.

BACKGROUND

[3] A clinical decision support system (CDSS) generally refers to a computer system that can support the clinical decision. The system can improve and enhance the decision efficiency through human-computer interaction for a semi-structured or unstructured medical problem by fully using available and appropriate computer technologies. The CDSS is an important tool to improve the medical quality. That is, the CDSS is used to analyze case history information in depth so as to make the most appropriate treatment decision, which has a fundamental purpose of assessing and improving the medical quality, and reducing a medical mistake, thereby controlling a medical expense.

[4] Currently, a medication recommendation model integrated on the CDSS is used to recommend medication by analyzing disease data, which mainly includes two types: a knowledge-driven medication recommendation model and a data-driven medication recommendation model. The knowledge-driven medication recommendation model is formed based on various medical guidelines and expert consensus. The data-driven medication recommendation model is formed by integrating various artificial intelligence (AI) techniques

such as machine learning and deep learning. Currently, whether a medication recommendation model is good is evaluated mainly based on a standard whether a recommendation medication is matched with an actually prescribed medication in clinic, which is realized by the inventor. If medication recommendation is performed by a medication recommendation model determined according to such standard, due to uneven clinical levels and a poor curative effect of the actually prescribed medication in clinic, a recommendation accuracy of the medication recommendation model is reduced. That is, effectiveness of the curative effect of the recommendation medication obtained is not high, thereby affecting the promotion of the medication recommendation model.

SUMMARY

[5] Implementations of the present disclosure provide an artificial intelligence-based (AI-based) medication recommendation method and apparatus, a device, and a storage medium, to solve a poor recommendation accuracy of current medication recommendation models in medication recommendation.

[6] An AI-based medication recommendation method includes the following. A medication recommendation request is obtained, where the medication recommendation request includes a disease type, current disease data, and user profile data. At least two target medication recommendation models each with a better target analysis result are obtained according to target analysis results of original medication recommendation models corresponding to the disease type. The current disease data is analyzed by using the at least two target medication recommendation models, to determine at least two original recommendation medications. Feature analysis is performed on each original recommendation medication, to obtain feature analysis values of at least two features to-be-analyzed. A recommendation propensity type is determined based on the user profile data, and feature weights of the at least two features to-be-analyzed are obtained according to the recommendation propensity type. At least two recommendation evaluation values of the at least two original recommendation medications are obtained based on the feature analysis values and the feature weights of the at least two features to-be-analyzed, and an original recommendation medication with a largest recommendation evaluation value is determined as a target recommendation medication.

[7] An AI-based medication recommendation apparatus includes a recommendation request obtaining module, a recommendation model determining module, an original

recommendation medication obtaining module, a feature analysis value obtaining module, a feature weight obtaining module, and a target recommendation medication obtaining module. The recommendation request obtaining module is configured to obtain a medication recommendation request, where the medication recommendation request includes a disease type, current disease data, and user profile data. The recommendation model determining module is configured to obtain at least two target medication recommendation models each with a better target analysis result according to target analysis results of original medication recommendation models corresponding to the disease type. The original recommendation medication obtaining module is configured to analyze the current disease data by using the at least two target medication recommendation models, and determine at least two original recommendation medications. The feature analysis value obtaining module is configured to obtain feature analysis values of at least two features to-be-analyzed by performing feature analysis on each original recommendation medication. The feature weight obtaining module is configured to determine a recommendation propensity type based on the user profile data, and obtain feature weights of the at least two features to-be-analyzed according to the recommendation propensity type. The target recommendation medication obtaining module is configured to obtain at least two recommendation evaluation values of the at least two original recommendation medications based on the feature analysis values and the feature weights of the at least two features to-be-analyzed, and determine an original recommendation medication with a largest recommendation evaluation value as a target recommendation medication.

[8] A computer device includes a memory, a processor, and a computer program stored in the memory and executable on the processor. When executing the computer program, the processor implements the AI-based medication recommendation method above, for example, the processor implements the following. A medication recommendation request is obtained, where the medication recommendation request includes a disease type, current disease data, and user profile data. At least two target medication recommendation models each with a better target analysis result are obtained according to target analysis results of original medication recommendation models corresponding to the disease type. The current disease data is analyzed by using the at least two target medication recommendation models, to determine at least two original recommendation medications. Feature analysis is performed on each original recommendation medication, to obtain feature analysis values of at least two features to-be-

analyzed. A recommendation propensity type is determined based on the user profile data, and feature weights of the at least two features to-be-analyzed are obtained according to the recommendation propensity type. At least two recommendation evaluation values of the at least two original recommendation medications are obtained based on the feature analysis values and the feature weights of the at least two features to-be-analyzed, and an original recommendation medication with a largest recommendation evaluation value is determined as a target recommendation medication.

[9] A computer readable storage medium is configured to store a computer program. When executed by a processor, the computer program causes the processor to implement the AI-based medication recommendation method above, for example, the processor implements the following. A medication recommendation request is obtained, where the medication recommendation request includes a disease type, current disease data, and user profile data. At least two target medication recommendation models each with a better target analysis result are obtained according to target analysis results of original medication recommendation models corresponding to the disease type. The current disease data is analyzed by using the at least two target medication recommendation models, to determine at least two original recommendation medications. Feature analysis is performed on each original recommendation medication, to obtain feature analysis values of at least two features to-be-analyzed. A recommendation propensity type is determined based on the user profile data, and feature weights of the at least two features to-be-analyzed are obtained according to the recommendation propensity type. At least two recommendation evaluation values of the at least two original recommendation medications are obtained based on the feature analysis values and the feature weights of the at least two features to-be-analyzed, and an original recommendation medication with a largest recommendation evaluation value is determined as a target recommendation medication.

[10] The AI-based medication recommendation method and apparatus, the device, and the storage medium above can improve the effectiveness and pertinence of intelligent medication recommendation.

BRIEF DESCRIPTION OF THE DRAWINGS

[11] FIG. 1 is a schematic diagram illustrating an application environment of an artificial intelligence-based (AI-based) medication recommendation method in implementations of the

disclosure.

[12] FIG. 2 is a flowchart illustrating an AI-based medication recommendation method in implementations of the disclosure.

[13] FIG. 3 is a flowchart illustrating an AI-based medication recommendation method in other implementations of the disclosure.

[14] FIG. 4 is a flowchart illustrating an AI-based medication recommendation method in other implementations of the disclosure.

[15] FIG. 5 is a flowchart illustrating an AI-based medication recommendation method in other implementations of the disclosure.

[16] FIG. 6 is a flowchart illustrating an AI-based medication recommendation method in other implementations of the disclosure.

[17] FIG. 7 is a flowchart illustrating an AI-based medication recommendation method in other implementations of the disclosure.

[18] FIG. 8 is a flowchart illustrating an AI-based medication recommendation method in other implementations of the disclosure.

[19] FIG. 9 is a schematic diagram illustrating an AI-based medication recommendation apparatus in implementations of the disclosure.

[20] FIG. 10 is a schematic diagram illustrating a computer device in implementations of the disclosure.

DETAILED DESCRIPTION

[21] The following will describe technical solutions of implementations of the disclosure with reference to accompanying drawings of implementations of the disclosure.

[22] The technical solutions of the disclosure can be applied in the artificial intelligence (AI) and/or block chain technology field. The data related such as a disease type, disease data, or user profile data, can be stored into a block chain node, such as a distributed storage via the block chain, etc., which will not be limited herein.

[23] An AI-based medication recommendation method is provided in implementations of the disclosure. The method can be applied in an application environment as illustrated in FIG. 1. Specifically, the method is applied in a clinical decision support system (CDSS). The CDSS includes a client and a server as illustrated in FIG. 1, and the client communicates with the server

via a network. The CDSS is used to perform intelligence analysis on current disease data and user profile data according to a medication recommendation request triggered by the client, to obtain a target recommendation medication, thereby ensuring the accuracy, efficiency, and pertinence of the recommendation medication. The client, also known as a user terminal, is a program corresponding to the server and providing a local service for a client. The client can be installed on various devices including, but not limited to, personal computers, laptops, smartphones, tablet computers, and portable wearable devices. The server can be implemented by a separate server or a server cluster consisting of multiple servers.

[24] In an implementation, as illustrated in FIG. 2, an AI-based medication recommendation method is provided. For example, the method is applied in the server in FIG. 1. The method includes the following.

[25] At S201, a medication recommendation request is obtained, where the medication recommendation request includes a disease type, current disease data, and user profile data.

[26] The medication recommendation request is used to trigger execution of a medication recommendation service. As an example, the server of the CDSS can receive a medication recommendation request triggered via the client by a user, to obtain a disease type, current disease data, and user profile data in the medication recommendation request.

[27] The disease type is used to reflect a type corresponding to a disease suffered by a patient. As an example, the disease type includes, but is not limited to, diabetes, hypertension, and chronic kidney disease. It can be understood that, determination of the disease type helps to determine a more accurate medication recommendation model for medication recommendation, thereby improving an accuracy of medication recommendation.

[28] The current disease data is used to reflect a current physical status of the patient. The current disease data is tested at a medical facility in real time and corresponds to a test indicator corresponding to the disease type. For example, for the disease type of diabetes, actual test data corresponding to indicators such as blood glucose, glycated hemoglobin, glycated serum protein, antibodies, etc., needs to be collected in real time.

[29] The user profile data is used to reflect related information of the patient. The user profile data may include data affecting a disease diagnostic effect, such as age, gender, and other data, and also include data affecting medication recommendation. For example, when the patient has a lower income, medication recommendation may tend more to recommend a low-cost

medication.

[30] At S202, at least two target medication recommendation models each with a better target analysis result are obtained according to target analysis results of original medication recommendation models corresponding to the disease type.

[31] The original medication recommendation models are pre-stored in the CDSS and correspond to the disease type, and can output medication recommendation according to the disease data. That is, for each disease type, the CDSS selects at least one original medication recommendation model corresponding to the disease type. As such, the CDSS can perform the intelligence analysis on the current disease data corresponding to the disease type based on the pre-selected original medication recommendation model, thereby improving the pertinence and effectiveness of a recommendation medication obtained through analysis. It can be understood that, different original medication recommendation models corresponding to a same disease type may be data obtained by performing, with different neural network models, a model training on clinical medical data (including clinical disease data and corresponding clinical medication data). As such, each original medication recommendation model is based on clinical medical guidelines, which can avoid making a clinical mistake in the recommendation medication, and medical big data is also used to realize personalized medication recommendation and learn medication solutions of similar patients, which can ensure the effectiveness of medication recommendation.

[32] Since different original medication recommendation models adopt different neural network models, the different original medication recommendation models have different training processes. As such, when original medication recommendation models obtained through training perform intelligent medication recommendation on same current disease data, there may be different medication recommendation results. Therefore, the CDSS may perform comprehensive evaluation on each original medication recommendation model in advance. That is, the CDSS performs the comprehensive evaluation on each original medication recommendation model based on clinical medical data of similar patients, to obtain target analysis results, and stores the target analysis results into the CDSS. As such, in a medication recommendation process, the CDSS can quickly query the target analysis results of the original medication recommendation models according to the disease type. The CDSS can then descend all original medication recommendation models according to the target analysis results, and

select at least two original medication recommendation models each with a target analysis result ranked front to be target medication recommendation models adopted by this medication recommendation. It can be understood that, the number of target medication recommendation models can be self-set according to actual needs, and the at least two original medication recommendation models each with a target analysis result ranked front in the target analysis results in descending order are determined as the target medication recommendation models. As such, the effectiveness of the medication recommendation result can be guaranteed when intelligent medication recommendation is performed based on the target medication recommendation models.

[33] At S203, the current disease data is analyzed by using the at least two target medication recommendation models, to determine at least two original recommendation medications.

[34] The original recommendation medications are output results of the target medication recommendation models after the current disease data is analyzed by the target medication recommendation models. As an example, the CDSS analyzes the current disease data by using the at least two target medication recommendation models in parallel after obtaining the at least two target medication recommendation models, to determine the at least two original recommendation medications output by the at least two target medication recommendation models.

[35] At S204, feature analysis is performed on each original recommendation medication, to obtain feature analysis values of at least two features to-be-analyzed.

[36] The features to-be-analyzed are features that are pre-configured and need to be analyzed. The features to-be-analyzed can be understood as features used to evaluate whether medication recommendation is good. In this example, the features to-be-analyzed include, but are not limited to, a medication cost, a curative effect time, a side effect, etc.

[37] As an example, the CDSS performs the feature analysis on each original recommendation medication by using a preset feature analysis strategy after obtaining the at least two original recommendation medications, to obtain the feature analysis values of the at least two features to-be-analyzed. In this example, the CDSS performs the feature analysis on each original recommendation medication by using the preset feature analysis strategy as follows. The CDSS queries a system database or an associated database based on the original recommendation

medication, to obtain feature original data corresponding to the features to-be-analyzed in the original recommendation medication. For example, obtain an actual cost corresponding to a feature to-be-analyzed (i.e., medication cost), that is, a cost of medications needed in a treatment course. Then, the feature original data corresponding to all features to-be-analyzed are normalized to be converted into the number of dimensionless quantity, thereby ensuring the feasibility of subsequent calculation of recommendation evaluation values.

[38] At S205, a recommendation propensity type is determined based on the user profile data, and feature weights of the at least two features to-be-analyzed are obtained according to the recommendation propensity type.

[39] The recommendation propensity type is analyzed according to the user profile data of the patient and is used to reflect a medication recommendation type to which the patient tends more. As an example, the medication recommendation type includes, but is not limited to, a low-cost recommendation type with a greater cost weight, a high-curative effect recommendation type with a greater curative effect time weight, and a low-risk recommendation type with a greater side effect weight. In this example, for each medication recommendation type, feature weights of the at least two features to-be-analyzed are pre-configured, and the corresponding feature weights are stored into the system database.

[40] As an example, the CDSS performs intelligence analysis on the user profile data by using a preset recommendation propensity analysis strategy, to determine a recommendation propensity type corresponding to the user profile data. The CDSS queries the system database according to the recommendation propensity type, to obtain a pre-configured feature weight of each feature to-be-analyzed.

[41] At S206, at least two recommendation evaluation values of the at least two original recommendation medications are obtained based on the feature analysis values and the feature weights of the at least two features to-be-analyzed, and an original recommendation medication with a largest recommendation evaluation value is determined as a target recommendation medication.

[42] The target recommendation medication is selected from the at least two original recommendation medications and best matches the user profile data.

[43] In this implementation, the CDSS performs a weighting operation on the feature analysis values and the feature weights of the at least two features to-be-analyzed with a

weighting algorithm after the feature analysis values and the feature weights of the at least two features to-be-analyzed are obtained, to obtain the at least two recommendation evaluation values of the at least two original recommendation medications. Then the CDSS compares the at least two recommendation evaluation values to determine the largest recommendation evaluation value, and determines the original recommendation medication with the largest recommendation evaluation value as the target recommendation medication. The recommendation evaluation values are obtained by performing the weighting operation on the feature analysis values and the feature weights of the at least two features to-be-analyzed, which can reflect the degree of fit with the user profile data of the patient. The higher the recommendation evaluation value, the better the original recommendation medication fits the actual needs of the patient, thereby improving the pertinence and effectiveness of medication recommendation.

[44] As an example, the CDSS can adopt $P = \sum S_i W_i$ to perform the weighting operation on the feature analysis values and the feature weights of the at least two features to-be-analyzed, to obtain the at least two recommendation evaluation values of the at least two original recommendation medications. The obtaining process of the recommendation evaluation values is convenient and simple in calculation. P is a recommendation evaluation value, S_i is a feature analysis value of an i -th feature to-be-analyzed, and W_i is a feature weight of the i -th feature to-be-analyzed.

[45] As another example, after the target analysis result of each original medication recommendation model is obtained at S202, the target analysis result can also be processed in a model weight conversion strategy, to obtain a model weight of each target analysis result. The CDSS can adopt $P = Q \sum S_i W_i$ to perform the weighting operation on the feature analysis values and the feature weights of the at least two features to-be-analyzed, to obtain the at least two recommendation evaluation values of the at least two original recommendation medications. Q is a model weight of an original medication recommendation model, P is a recommendation evaluation value, S_i is a feature analysis value of an i -th feature to-be-analyzed, and W_i is a feature weight of the i -th feature to-be-analyzed. It can be understood that, the target analysis result of the original medication recommendation model is converted into the model weight, and the recommendation evaluation value is determined by using the model weight, the feature analysis value, and the feature weight. As such, the recommendation evaluation value can

effectively reflect the effectiveness of medication recommendation and the degree of fit with the user profile data, thereby improving the effectiveness and pertinence of intelligent medication recommendation.

[46] In the AI-based medication recommendation method provided in this implementation, the at least two target medication recommendation models each with a better target analysis result are obtained according to the target analysis results of original medication recommendation models corresponding to the disease type. Then the current disease data is analyzed by using the target medication recommendation models, to determine the original recommendation medications. Therefore, the effectiveness and pertinence of original recommendation medication can be ensured. The feature analysis is performed on each original recommendation medication, to determine the feature analysis values of the features to-be-analyzed. The feature weights of the features to-be-analyzed are determined according to the recommendation propensity type determined by analyzing the user profile data. The recommendation evaluation values are determined by performing the weighting operation on the feature analysis values and the feature weights of the features to-be-analyzed. As such, the recommendation evaluation value can effectively reflect the effectiveness of medication recommendation and the degree of fit with the user profile data, thereby improving the effectiveness and pertinence of intelligent medication recommendation.

[47] In an implementation, as illustrated in FIG. 3, the AI-based medication recommendation method further includes the following, before the medication recommendation request is obtained.

[48] At S301, retrospective data corresponding to the disease type is obtained, where the retrospective data includes previous disease data and actual medication data.

[49] The retrospective data is used to evaluate whether the original medication recommendation model is good, to determine the target analysis result. As an example, the retrospective data may be obtained from a hospital information system or the system database of the CDSS, and also be some public medical data sets, which are specific structural data.

[50] In this example, the retrospective data is one visit record, i.e., data determined for a patient at a visit. Specifically, the retrospective data includes the previous disease data and the actual medication data. The previous disease data is related to a disease and recorded when patient visits, and includes a symptom and information of test and inspection results. The actual

medication data refers to medication data given by a doctor at a visit and specifically includes a disease diagnostic result, a prescribed medication, a duration of treatment, etc. It can be understood that, during comprehensive evaluation for the original medication recommendation model, since a medical effect of the disease symptom corresponding to the previous disease data needs to be analyzed in combination with the actual medication data, the retrospective data further includes the short-term effect data and the long-term effect data. The short-term effect data refers to data on compliance of test and inspection indicators within a shorter period after this visit, for example, data on whether glycated hemoglobin reaches a standard after treatment around three months can be determined as the short-term effect data. The long-term effect data refers to data on whether complications or adverse events occur within a longer period after this visit, for example, the long-term effect data can be determined according to follow-up outpatient or inpatient diagnostic results. It can be understood that, a time boundary between the short-term effect data and the long-term effect data can be determined according to previous experience.

[51] As an example, according to the disease type, the CDSS can query the hospital information system or the system database of the CDSS or crawl the hospital data set, to obtain all previous visit records corresponding to the disease type. Then the CDSS verifies all previous visit records to determine whether the previous visit records include necessary data such as the previous disease data, the actual medication data, the short-term effect data, the long-term effect data, etc. If the previous visit records include all necessary data, the previous visit records are determined as retrospective data that can be used to evaluate the original medication recommendation model, thereby ensuring the feasibility of subsequent evaluation of the original medication recommendation model.

[52] At S302, the previous disease data is analyzed by using an original medication recommendation model corresponding to the disease type, to obtain previous recommendation medication data, a comparison result is obtained by comparing the previous recommendation medication data with the actual medication data, and the retrospective data corresponding to the disease type is categorized into a first data set conforming to model recommendation and a second data set not conforming to model recommendation, based on the comparison result.

[53] Since the original medication recommendation model can output medication recommendation according to the disease data, the CDSS can analyze the previous disease data by using the original medication recommendation model, to obtain previous recommendation

medication data. That is, the previous recommendation medication data is medication data output by analyzing, with the original medication recommendation model, the previous disease data.

[54] The CDSS can compare the previous recommendation medication data with the actual medication data after obtaining the previous recommendation medication data, to determine whether the previous recommendation medication data is matched with the actual medication data. According to the comparison result, the retrospective data is respectively categorized into the first data set conforming to model recommendation and the second data set not conforming to model recommendation. That is, if the previous recommendation medication data is matched with the actual medication data, the retrospective data is classified into the first data set conforming to model recommendation. If the previous recommendation medication data is not matched with the actual medication data, the retrospective data is classified into the second data set not conforming to model recommendation.

[55] At S303, for retrospective data in the first data set and retrospective data in the second data set, a short-term effectiveness indicator compliance rate and a long-term complication rate are counted respectively, and a significance test is performed, to obtain an effect analysis result.

[56] The short-term effectiveness indicator compliance rate is used to evaluate in a visit level or a patient level, according to the retrospective data, whether model recommendation is conformed to an influence on whether a short-term effectiveness indicator reaches a standard. The long-term complication rate is used to evaluate in a visit level or a patient level, according to the retrospective data, whether model recommendation is conformed to an influence on whether a long-term complication occurs. The visit level is a visit record of a patient and is mainly applicable to evaluate whether a short-term effectiveness indicator reaches the standard. For example, whether the short-term effectiveness indicator reaches the standard within a shorter period after each visit. The patient level refers to all visit records of a same patient and is mainly applicable to evaluate whether a long-term complication occurs. As an example, a recommendation conforming rate of the actual medication data to the previous recommendation medication data can be determined according to multiple visit records of a same patient. A relation between the recommendation conforming rate and the long-term complication rate can be further analyzed in the patient level according to the recommendation conforming rate. For example, if a patient totally visits for ten times, ten visits records are formed, where actual medication data are conformed to the previous recommendation medication data for six times,

i.e., the recommendation conforming rate is 60%. The significance test is performed according to the recommendation conforming rate, to obtain the effect analysis result reflecting the relation between the recommendation conforming rate and the long-term complication rate. The significance test is to make a hypothesis in advance about parameters of the population (random variables) or a distribution form of the population, and then use sample information to determine whether this hypothesis (alternative hypothesis) is reasonable, that is, to determine whether a true situation of the population is significantly different from the null hypothesis.

[57] As an example, the CDSS counts respectively a corresponding short-term effectiveness indicator compliance rate and a corresponding long-term complication rate according to the retrospective data in the first data set and the retrospective data in the second data set. The significance test is performed based on the counted short-term effectiveness indicator compliance rate and the counted long-term complication rate, to obtain the effect analysis result. The effect analysis result can efficiently reflect a relation between the recommendation conforming rate and the short-term effectiveness indicator compliance rate as well as the relation between the recommendation conforming rate and the long-term complication rate, thereby facilitating follow-up comprehensive evaluation.

[58] At S304, difference analysis is performed on the retrospective data in the first data set and the retrospective data in the second data set if the effect analysis result satisfies a preset analysis condition, to obtain a target short-term confounding factor and a target long-term confounding factor.

[59] The preset analysis condition is a preset condition indicating follow-up difference analysis is required. As an example, when the effect analysis result is P-value obtained in the significance test, the preset analysis result can be set to be smaller than a preset value, such as smaller than 0.05.

[60] Differences of the retrospective data in the first data set and the retrospective data in the second data set in the short-term effectiveness indicator compliance rate and the long-term complication rate may be resulted with a treatment factor or a non-treatment factor. The treatment factor is related to medication while the non-treatment factor is not related to medication. In order to avoid influence of the non-treatment factor to the effectiveness of model recommendation medication, the difference analysis needs to be performed on the retrospective data in the first data set and the retrospective data in the second data set, to obtain the target

short-term confounding factor and the target long-term confounding factor. The confounding factor can be understood as the non-treatment factor. The target short-term confounding factor refers to a non-treatment factor with a maximum influence on the short-term effectiveness indicator compliance rate or several non-treatment factors ranked front with greater influence on the short-term effectiveness indicator compliance rate. The target long-term confounding factor refers to a non-treatment factor with a maximum influence on the long-term complication rate or several non-treatment factors ranked front with greater influence on the long-term complication rate.

[61] For example, the retrospective data includes N confounding factors such as F1, F2, F3, ..., or Fn. When the difference analysis is performed on the retrospective data in the first data set and the retrospective data in the second data set, for any one confounding factor, a corresponding short-term effectiveness indicator compliance rate and a corresponding long-term complication rate are counted respectively, to obtain an effect analysis result of this confounding factor. Based on the effect analysis result, a confounding factor with a maximum influence on the short-term effectiveness indicator compliance rate or several confounding factors ranked front with greater influence on the short-term effectiveness indicator compliance rate is/are determined as the target short-term confounding factor(s). Based on the effect analysis result, a confounding factor with a maximum influence on the long-term complication rate or several confounding factors ranked front with greater influence on the long-term complication rate is/are determined as the target long-term confounding factor(s).

[62] At S305, propensity analysis is performed on the retrospective data in the first data set and the retrospective data in the second data set based on the target short-term confounding factor and the target long-term confounding factor, to obtain and store a target analysis result of the original medication recommendation model.

[63] In this example, the propensity analysis is performed on the retrospective data in the first data set and the retrospective data in the second data set based on the target short-term confounding factor and the target long-term confounding factor determined through analysis, to weaken influence of confounding factors to the short-term effectiveness indicator compliance rate and the long-term complication rate, such that the obtained target analysis result is reasonable. In this example, the CDSS needs to store the target analysis result in the system database after obtaining the target analysis result of the original medication recommendation

model. As such, the CDSS can invoke the target analysis result of the original medication recommendation model after obtaining the medication recommendation request, and quickly determine the at least two target medication recommendation models each with a better target analysis result, so as to ensure effectiveness of the selected target medication recommendation model that has been clinically verified and has learned medication solutions of similar patients.

[64] In an implementation, as illustrated in FIG. 4, at S302, the comparison result is obtained by comparing the previous recommendation medication data with the actual medication data as follows.

[65] At S401, at least one recommendation medication type is obtained based on the previous recommendation medication data, and at least one actual medication type is obtained based on the actual medication data.

[66] At S402, it is determined that the comparison result is “conforming to the model recommendation” on condition that all recommendation medication types are matched with all actual medication types.

[67] At S403, it is determined that the comparison result is “not conforming to the model recommendation” on condition that at least one recommendation medication type is not matched with at least one actual medication type.

[68] In this implementation, the recommendation medication type can be determined according to the previous recommendation medication data, the actual medication type can be determined according to the actual medication data, and all recommendation medication types are compared with all actual medication types to determine whether all recommendation medication types are matched with all actual medication types. If all recommendation medication types are matched with all actual medication types, i.e., a combination of recommendation medication types is matched with a combination of actual medication types, the comparison result is “conforming to the model recommendation”. If there is at least one recommendation medication type is not matched with at least one actual medication type, i.e., a combination of recommendation medication types is not matched with a combination of actual medication types, the comparison result is “not conforming to the model recommendation”.

[69] For example, the medication of diabetes can be categorized into medication types such as biguanide, sulfonylurea, etc. If the actual medication of the patient contains metformin, the patient is considered to use the biguanide medication. It can be understood that, the actual

medication data can be defined as a combination of multiple medication types, such as biguanide plus sulfonylurea, i.e., a medication of a single medication type can be used or medications of multiple medication types can be used. The previous recommendation medication data being matched with the actual medication data prescribed by a doctor means complete consistence in the combination of medication types. If there is a difference in the number of medication types or the name of the medication types, the previous recommendation medication data is not matched with the actual medication data prescribed by the doctor. It can be understood that, since different medications of a same medication type have different effects, accordingly different dosages are used, and thus it is unnecessary to consider whether dosages are matched. Therefore, whether the previous recommendation medication data is matched with the actual medication data can be determined based on whether the medication types are matched, which helps to simplify calculation amount of the comparing process, thereby improving processing efficiency.

[70] In an implementation, the retrospective data further includes the short-term effect data and the long-term effect data. As illustrated in FIG. 5, at S303, for the retrospective data in the first data set and the retrospective data in the second data set, the short-term effectiveness indicator compliance rate and the long-term complication rate are counted respectively, and the significance test is performed, to obtain the effect analysis result as follows.

[71] At S501, a first short-term effectiveness indicator compliance rate and a first long-term complication rate are obtained based on the retrospective data in the first data set.

[72] At S502, a second short-term effectiveness indicator compliance rate and a second long-term complication rate are obtained based on the retrospective data in the second data set.

[73] At S503, the significance test is performed on the first short-term effectiveness indicator compliance rate, the first long-term complication rate, the second short-term effectiveness indicator compliance rate, and the second long-term complication rate, to obtain the effect analysis result.

[74] The short-term effectiveness indicator compliance rate refers to a ratio of the number of samples whose short-term effectiveness indicator reaches the standard to the total number of all samples. The long-term complication rate refers to a ratio of the number of samples whose long-term complication occurs to the total number of all samples.

[75] As an example, assume the number of retrospective data corresponding to a disease type and obtained by the CDSS is A. The CDSS can categorize the retrospective data into a first

data set and a second data set according to a comparison result between previous recommendation medication data and actual medication data. Assume the number of retrospective data in the first data set is A1, and number of retrospective data in the second data set is A2.

[76] Accordingly, the CDSS can determine whether the short-term effect data reaches a standard range corresponding to the short-term effectiveness indicator according to the short-term effect data in the retrospective data. If the short-term effect data reaches the standard range corresponding to the short-term effectiveness indicator, the short-term effectiveness indicator reaches the standard. Then, the number of samples whose short-term effectiveness indicator reaches the standard is updated, that is, the number of samples whose short-term effectiveness indicator reaches the standard adds 1. Until all retrospective data are completely analyzed, the number of samples whose short-term effectiveness indicator reaches the standard is determined as B, where the number of samples whose short-term effectiveness indicator reaches the standard in the first data set is B1, and the number of samples whose short-term effectiveness indicator reaches the standard in the second data set is B2.

[77] Accordingly, the CDSS can determine whether the long-term effect data reaches a considered long-term complication standard according to the long-term effect data in the retrospective data. If the long-term effect data reaches the considered long-term complication standard, the long-term complication occurs. Then, the number of samples whose long-term complication occurs is updated, that is, the number of samples whose long-term complication occurs adds 1. Until all retrospective data are completely analyzed, the number of samples whose long-term complication occurs is determined as C, where the number of samples whose long-term complication occurs in the first data set is determined as C1, and the number of samples whose long-term complication occurs in the second data set is determined as C2.

[78] In this example, for the retrospective data in the first data set and the retrospective data in the second data set, the short-term effectiveness indicator compliance rate and the long-term complication rate are counted respectively, and the significance test is performed as follows. (1) The CDSS obtains a first short-term effectiveness indicator compliance rate and a first long-term complication rate based on the retrospective data in the first data set. Supposing the first short-term effectiveness indicator compliance rate is Q1, $Q1 = B1 / A1$. Supposing the first long-term complication rate is P1, $P1 = C1 / A1$. (2) The CDSS obtains a second short-term

effectiveness indicator compliance rate and a second long-term complication rate based on the retrospective data in the second data set. Supposing the second short-term effectiveness indicator compliance rate is $Q2$, $Q2 = B2 / A2$. Supposing the second long-term complication rate is $P2$, then $P2 = C2 / A2$. (3) The CDSS performs the significance test on first short-term effectiveness indicator compliance rate $Q1$, first long-term complication rate $P1$, second short-term effectiveness indicator compliance rate $Q2$, and second long-term complication rate $P2$ in a chi-square test method, to obtain the effect analysis result.

[79] As illustrated in Table 1 below, for retrospective data whose all short-term effectiveness indicators reach the standard, retrospective data is marked “YES” if “conforming to the model recommendation”, or retrospective data is marked “NO” if “not conforming to the model recommendation”. The number of samples $B1$ in the first data set and the number of samples $B2$ in the second data set are counted. First short-term effectiveness indicator compliance rate $Q1$ and second short-term effectiveness indicator compliance rate $Q2$ are respectively calculated based on $B1$ and $B2$. $P\text{-value}1$ is calculated through the significance test according to a difference value between $Q1$ and $Q2$. Accordingly, for retrospective data whose long-term complication occurs, retrospective data is marked “YES” if “conforming to the model recommendation”, or retrospective data is marked “NO” if “not conforming to the model recommendation”. The number of samples $C1$ in the first data set and the number of samples $C2$ in the second data set are counted. First long-term complication rate $P1$ and second long-term complication rate $P2$ are respectively calculated based on $C1$ and $C2$. $P\text{-value}2$ is calculated through the significance test according to a difference value between $P1$ and $P2$.

In this example, conforming to the model recommendation or not is determined as an exposure variable, and whether the short-term effectiveness indicator reaches the standard and whether the long-term complication occurs are determined as outcome variables. $P\text{-value}$ between the exposure variable and the outcome variables is calculated in the chi-square test method. If $P\text{-value} < 0.05$, it shows that there is significance between the exposure variable and the outcome variables, and then the effect analysis result is obtained, to analyze whether the model recommendation has a relation with the short-term effectiveness indicator compliance rate and the long-term complication rate.

Outcome types	Grouping statistics		Outcome evaluation indicators		
	conforming to the model recommendation or not	number of samples	evaluation indicator	difference value (%)	P-value
retrospective data whose short-term effectiveness indicator reaches the standard	YES	B1	first short-term effectiveness indicator compliance rate Q1	Q1-Q2	P-value1
	NO	B2	second short-term effectiveness indicator compliance rate Q2		
retrospective data whose long-term complication occurs	YES	C1	first long-term complication rate P1	P1-P2	P-value2
	NO	C2	second long-term complication rate P2		

[80] In an implementation, as illustrated in FIG. 6, at S304, the difference analysis is performed on the retrospective data in the first data set and the retrospective data in the second data set, to obtain the target short-term confounding factor and the target long-term confounding factor as follows.

[81] At S601, a confounding factor to-be-analyzed is determined.

[82] The confounding factor to-be-analyzed refers to a confounding factor (or called

confounder) that needs to be analyzed this time. For example, if the retrospective data includes N confounding factors such as F1, F2, F3, ..., or Fn, a confounding factor can be randomly selected each time as the confounding factor to-be-analyzed. For example, for a glycation compliance rate of diabetes, initial glycated hemoglobin can be determined as a confounding factor to-be-analyzed.

[83] At S602, a first analysis subset corresponding to the confounding factor to-be-analyzed is selected from the retrospective data in the first data set, and a second analysis subset corresponding to the confounding factor to-be-analyzed is selected from the retrospective data in the second data set, based on the confounding factor to-be-analyzed.

[84] In this example, the CDSS can categorize in a preset categorization standard the first data set into multiple first analysis subsets corresponding to the categorization standard and the second data set into multiple second analysis subsets corresponding to the categorization standard, based on the confounding factor to-be-analyzed. The CDSS categorizes the retrospective data into a corresponding first analysis subset and a corresponding second analysis subset according to a principle that a specific value corresponding to the confounding factor to-be-analyzed in the retrospective data satisfies a corresponding categorization standard.

[85] At S603, for retrospective data in the first analysis subset and retrospective data in the second analysis subset, a short-term effectiveness indicator compliance rate and a long-term complication rate are counted respectively, and the significance test is performed, to obtain an effect analysis result, and the obtained effect analysis result is determined as a confounding analysis result corresponding to the confounding factor to-be-analyzed.

[86] It can be understood that, processes at S603 and S303 are basically the same. For the detailed implementation solutions, reference can be made to the operations at S501-S503, where the difference lies in data set, which will not be repeated herein for the sake of avoiding repetition.

[87] At S604, the target short-term confounding factor and the target long-term confounding factor are obtained according to the confounding analysis result corresponding to the confounding factor to-be-analyzed.

[88] In this example, for the retrospective data in the first analysis subset and the retrospective data in the second analysis subset, after the short-term effectiveness indicator compliance rate and the long-term complication rate are counted and the significance test is

performed, the corresponding effect analysis result is determined as the confounding analysis result corresponding to the confounding factor to-be-analyzed. According to the confounding analysis result, a confounding factor with a maximum influence on the short-term effectiveness indicator compliance rate or several confounding factors ranked front with greater influence on the short-term effectiveness indicator compliance rate is/are determined as the target short-term confounding factor(s). According to the confounding analysis result, a confounding factor with a maximum influence on the long-term complication rate or several confounding factors ranked front with greater influence on the long-term complication rate is/are determined as target long-term confounding factor(s). For example, for the glycation compliance rate, the initial glycated hemoglobin is a confounding factor with a maximum influence, and thus the initial glycated hemoglobin is determined as a target short-term confounding factor. For the complication rate, an initial complication risk is a confounding factor with a maximum influence, and thus the initial complication risk is determined as a target long-term confounding factor.

[89] In an implementation, as illustrated in FIG. 7, at S305, the propensity analysis is performed on the retrospective data in the first data set and the retrospective data in the second data set based on the target short-term confounding factor and the target long-term confounding factor, to obtain and store the target analysis result of the original medication recommendation model as follows.

[90] At S701, the first data set and the second data set are layered based on the target short-term confounding factor and the target long-term confounding factor, to obtain at least one layered data set.

[91] At S702, the propensity analysis is performed on retrospective data in each layered data set, to obtain a propensity result corresponding to each layered data set.

[92] At S703, the target analysis result of the original medication recommendation model is obtained and stored based on the propensity result corresponding to each layered data set.

[93] The at least one layered data set is formed by partitioning the first data set and the second data set according to the target short-term confounding factor and the target long-term confounding factor. As an example, when the initial glycated hemoglobin is the target short-term confounding factor, the initial glycated hemoglobin can be partitioned into three layered data sets of initial compliance, initial exceedance, and severe exceedance. In each layered data set, a short-term effectiveness indicator compliance rate conforming to model recommendation is compared

with a short-term effectiveness indicator compliance rate not conforming to model recommendation, i.e., a treat team is compared with a control team, and other confounding factors are controlled in a propensity score matching method. As such, a propensity result corresponding to each layered data set is obtained. As another example, when the initial complication risk is the target long-term confounding factor, the initial complication risk can be partitioned into three layered data sets of low risk, medium risk, and high risk. In each layered data set, a long-term complication rate conforming to model recommendation is compared with a long-term complication rate not conforming to model recommendation, i.e., a treat team is compared with a control team, and other confounding factors are controlled in the propensity score matching method. As such, a propensity result corresponding to each layered data set is obtained.

[94] In this example, after obtaining the propensity result corresponding to each layered data set, the CDSS compares the propensity result with a preset qualification evaluation threshold used for determining whether the propensity result is qualified according to the propensity result, to determine whether a corresponding layered data set is qualified. Then the CDSS counts a ratio of the number of qualified layered data sets to the total number of layered data sets, to obtain the target analysis result. Therefore, objective analysis can be performed on curative effect effectiveness of the original medication recommendation model based on short-term effect data and long-term effect data objectively existed in the retrospective data, thereby ensuring objectivity of the target analysis result.

[95] In an implementation, as illustrated in FIG. 8, at S205, the recommendation propensity type is determined based on the user profile data as follows.

[96] At S801, whether the user profile data contains an existing propensity type is determined.

[97] At S802, the existing propensity type is determined as the recommendation propensity type based on a determination that the user profile data contains the existing propensity type.

[98] At S803, based on a determination that the user profile data contains no existing propensity type, a similar crowd is determined based on the user profile data and a common propensity type corresponding to the similar crowd is determined as the recommendation propensity type, or associated webpage data is obtained based on the user profile data and feature

tags of the associated webpage data are counted, to obtain the recommendation propensity type.

[99] The existing propensity type is a type clearly indicated in the user profile data. For example, existing propensity types are configured in an entry interface of the CDSS for selection of a user, such that a corresponding propensity type can be configured by the user through the entry interface.

[100] As an example, the CDSS analyzes the user profile data with a character matching algorithm or other algorithms, and determines whether the user profile data contains the existing propensity type. If the user profile data contains the existing propensity type, the existing propensity type is directly determined as the recommendation propensity type. A feature weight of each feature to-be-analyzed in the original recommendation medication is determined based on the recommendation propensity type. As such, the target recommendation medication determined based on the finally determined recommendation evaluation value is more consistent with the user profile data, thereby facilitating to improve the pertinence and effectiveness of the target recommendation medication.

[101] As an example, the CDSS analyzes the user profile data with the character matching algorithm or other algorithms, and determines whether the user profile data contains the existing propensity type. If the user profile data contains no existing propensity type, the similar crowd is determined based on the user profile data, and the common propensity type corresponding to the similar crowd is determined as the recommendation propensity type. The similar crowd is a crowd closest or most similar to the user profile data of the patient. Specifically, the similar crowd refers to a crowd suffering from a disease corresponding to the disease type and closest or most similar to the user profile data. The similar crowd includes multiple similar users closet or most similar to the user profile data of the patient. Each similar user corresponds to a medication propensity type, and this medication propensity type refers to an existing propensity type of the similar user. The common propensity type corresponding to the similar crowd refers to a medication propensity type with a largest proportion determined by the statistics of medication propensity types of all similar users in all similar crowds.

[102] For example, the user profile data includes, but is not limited to, gender, age, address, residence, occupation, consumption habit, sports data, etc. The CDSS determines the similar crowd based on the user profile data and determines the common propensity type corresponding to the similar crowd as the recommendation propensity type as follows. (1) The CDSS performs

distance calculation on the user profile data of the patient and user profile data of any existing user stored in the system database with a distance algorithm, to obtain a similar distance corresponding to two user profile data. (2) The CDSS determines an existing user of whom the similar distance reaches a preset distance threshold as a similar user, and a similar crowd is formed based on all similar users. (3) The CDSS counts and analyzes medication propensity types of all similar users in the similar crowd, determines a medication propensity type with a largest proportion as the common propensity type, and determines the common propensity type as a recommendation propensity type of the patient. The distance algorithm includes, but is not limited to the Euclidean distance algorithm. It can be understood that, since the user profile data of the similar crowd is closest or most similar to that of the patient, accordingly, the propensity type of the similar crowd is relatively similar to that of the patient, and thus the common propensity type of the similar crowd can be determined as the recommendation propensity type of the patient.

[103] As an example, the CDSS analyzes the user profile data with the character matching algorithm or other algorithms, and determines whether the user profile data contains the existing propensity type. If the user profile data contains no existing propensity type, the associated webpage data is obtained based on the user profile data, and the feature tags of the associated webpage data are counted, to obtain the recommendation propensity type. The associated webpage data refers to content data in an associated webpage related to treatment of a disease corresponding to the disease type. The feature tags of the associated webpage data refer to tags that are related to features to-be-analyzed and pre-configured for the content data in each associated webpage, such as low cost, short curative effect time, few side effects, etc.

[104] For example, the associated webpage data is obtained based on the user profile data, and the feature tags of the associated webpage data are counted, to obtain the recommendation propensity type as follows. (1) All previous webpage data visited by a patient corresponding to identity number and/or phone number are obtained based on the identity number and/or phone number in the user profile data. (2) Previous webpage data related to the disease type in the user profile data in all previous webpage data is determined as the associated webpage data. (3) The numbers of feature tags of all associated webpage data are counted, and the recommendation propensity type is determined according to magnitude of the numbers of feature tags. It can be understood that, feature tags of each associated webpage data can be obtained with a word

segmentation tool Jieba and a term frequency-inverse document frequency (TF-IDF) algorithm. That is, the word segmentation tool Jieba is used to perform scanning, segmentation, and lexical annotation on text information in the associated webpage data, to obtain a segmentation result, and then the TF-IDF algorithm is used to perform keyword extraction on the segmentation result, to obtain the feature tags corresponding to the associated webpage data.

[105] It can be understood that, in the above implementations, a magnitude of a sequence number of each step does not mean an execution sequence. The execution sequence of each process should be determined by its function and an internal logic and should not form any limit to an implementation process of the implementations of the disclosure.

[106] In an implementation, an AI-based medication recommendation apparatus is provided, which corresponds to the AI-based medication recommendation method in the above implementations. As illustrated in FIG. 9, the AI-based medication recommendation apparatus includes a recommendation request obtaining module 901, a recommendation model determining module 902, an original recommendation medication obtaining module 903, a feature analysis value obtaining module 904, a feature weight obtaining module 905, and a target recommendation medication obtaining module 906. Each functional module is described in detail below.

[107] The recommendation request obtaining module 901 is configured to obtain a medication recommendation request, where the medication recommendation request includes a disease type, current disease data, and user profile data.

[108] The recommendation model determining module 902 is configured to obtain at least two target medication recommendation models each with a better target analysis result according to target analysis results of original medication recommendation models corresponding to the disease type.

[109] The original recommendation medication obtaining module 903 is configured to analyze the current disease data by using the at least two target medication recommendation models, and determine at least two original recommendation medications.

[110] The feature analysis value obtaining module 904 is configured to obtain feature analysis values of at least two features to-be-analyzed by performing feature analysis on each original recommendation medication.

[111] The feature weight obtaining module 905 is configured to determine a

recommendation propensity type based on the user profile data, and obtain feature weights of the at least two features to-be-analyzed according to the recommendation propensity type.

[112] The target recommendation medication obtaining module 906 is configured to obtain at least two recommendation evaluation values of the at least two original recommendation medications based on the feature analysis values and the feature weights of the at least two features to-be-analyzed, and determine an original recommendation medication with a largest recommendation evaluation value as a target recommendation medication.

[113] Preferably, the AI-based medication recommendation apparatus further includes a retrospective data obtaining module, a data categorizing module, an effect analysis result obtaining module, a confounding factor determining module, and a target analysis result obtaining module.

[114] The retrospective data obtaining module is configured to obtain retrospective data corresponding to the disease type, where the retrospective data includes previous disease data and actual medication data.

[115] The data categorizing module is configured to analyze the previous disease data by using an original medication recommendation model corresponding to the disease type to obtain previous recommendation medication data, obtain a comparison result by comparing the previous recommendation medication data with the actual medication data, and categorize, based on the comparison result, the retrospective data corresponding to the disease type into a first data set conforming to model recommendation and a second data set not conforming to model recommendation.

[116] The effect analysis result obtaining module is configured to, for retrospective data in the first data set and retrospective data in the second data set, count respectively a short-term effectiveness indicator compliance rate and a long-term complication rate, and perform a significance test, to obtain an effect analysis result.

[117] The confounding factor determining module is configured to perform difference analysis on the retrospective data in the first data set and the retrospective data in the second data set if the effect analysis result satisfies a preset analysis condition, to obtain a target short-term confounding factor and a target long-term confounding factor.

[118] The target analysis result obtaining module is configured to perform propensity analysis on the retrospective data in the first data set and the retrospective data in the second data

set based on the target short-term confounding factor and the target long-term confounding factor, to obtain and store a target analysis result of the original medication recommendation model.

[119] Preferably, the data categorizing module includes a medication type obtaining unit, a first comparison result obtaining unit, and a second comparison result obtaining unit.

[120] The medication type obtaining unit is configured to obtain at least one recommendation medication type based on the previous recommendation medication data, and obtain at least one actual medication type based on the actual medication data.

[121] The first comparison result obtaining unit is configured to determine that the comparison result is “conforming to the model recommendation” if all recommendation medication types are matched with all actual medication types.

[122] The second comparison result obtaining unit is configured to determine that the comparison result is “not conforming to the model recommendation” if at least one recommendation medication type is not matched with at least one actual medication type.

[123] Preferably, the retrospective data further includes short-term effect data and long-term effect data.

[124] The effect analysis result obtaining module includes a first indicator obtaining unit, a second indicator obtaining unit, and a significance test unit.

[125] The first indicator obtaining unit is configured to obtain a first short-term effectiveness indicator compliance rate and a first long-term complication rate based on the retrospective data in the first data set.

[126] The second indicator obtaining unit is configured to obtain a second short-term effectiveness indicator compliance rate and a second long-term complication rate based on the retrospective data in the second data set.

[127] The significance test unit is configured to perform the significance test on the first short-term effectiveness indicator compliance rate, the first long-term complication rate, the second short-term effectiveness indicator compliance rate, and the second long-term complication rate, to obtain the effect analysis result.

[128] Preferably, the confounding factor determining module includes a factor to-be-analyzed determining unit, an analysis subset categorizing unit, a confounding analysis result obtaining unit, and a target confounding factor obtaining unit.

[129] The factor to-be-analyzed determining unit is configured to determine a confounding factor to-be-analyzed.

[130] The analysis subset categorizing unit is configured to select, based on the confounding factor to-be-analyzed, from the retrospective data in the first data set a first analysis subset corresponding to the confounding factor to-be-analyzed and from the retrospective data in the second data set a second analysis subset corresponding to the confounding factor to-be-analyzed.

[131] The confounding analysis result obtaining unit is configured to, for retrospective data in the first analysis subset and retrospective data in the second analysis subset, count respectively a short-term effectiveness indicator compliance rate and a long-term complication rate, and perform the significance test, to obtain an effect analysis result, and determine the obtained effect analysis result as a confounding analysis result corresponding to the confounding factor to-be-analyzed.

[132] The target confounding factor obtaining unit is configured to obtain the target short-term confounding factor and the target long-term confounding factor according to the confounding analysis result corresponding to the confounding factor to-be-analyzed.

[133] Preferably, the target analysis result obtaining module includes a layered data set obtaining unit, a propensity result obtaining unit, and a target analysis result obtaining unit.

[134] The layered data set obtaining unit is configured to layer the first data set and the second data set based on the target short-term confounding factor and the target long-term confounding factor, to obtain at least one layered data set.

[135] The propensity result obtaining unit is configured to perform the propensity analysis on retrospective data in each layered data set, to obtain a propensity result corresponding to each layered data set.

[136] The target analysis result obtaining unit is configured to obtain and store the target analysis result of the original medication recommendation model based on the propensity result corresponding to each layered data set.

[137] Preferably, the feature weight obtaining module 905 includes an existing propensity determining unit, a first propensity type determining unit, and a second propensity type determining unit.

[138] The existing propensity determining unit is configured to determine whether the user

profile data contains an existing propensity type.

[139] The first propensity type determining unit is configured to determine the existing propensity type as the recommendation propensity type based on a determination that the user profile data contains the existing propensity type.

[140] The second propensity type determining unit is configured to determine a similar crowd based on the user profile data and determine a common propensity type corresponding to the similar crowd as the recommendation propensity type, or configured to obtain associated webpage data based on the user profile data and count feature tags of the associated webpage data to obtain the recommendation propensity type, based on a determination that the user profile data contains no existing propensity type.

[141] For specific limitations of the AI-based medication recommendation apparatus, reference can be made to the above limitations of the AI-based medication recommendation method, which will not be repeated here. Each module in the AI-based medication recommendation apparatus may be realized in whole or in part by software, hardware and their combination. Each above module may be embedded in or independent of a processor in computer device in the form of hardware, or stored in a memory in the computer device in the form of software, so that the processor may call and perform the operation corresponding to each module above.

[142] In an implementation, a computer device is provided. The computer device may be a server, and its internal structure may be illustrated in FIG. 10. The computer device includes a processor, a memory, a network interface and a database connected through a system bus. The processor of the computer device is used to provide computing and control capabilities. The memory of the computer device includes a non-volatile readable storage medium and an internal memory. The non-volatile readable storage medium stores an operating system, computer programs and a database. The internal memory provides an environment for the operation of the operating system and the computer programs in the non-volatile readable storage medium. The database of the computer device is used for storing the data adopted or generated in the AI-based medication recommendation method. The network interface of the computer device is used to communicate with an external terminal through a network connection. The computer programs, when executed by the processor, implements the AI-based medication recommendation method.

[143] In an implementation, a computer device is provided. The computer device includes a

memory, a processor and computer programs stored in the memory and capable of running on the processor. The processor, when executing the computer programs, implements the AI-based medication recommendation method, such as S201 to S206 illustrated in FIG. 2, or operations illustrated in FIG. 3 to FIG. 8, which will not be repeated herein. Alternatively, the processor, when executing the computer programs, realizes the functions of the modules/units of the AI-based medication recommendation apparatus, such as the functions of the modules as illustrated in FIG. 9. In order to avoid repetition, the above will not be described herein in detail.

[144] In an implementation, a computer-readable storage media storing computer programs is provided. The computer programs, when executed by a processor, realize the AI-based medication recommendation method such as S201 to S206 illustrated in FIG. 2, or illustrated in FIG. 3 to FIG. 8, which will not be described herein in detail in order to avoid repetition; or, the computer programs, when executed by the processor, realize the functions of the modules/units in the AI-based medication recommendation apparatus such as the functions of the modules as illustrated in FIG. 9. In order to avoid repetition, the above will not be described herein in detail.

[145] Alternatively, the above storage medium, such as the computer-readable storage media, may be non-volatile and volatile.

[146] It can be understood by those of ordinary skill in the art that all or a part of the methods of the implementations described above may be accomplished by means of computer programs to instruct associated hardware. The computer programs may be stored in a non-volatile computer-readable storage medium. The computer programs, when executed, may include flows of implementations of the various methods described above. Any reference to memory, storage, data base, or other media used in the implementations provided in this disclosure may include a non-volatile and/or a volatile memory. The non-volatile memory may include a read-only memory (ROM), a programmable ROM (PROM), an electrically PROM (EPROM), an electrically erasable PROM (EEPROM), or a flash memory. The volatile memory may include a random access memory (RAM) or an external cache. By way of example but not limitation, many forms of RAM are available, such as a static SAM (SRAM), a dynamic RAM (DRAM), a synchronous DRAM (SDRAM), a double data rate SDRAM (DDRSDRAM), an enhanced SDRAM (ESDRAM), a sync link DRAM (SLDRAM), a Rambus direct RAM (RDRAM), and a direct Rambus dynamic RAM (DRDRAM), and a Rambus dynamic RAM (RDRAM).

[147] Those skilled in the art can clearly understand that, for the sake of convenience and conciseness of description, only the division of each functional unit and module mentioned above is given as an example. In practice, the above functions can be assigned to be completed by different functional units and modules as needed, i.e., the internal structure of the apparatus is divided into different functional units or modules to perform all or part of the above described functions.

[148] The above implementations are only used for illustrating, but not limiting, the technical solutions of the disclosure. Although the disclosure is elaborated referring to the above implementations, those of ordinary skill in the art should understand that they may still modify the technical solutions in each above implementation, or equivalently replace a part of technical features. However, these modifications and replacements do not make the nature of the corresponding technical solutions depart from the spirit and scope of the technical solutions in each implementation of the disclosure, and these modifications and replacements should be included in the scope of protection of the disclosure.

What is claimed is:

1. An artificial intelligence-based (AI-based) medication recommendation method, comprising:

obtaining a medication recommendation request, the medication recommendation request comprising a disease type, current disease data, and user profile data;

obtaining at least two target medication recommendation models each with a better target analysis result according to target analysis results of original medication recommendation models corresponding to the disease type;

analyzing the current disease data by using the at least two target medication recommendation models, to determine at least two original recommendation medications;

performing feature analysis on each original recommendation medication, to obtain feature analysis values of at least two features to-be-analyzed;

determining a recommendation propensity type based on the user profile data, and obtaining feature weights of the at least two features to-be-analyzed according to the recommendation propensity type; and

obtaining at least two recommendation evaluation values of the at least two original recommendation medications based on the feature analysis values and the feature weights of the at least two features to-be-analyzed, and determining an original recommendation medication with a largest recommendation evaluation value as a target recommendation medication.

2. The method of claim 1, further comprising:

before obtaining the medication recommendation request,

obtaining retrospective data corresponding to the disease type, wherein the retrospective data comprises previous disease data and actual medication data;

analyzing the previous disease data by using an original medication recommendation model corresponding to the disease type, to obtain previous recommendation medication data, obtaining a comparison result by comparing the previous recommendation medication data with the actual medication data, and categorizing, based on the comparison result, the retrospective data corresponding to the disease type into a first data set conforming to model recommendation and a second data set not conforming to model recommendation;

for retrospective data in the first data set and retrospective data in the second data set, counting respectively a short-term effectiveness indicator compliance rate and a long-term complication rate, and performing a significance test, to obtain an effect analysis result;

performing difference analysis on the retrospective data in the first data set and the retrospective data in the second data set if the effect analysis result satisfies a preset analysis condition, to obtain a target short-term confounding factor and a target long-term confounding factor; and

performing propensity analysis on the retrospective data in the first data set and the retrospective data in the second data set based on the target short-term confounding factor and the target long-term confounding factor, to obtain and store a target analysis result of the original medication recommendation model.

3. The method of claim 2, wherein obtaining the comparison result by comparing the previous recommendation medication data with the actual medication data comprises:

obtaining at least one recommendation medication type based on the previous recommendation medication data, and obtaining at least one actual medication type based on the actual medication data;

determining that the comparison result is “conforming to the model recommendation” on condition that all recommendation medication types are matched with all actual medication types; and

determining that the comparison result is “not conforming to the model recommendation” on condition that at least one recommendation medication type is not matched with at least one actual medication type.

4. The method of claim 2, wherein

the retrospective data further comprises short-term effect data and long-term effect data; and

for the retrospective data in the first data set and the retrospective data in the second data set, counting respectively the short-term effectiveness indicator compliance rate and the long-term complication rate, and performing the significance test, to obtain the effect analysis result

comprises:

obtaining, based on the retrospective data in the first data set, a first short-term effectiveness indicator compliance rate and a first long-term complication rate;

obtaining, based on the retrospective data in the second data set, a second short-term effectiveness indicator compliance rate and a second long-term complication rate;
and

performing the significance test on the first short-term effectiveness indicator compliance rate, the first long-term complication rate, the second short-term effectiveness indicator compliance rate, and the second long-term complication rate, to obtain the effect analysis result.

5. The method of claim 2, wherein performing the difference analysis on the retrospective data in the first data set and the retrospective data in the second data set, to obtain the target short-term confounding factor and the target long-term confounding factor comprises:

determining a confounding factor to-be-analyzed;

selecting, based on the confounding factor to-be-analyzed, from the retrospective data in the first data set a first analysis subset corresponding to the confounding factor to-be-analyzed and from the retrospective data in the second data set a second analysis subset corresponding to the confounding factor to-be-analyzed;

for retrospective data in the first analysis subset and retrospective data in the second analysis subset, counting respectively a short-term effectiveness indicator compliance rate and a long-term complication rate, and performing the significance test, to obtain an effect analysis result, and determining the obtained effect analysis result as a confounding analysis result corresponding to the confounding factor to-be-analyzed; and

obtaining, according to the confounding analysis result corresponding to the confounding factor to-be-analyzed, the target short-term confounding factor and the target long-term confounding factor.

6. The method of claim 2, wherein performing the propensity analysis on the retrospective data in the first data set and the retrospective data in the second data set based on the target short-term confounding factor and the target long-term confounding factor, to obtain and store the

target analysis result of the original medication recommendation model comprises:

- layering, based on the target short-term confounding factor and the target long-term confounding factor, the first data set and the second data set, to obtain at least one layered data set;

- performing the propensity analysis on retrospective data in each layered data set, to obtain a propensity result corresponding to each layered data set; and

- obtaining and storing, based on the propensity result corresponding to each layered data set, the target analysis result of the original medication recommendation model.

7. The method of claim 1, wherein determining the recommendation propensity type based on the user profile data comprises:

- determining whether the user profile data contains an existing propensity type; and

- determining the existing propensity type as the recommendation propensity type based on a determination that the user profile data contains the existing propensity type; or

- based on a determination that the user profile data contains no existing propensity type:

- determining a similar crowd based on the user profile data, and determining a common propensity type corresponding to the similar crowd as the recommendation propensity type; or

- obtaining associated webpage data based on the user profile data, and counting feature tags of the associated webpage data, to obtain the recommendation propensity type.

8. An artificial intelligence-based (AI-based) medication recommendation apparatus, comprising:

- a recommendation request obtaining module configured to obtain a medication recommendation request, the medication recommendation request comprising a disease type, current disease data, and user profile data;

- a recommendation model determining module configured to obtain at least two target medication recommendation models each with a better target analysis result according to target analysis results of original medication recommendation models corresponding to the disease type;

an original recommendation medication obtaining module configured to analyze the current disease data by using the at least two target medication recommendation models, and determine at least two original recommendation medications;

a feature analysis value obtaining module configured to obtain feature analysis values of at least two features to-be-analyzed by performing feature analysis on each original recommendation medication;

a feature weight obtaining module configured to determine a recommendation propensity type based on the user profile data, and obtain feature weights of the at least two features to-be-analyzed according to the recommendation propensity type; and

a target recommendation medication obtaining module configured to obtain at least two recommendation evaluation values of the at least two original recommendation medications based on the feature analysis values and the feature weights of the at least two features to-be-analyzed, and determine an original recommendation medication with a largest recommendation evaluation value as a target recommendation medication.

9. A computer device, comprising:

a memory;

a processor; and

a computer program stored in the memory and executable on the processor, wherein when executing the computer program, the processor implements:

obtaining a medication recommendation request, the medication recommendation request comprising a disease type, current disease data, and user profile data;

obtaining at least two target medication recommendation models each with a better target analysis result according to target analysis results of original medication recommendation models corresponding to the disease type;

analyzing the current disease data by using the at least two target medication recommendation models, to determine at least two original recommendation medications;

performing feature analysis on each original recommendation medication, to obtain feature analysis values of at least two features to-be-analyzed;

determining a recommendation propensity type based on the user profile data, and obtaining feature weights of the at least two features to-be-analyzed according to the

recommendation propensity type; and

obtaining at least two recommendation evaluation values of the at least two original recommendation medications based on the feature analysis values and the feature weights of the at least two features to-be-analyzed, and determining an original recommendation medication with a largest recommendation evaluation value to be a target recommendation medication.

10. The computer device of claim 9, wherein when executing the computer programs, the processor further implements:

before obtaining the medication recommendation request,

obtaining retrospective data corresponding to the disease type comprising previous disease data and actual medication data;

analyzing the previous disease data by using an original medication recommendation model corresponding to the disease type, to obtain previous recommendation medication data, obtaining a comparison result by comparing the previous recommendation medication data with the actual medication data, and categorizing, based on the comparison result, the retrospective data corresponding to the disease type into a first data set conforming to model recommendation and a second data set not conforming to model recommendation;

for retrospective data in the first data set and retrospective data in the second data set, counting respectively a short-term effectiveness indicator compliance rate and a long-term complication rate, and performing a significance test, to obtain an effect analysis result;

performing difference analysis on the retrospective data in the first data set and the retrospective data in the second data set if the effect analysis result satisfies a preset analysis condition, to obtain a target short-term confounding factor and a target long-term confounding factor; and

performing propensity analysis on the retrospective data in the first data set and the retrospective data in the second data set based on the target short-term confounding factor and the target long-term confounding factor, to obtain and store a target analysis result of the original medication recommendation model.

11. The computer device of claim 10, wherein the processor implementing obtaining the comparison result by comparing the previous recommendation medication data with the actual medication data implements:

obtaining at least one recommendation medication type based on the previous recommendation medication data, and obtaining at least one actual medication type based on the actual medication data;

determining that the comparison result is “conforming to the model recommendation” on condition that all recommendation medication types are matched with all actual medication types; and

determining that the comparison result is “not conforming to the model recommendation” on condition that at least one recommendation medication type is not matched with at least one actual medication type.

12. The computer device of claim 10, wherein

the retrospective data further comprises short-term effect data and long-term effect data; and

the processor implementing for the retrospective data in the first data set and the retrospective data in the second data set, counting respectively the short-term effectiveness indicator compliance rate and the long-term complication rate, and performing the significance test, to obtain the effect analysis result implements:

obtaining, based on the retrospective data in the first data set, a first short-term effectiveness indicator compliance rate and a first long-term complication rate;

obtaining, based on the retrospective data in the second data set, a second short-term effectiveness indicator compliance rate and a second long-term complication rate; and

performing the significance test on the first short-term effectiveness indicator compliance rate, the first long-term complication rate, the second short-term effectiveness indicator compliance rate, and the second long-term complication rate, to obtain the effect analysis result.

13. The computer device of claim 10, wherein the processor implementing performing the difference analysis on the retrospective data in the first data set and the retrospective data in the second data set, to obtain the target short-term confounding factor and the target long-term confounding factor implements:

determining a confounding factor to-be-analyzed;

selecting, based on the confounding factor to-be-analyzed, from the retrospective data in the first data set a first analysis subset corresponding to the confounding factor to-be-analyzed and from the retrospective data in the second data set a second analysis subset corresponding to the confounding factor to-be-analyzed;

for retrospective data in the first analysis subset and retrospective data in the second analysis subset, counting respectively a short-term effectiveness indicator compliance rate and a long-term complication rate, and performing the significance test, to obtain an effect analysis result, and determining the obtained effect analysis result as a confounding analysis result corresponding to the confounding factor to-be-analyzed; and

obtaining, according to the confounding analysis result corresponding to the confounding factor to-be-analyzed, the target short-term confounding factor and the target long-term confounding factor.

14. The computer device of claim 10, wherein the processor implementing performing the propensity analysis on the retrospective data in the first data set and the retrospective data in the second data set, based on the target short-term confounding factor and the target long-term confounding factor, to obtain and store the target analysis result of the original medication recommendation model implements:

layering, based on the target short-term confounding factor and the target long-term confounding factor, the first data set and the second data set, to obtain at least one layered data set;

performing the propensity analysis on retrospective data in each layered data set, to obtain a propensity result corresponding to each layered data set; and

obtaining and storing, based on the propensity result corresponding to each layered data set, the target analysis result of the original medication recommendation model.

15. The computer device of claim 9, wherein the processor implementing determining the recommendation propensity type based on the user profile data implements:
- determining whether the user profile data contains an existing propensity type; and
 - determining the existing propensity type as the recommendation propensity type based on a determination that the user profile data contains the existing propensity type; or
 - based on a determination that the user profile data contains no existing propensity type:
 - determining a similar crowd based on the user profile data, and determining a common propensity type corresponding to the similar crowd as the recommendation propensity type; or
 - obtaining associated webpage data based on the user profile data, and counting feature tags of the associated webpage data, to obtain the recommendation propensity type.
16. A computer readable storage medium configured to store a computer program, wherein when executed by a processor, the computer program causes the processor to implement:
- obtaining a medication recommendation request, the medication recommendation request comprising a disease type, current disease data, and user profile data;
 - obtaining at least two target medication recommendation models each with a better target analysis result according to target analysis results of original medication recommendation models corresponding to the disease type;
 - analyzing the current disease data by using the at least two target medication recommendation models, to determine at least two original recommendation medications;
 - performing feature analysis on each original recommendation medication, to obtain feature analysis values of at least two features to-be-analyzed;
 - determining a recommendation propensity type based on the user profile data, and obtaining feature weights of the at least two features to-be-analyzed according to the recommendation propensity type; and
 - obtaining at least two recommendation evaluation values of the at least two original recommendation medications based on the feature analysis values and the feature weights of the at least two features to-be-analyzed, and determining an original recommendation medication with a largest recommendation evaluation value as a target recommendation medication.

17. The computer readable storage medium of claim 16, wherein when executed by the processor, the computer program further causes the processor to implement:

before obtaining the medication recommendation request,

obtaining retrospective data corresponding to the disease type comprising previous disease data and actual medication data;

analyzing the previous disease data by using an original medication recommendation model corresponding to the disease type, to obtain previous recommendation medication data, obtaining a comparison result by comparing the previous recommendation medication data with the actual medication data, and categorizing, based on the comparison result, the retrospective data corresponding to the disease type into a first data set conforming to model recommendation and a second data set not conforming to model recommendation;

for retrospective data in the first data set and retrospective data in the second data set, counting respectively a short-term effectiveness indicator compliance rate and a long-term complication rate, and performing a significance test, to obtain an effect analysis result;

performing difference analysis on the retrospective data in the first data set and the retrospective data in the second data set if the effect analysis result satisfies a preset analysis condition, to obtain a target short-term confounding factor and a target long-term confounding factor; and

performing propensity analysis on the retrospective data in the first data set and the retrospective data in the second data set based on the target short-term confounding factor and the target long-term confounding factor, to obtain and store a target analysis result of the original medication recommendation model.

18. The computer readable storage medium of claim 17, wherein the retrospective data further comprises short-term effect data and long-term effect data; and

the computer program causing the processor to implement: for the retrospective data in the first data set and the retrospective data in the second data set, counting respectively the short-

term effectiveness indicator compliance rate and the long-term complication rate, and performing the significance test, to obtain the effect analysis result causes the processor to implement:

- obtaining, based on the retrospective data in the first data set, a first short-term effectiveness indicator compliance rate and a first long-term complication rate;

- obtaining, based on the retrospective data in the second data set, a second short-term effectiveness indicator compliance rate and a second long-term complication rate;
- and

- performing the significance test on the first short-term effectiveness indicator compliance rate, the first long-term complication rate, the second short-term effectiveness indicator compliance rate, and the second long-term complication rate, to obtain the effect analysis result.

19. The computer readable storage medium of claim 17, wherein the computer program causing the processor to implement performing the propensity analysis on the retrospective data in the first data set and the retrospective data in the second data set based on the target short-term confounding factor and the target long-term confounding factor, to obtain and store the target analysis result of the original medication recommendation model causes the processor to implement:

- layering, based on the target short-term confounding factor and the target long-term confounding factor, the first data set and the second data set, to obtain at least one layered data set;

- performing the propensity analysis on retrospective data in each layered data set, to obtain a propensity result corresponding to each layered data set; and

- obtaining and storing, based on the propensity result corresponding to each layered data set, the target analysis result of the original medication recommendation model.

20. The computer readable storage medium of claim 16, wherein the computer program causing the processor to implement determining the recommendation propensity type based on the user profile data causes the processor to implement:

- determining whether the user profile data contains an existing propensity type; and

- determining the existing propensity type as the recommendation propensity type based on

a determination that the user profile data contains the existing propensity type; or

based on a determination that the user profile data contains no existing propensity type:

determining a similar crowd based on the user profile data, and determining a common propensity type corresponding to the similar crowd as the recommendation propensity type; or

obtaining associated webpage data based on the user profile data, and counting feature tags of the associated webpage data, to obtain the recommendation propensity type.