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(54) **COLLATION APPARATUS, COLLATION METHOD, AND COLLATION PROGRAM**

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(57) **ABSTRACT**

An object of the invention is to improve reliability of an annotation. A collation apparatus includes: a grouping processing unit configured to group, based on each explanatory variable of a sample group, the sample group into a first group indicating a first classification and a second group indicating a second classification having a lower evaluation than the first classification; a collation unit configured to collate the classification of the first group and the second group that are obtained by the grouping processing unit with a classification identified by each objective variable of the sample group; and an output unit configured to output a collation result obtained by the collation unit.

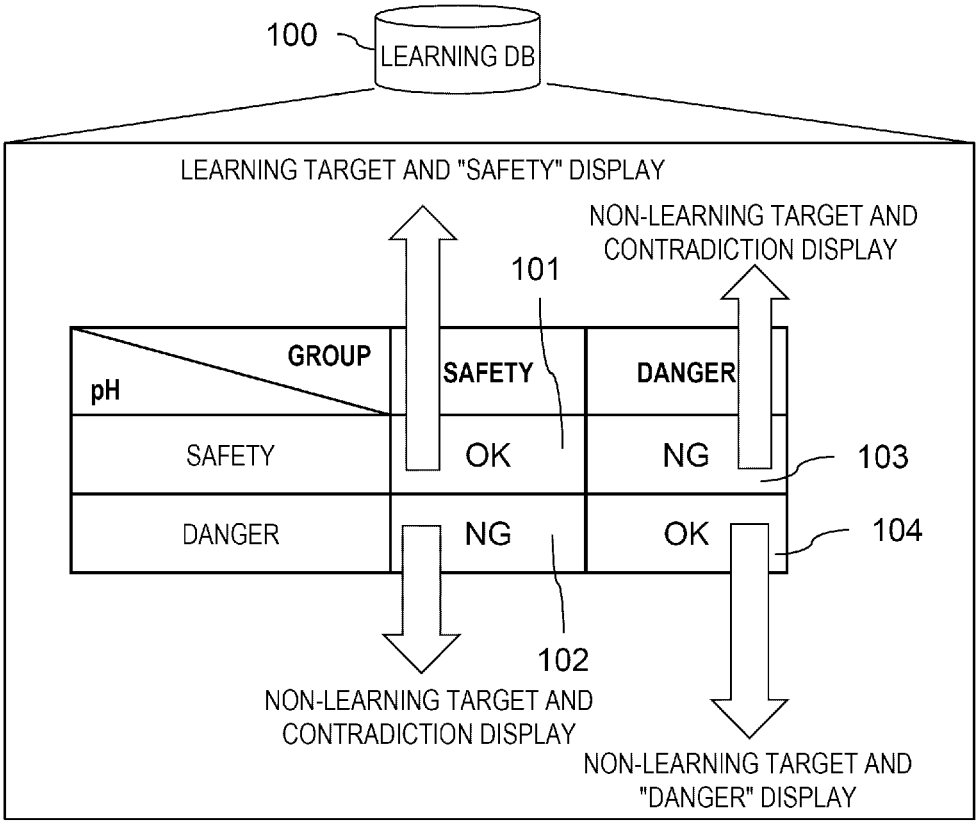


FIG. 1

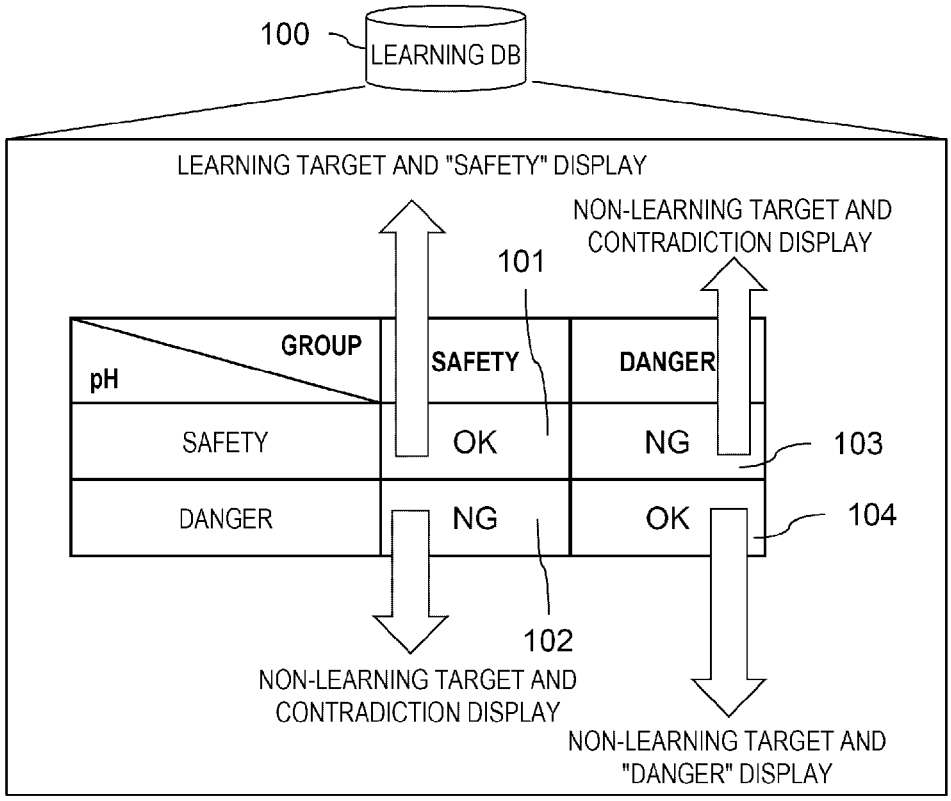

100
LEARNING DB
LEARNING TARGET AND "SAFETY" DISPLAY
NON-LEARNING TARGET AND CONTRADICTION DISPLAY
101
GROUP
pH
SAFETY
DANGER
SAFETY
OK
NG
103
DANGER
NG
OK
104
102
NON-LEARNING TARGET AND CONTRADICTION DISPLAY
NON-LEARNING TARGET AND "DANGER" DISPLAY

FIG. 2

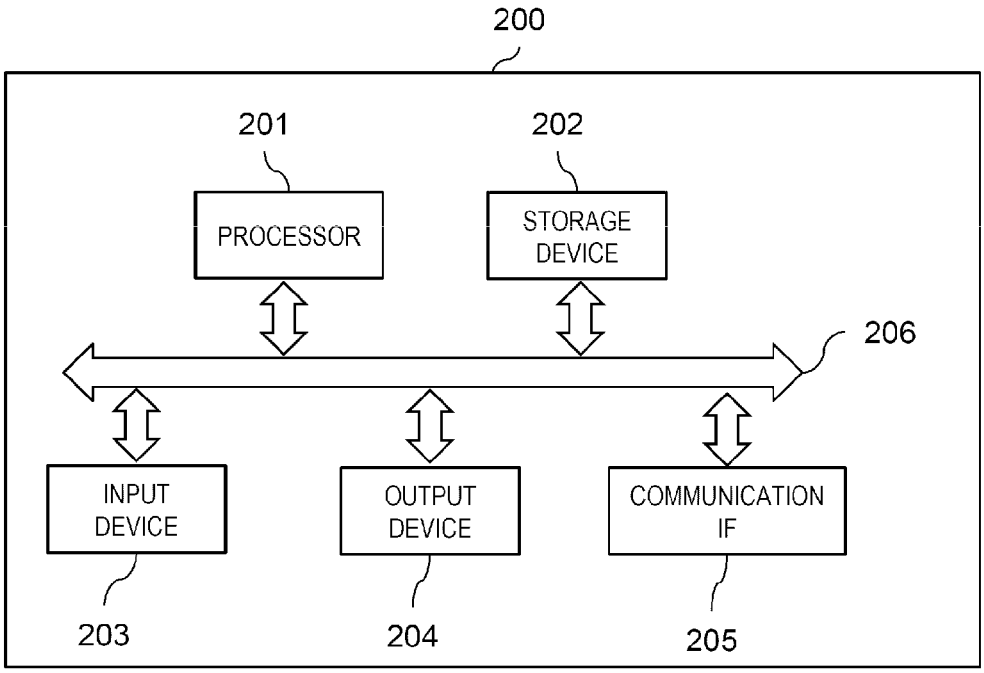
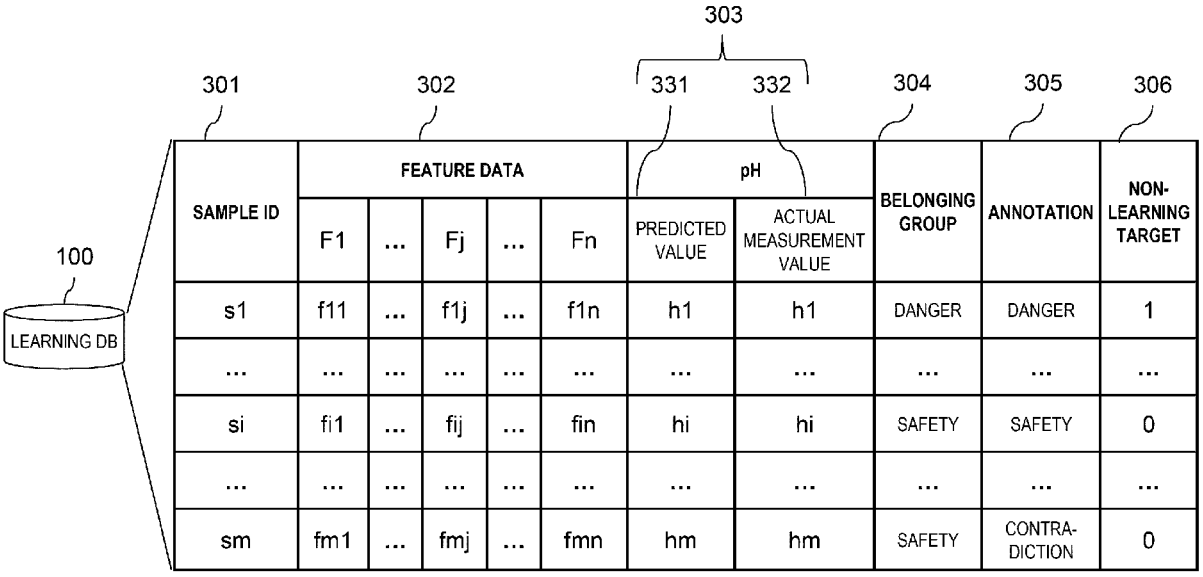
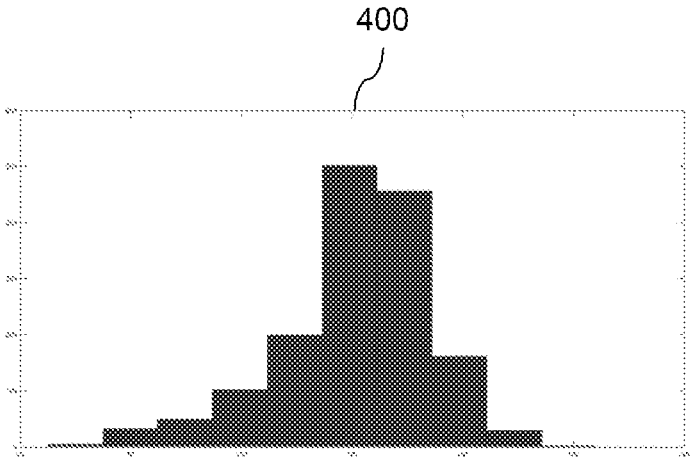

200
201
202
PROCESSOR
STORAGE DEVICE
206
INPUT DEVICE
OUTPUT DEVICE
COMMUNICATION IF
203
204
205

FIG. 3



SAMPLE ID	FEATURE DATA					pH		BELONGING GROUP	ANNOTATION	NON-LEARNING TARGET
	F1	...	Fj	...	Fn	PREDICTED VALUE	ACTUAL MEASUREMENT VALUE			
s1	f11	...	f1j	...	f1n	h1	h1	DANGER	DANGER	1
...	...	...	...	...	...	...	...	...	...	...
si	fi1	...	fij	...	fin	hi	hi	SAFETY	SAFETY	0
...	...	...	...	...	...	...	...	...	...	...
sm	fm1	...	fmj	...	fmn	hm	hm	SAFETY	CONTRA-DICTION	0

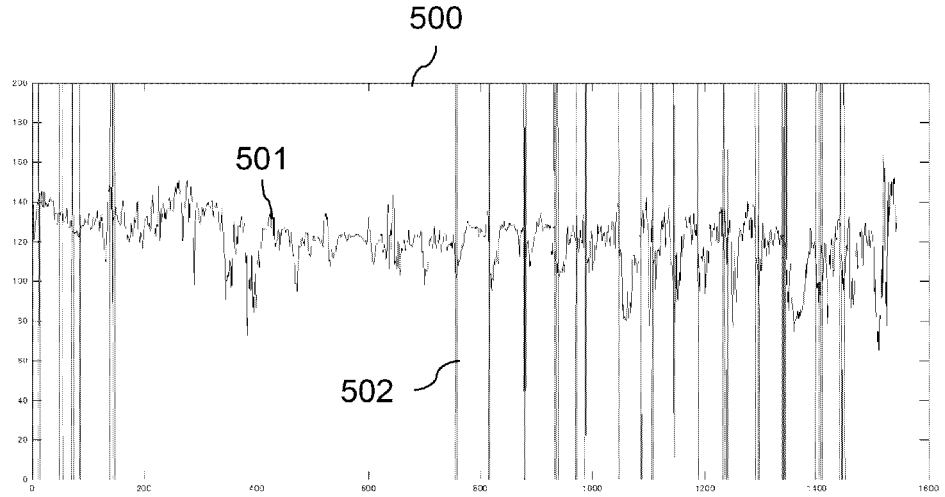
FIG. 4



histogram mode
histogram AVERAGE
Histogram MEDIAN VALUE
Histogram VARIANCE
histogram width
low frequency
histogram tendency

FIG. 5

EXAMPLE OF WAVEFORMS



baseline
WAVEFORM MAXIMUM VALUE
WAVEFORM MINIMUM VALUE
WAVEFORM AVERAGE VALUE
WAVEFORM MEDIAN VALUE
WAVEFORM VARIANCE
PROPORTION OF LABOR

THE NUMBER OF TIMES FETAL HEART RATE DROPS TO 80 OR LESS
THE NUMBER OF TIMES FETAL HEART RATE DROPS FROM baseline BY 30 OR MORE
DURATION OF FETAL HEART RATE DROPPING TO 80 OR LESS
DURATION OF FETAL HEART RATE DROPPING FROM baseline BY 30 OR MORE
TIME FROM THE LOWEST FETAL HEART RATE TO BIRTH

FIG. 6

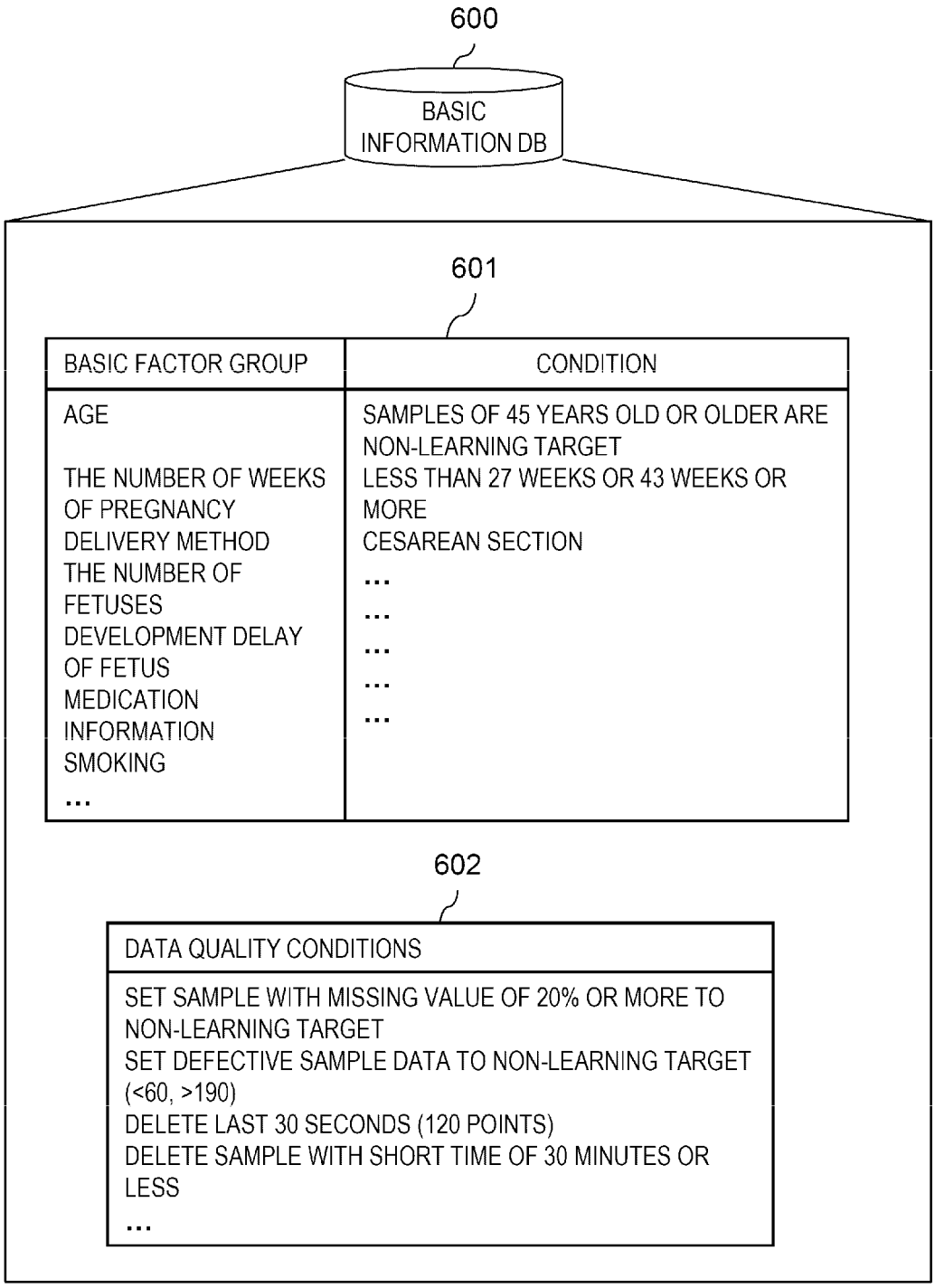

600
BASIC INFORMATION DB
601
BASIC FACTOR GROUP
CONDITION
AGE
SAMPLES OF 45 YEARS OLD OR OLDER ARE NON-LEARNING TARGET
THE NUMBER OF WEEKS OF PREGNANCY
LESS THAN 27 WEEKS OR 43 WEEKS OR MORE
DELIVERY METHOD
CESAREAN SECTION
THE NUMBER OF FETUSES
DEVELOPMENT DELAY OF FETUS
MEDICATION INFORMATION
SMOKING
...
602
DATA QUALITY CONDITIONS
SET SAMPLE WITH MISSING VALUE OF 20% OR MORE TO NON-LEARNING TARGET
SET DEFECTIVE SAMPLE DATA TO NON-LEARNING TARGET (<60, >190)
DELETE LAST 30 SECONDS (120 POINTS)
DELETE SAMPLE WITH SHORT TIME OF 30 MINUTES OR LESS
...

FIG. 7

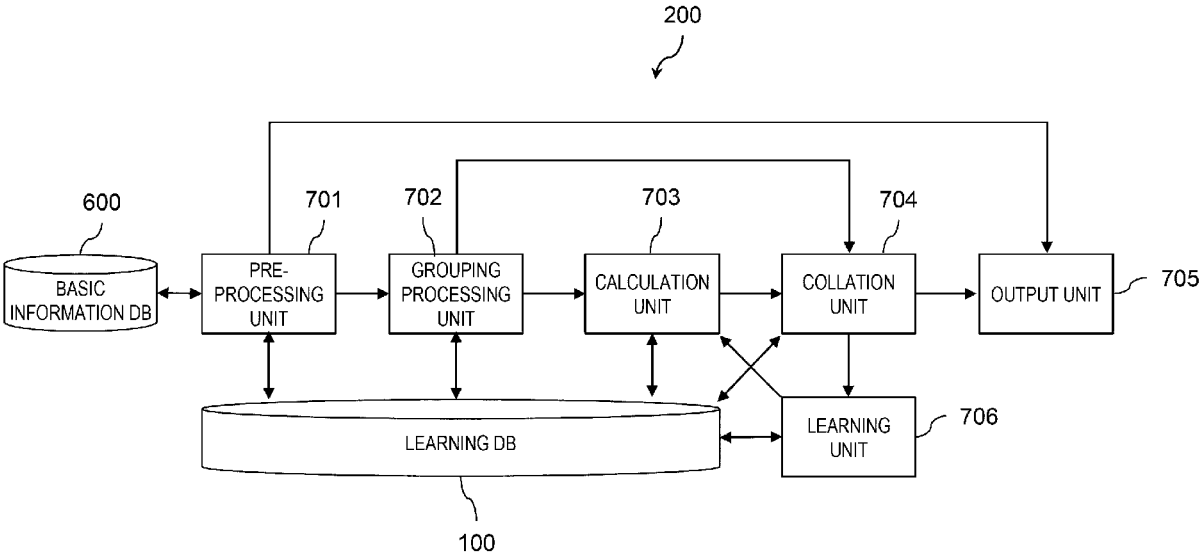

200
600
701
702
703
704
705
706
BASIC INFORMATION DB
PRE-PROCESSING UNIT
GROUPING PROCESSING UNIT
CALCULATION UNIT
COLLATION UNIT
OUTPUT UNIT
LEARNING DB
LEARNING UNIT
100

FIG. 8

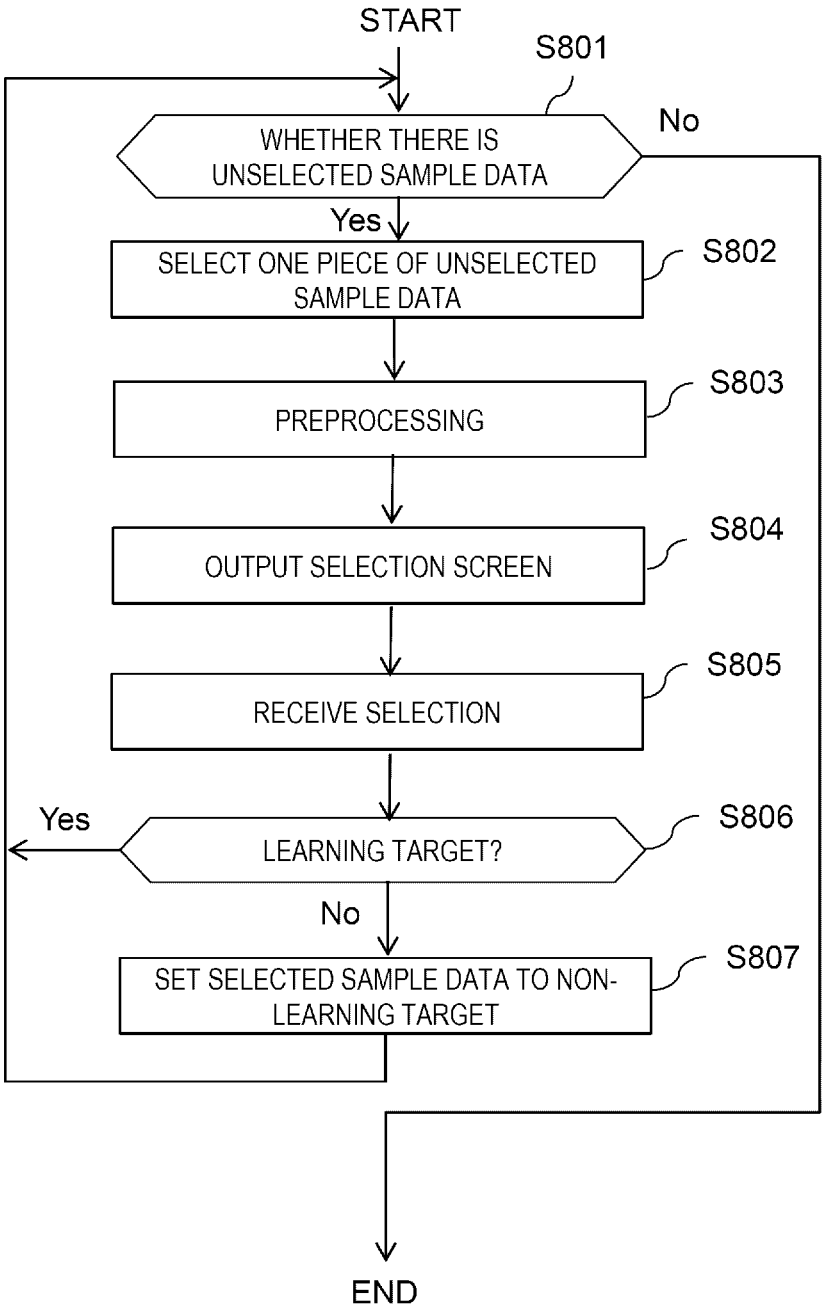

START
S801
WHETHER THERE IS UNSELECTED SAMPLE DATA
No
Yes
SELECT ONE PIECE OF UNSELECTED SAMPLE DATA
S802
PREPROCESSING
S803
OUTPUT SELECTION SCREEN
S804
RECEIVE SELECTION
S805
Yes
LEARNING TARGET?
S806
No
SET SELECTED SAMPLE DATA TO NON-LEARNING TARGET
S807
END

FIG. 9

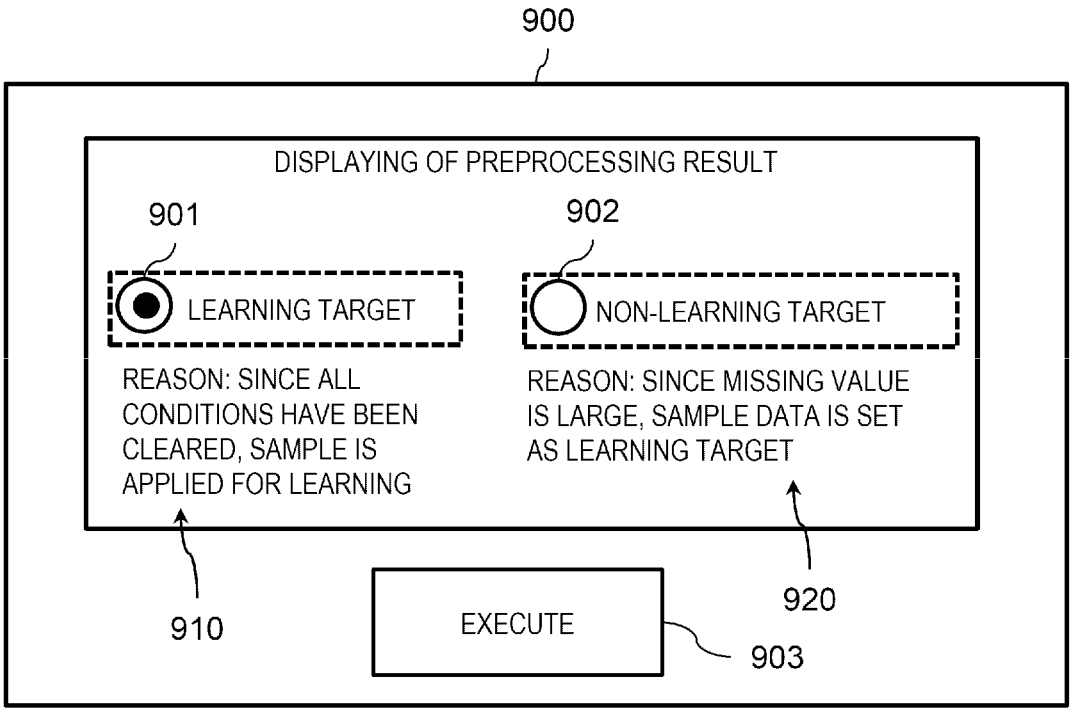

900
DISPLAYING OF PREPROCESSING RESULT
901
902
LEARNING TARGET
NON-LEARNING TARGET
REASON: SINCE ALL CONDITIONS HAVE BEEN CLEARED, SAMPLE IS APPLIED FOR LEARNING
REASON: SINCE MISSING VALUE IS LARGE, SAMPLE DATA IS SET AS LEARNING TARGET
910
920
EXECUTE
903

FIG. 10

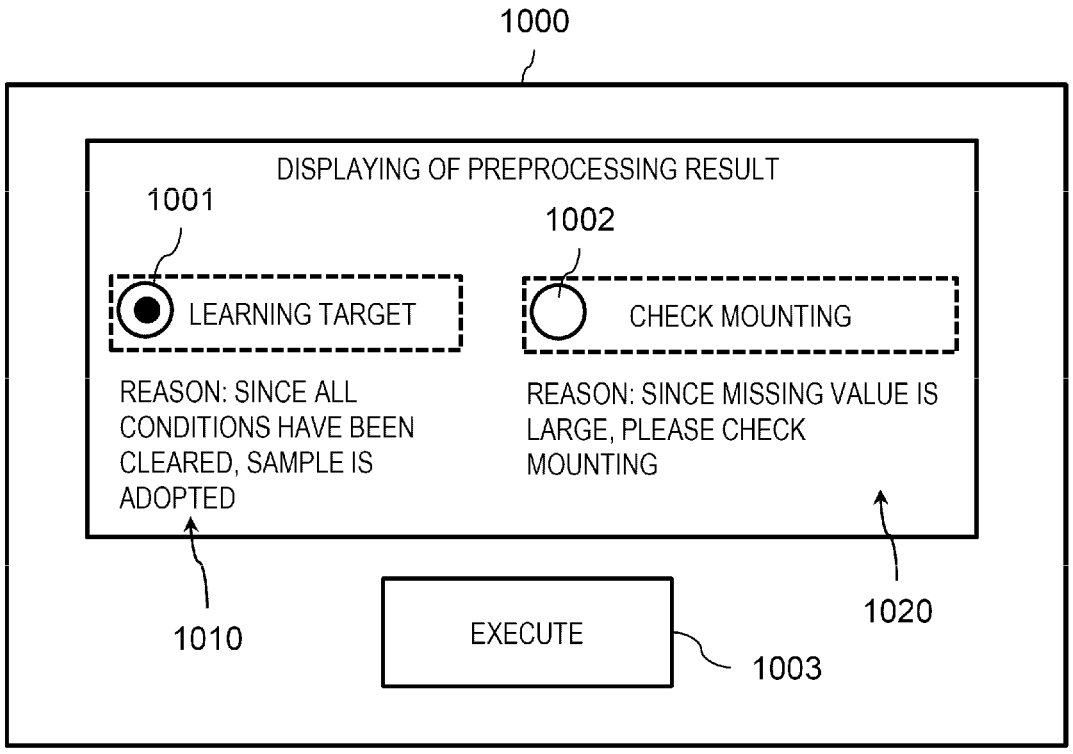

1000
DISPLAYING OF PREPROCESSING RESULT
1001
1002
LEARNING TARGET
CHECK MOUNTING
REASON: SINCE ALL CONDITIONS HAVE BEEN CLEARED, SAMPLE IS ADOPTED
REASON: SINCE MISSING VALUE IS LARGE, PLEASE CHECK MOUNTING
1010
1020
EXECUTE
1003

FIG. 11

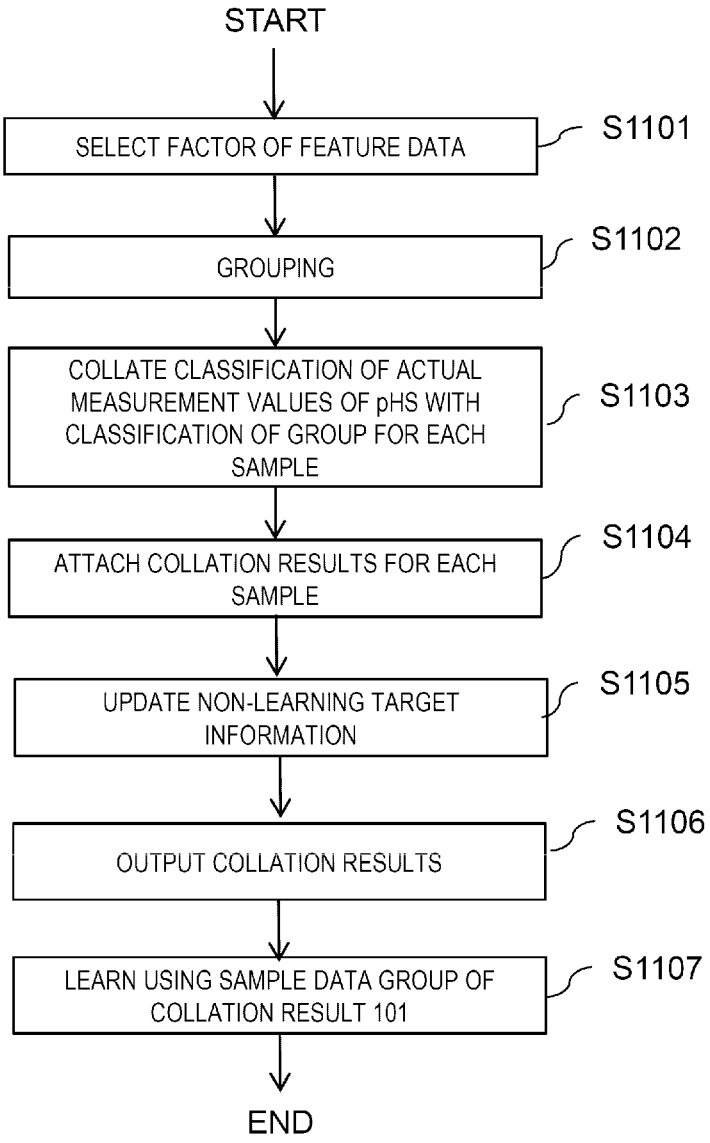

START
SELECT FACTOR OF FEATURE DATA
S1101
GROUPING
S1102
COLLATE CLASSIFICATION OF ACTUAL MEASUREMENT VALUES OF pHS WITH CLASSIFICATION OF GROUP FOR EACH SAMPLE
S1103
ATTACH COLLATION RESULTS FOR EACH SAMPLE
S1104
UPDATE NON-LEARNING TARGET INFORMATION
S1105
OUTPUT COLLATION RESULTS
S1106
LEARN USING SAMPLE DATA GROUP OF COLLATION RESULT 101
S1107
END

FIG. 12

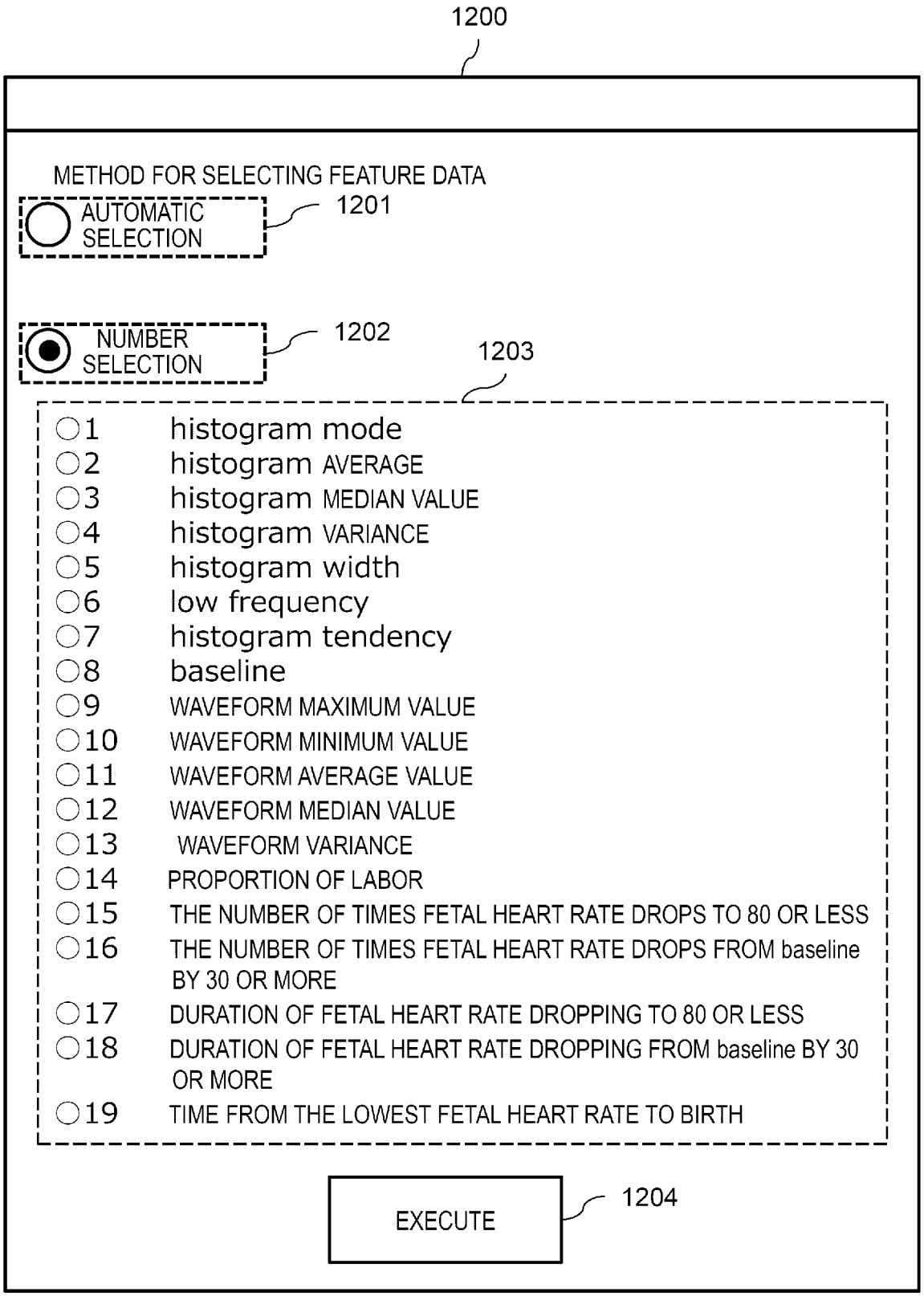

1200
METHOD FOR SELECTING FEATURE DATA
AUTOMATIC SELECTION
1201
NUMBER SELECTION
1202
1203
1 histogram mode
2 histogram AVERAGE
3 histogram MEDIAN VALUE
4 histogram VARIANCE
5 histogram width
6 low frequency
7 histogram tendency
8 baseline
9 WAVEFORM MAXIMUM VALUE
10 WAVEFORM MINIMUM VALUE
11 WAVEFORM AVERAGE VALUE
12 WAVEFORM MEDIAN VALUE
13 WAVEFORM VARIANCE
14 PROPORTION OF LABOR
15 THE NUMBER OF TIMES FETAL HEART RATE DROPS TO 80 OR LESS
16 THE NUMBER OF TIMES FETAL HEART RATE DROPS FROM baseline BY 30 OR MORE
17 DURATION OF FETAL HEART RATE DROPPING TO 80 OR LESS
18 DURATION OF FETAL HEART RATE DROPPING FROM baseline BY 30 OR MORE
19 TIME FROM THE LOWEST FETAL HEART RATE TO BIRTH
EXECUTE
1204

FIG. 13

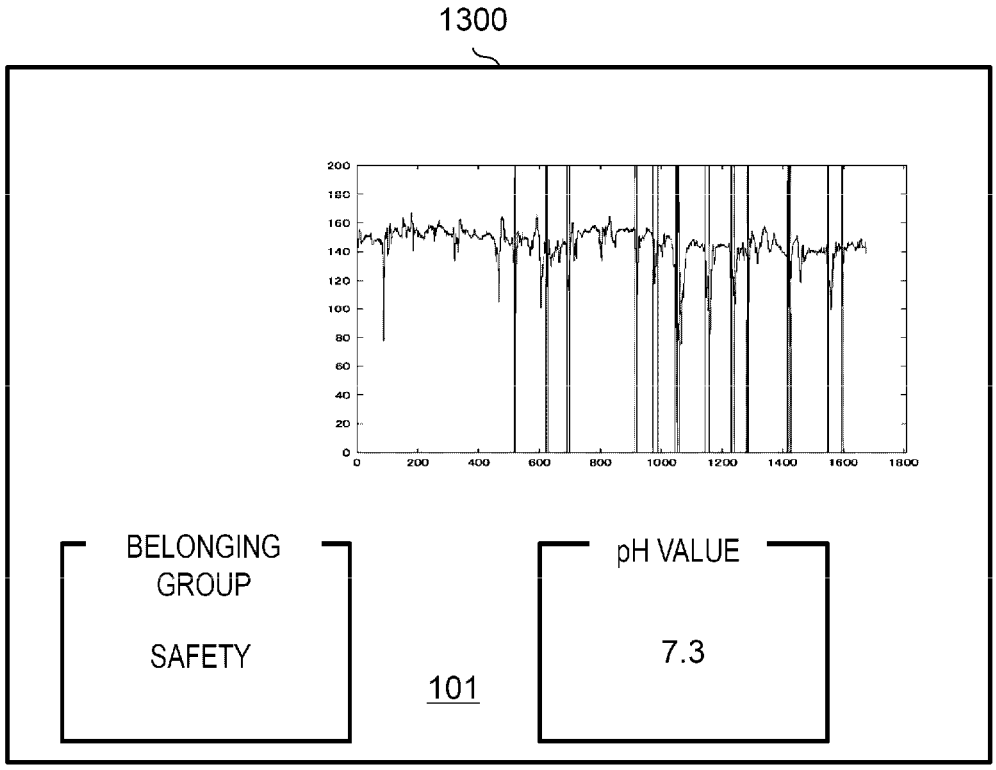

1300
200
180
160
140
120
100
80
60
40
20
0
0
200
400
600
800
1000
1200
1400
1600
1800
BELONGING GROUP
SAFETY
101
pH VALUE
7.3

FIG. 14

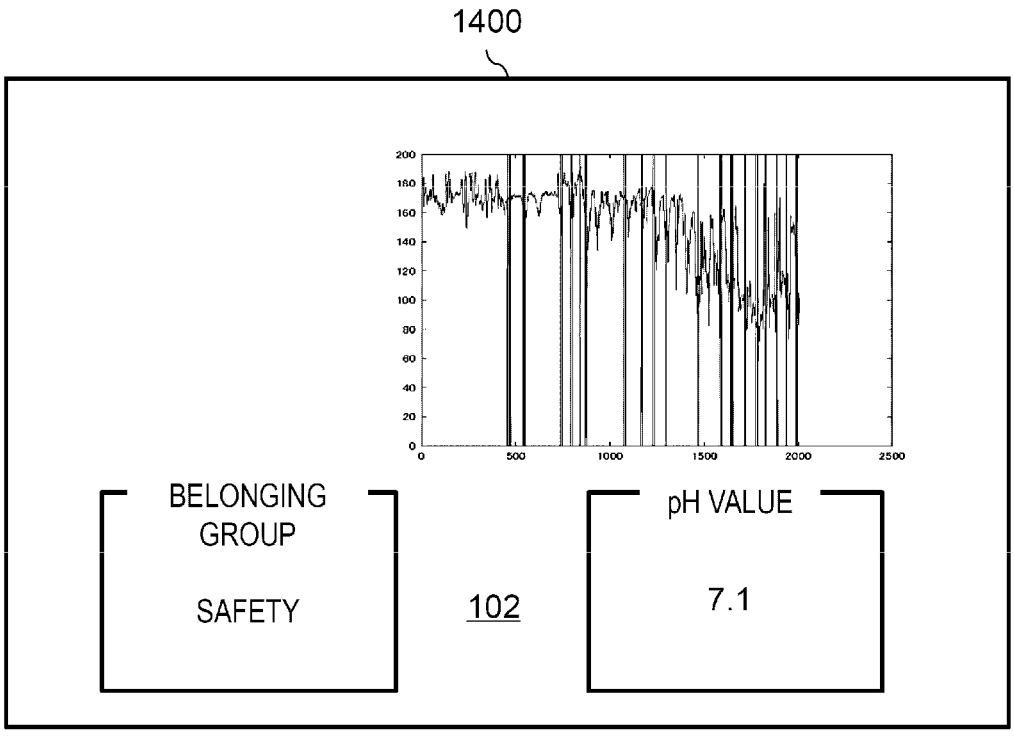

1400
200
180
160
140
120
100
80
60
40
20
0
0
500
1000
1500
2000
2500
BELONGING GROUP
SAFETY
102
pH VALUE
7.1

FIG. 15

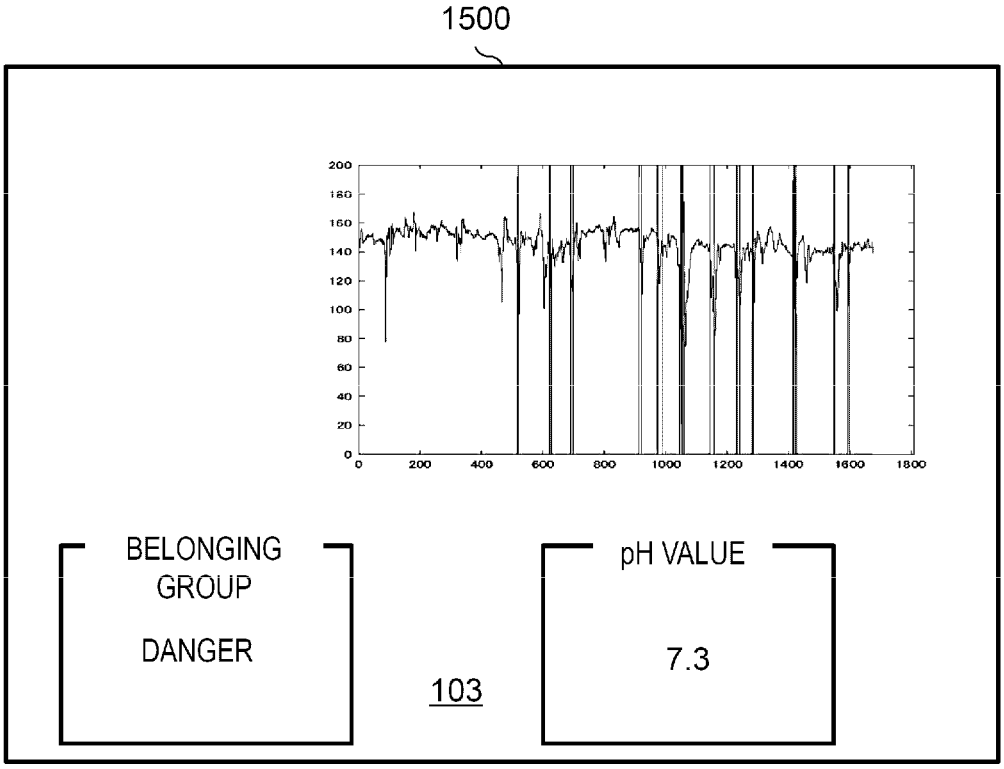

1500
200
180
160
140
120
100
80
60
40
20
0
0
200
400
600
800
1000
1200
1400
1600
1800
BELONGING GROUP
DANGER
103
pH VALUE
7.3

FIG. 16

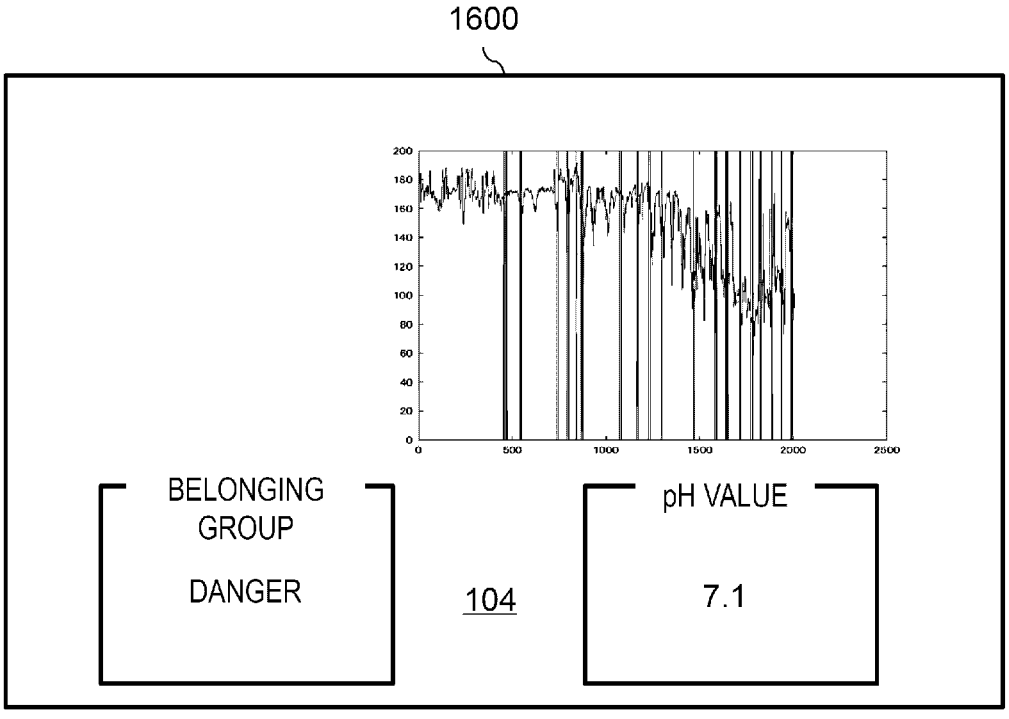
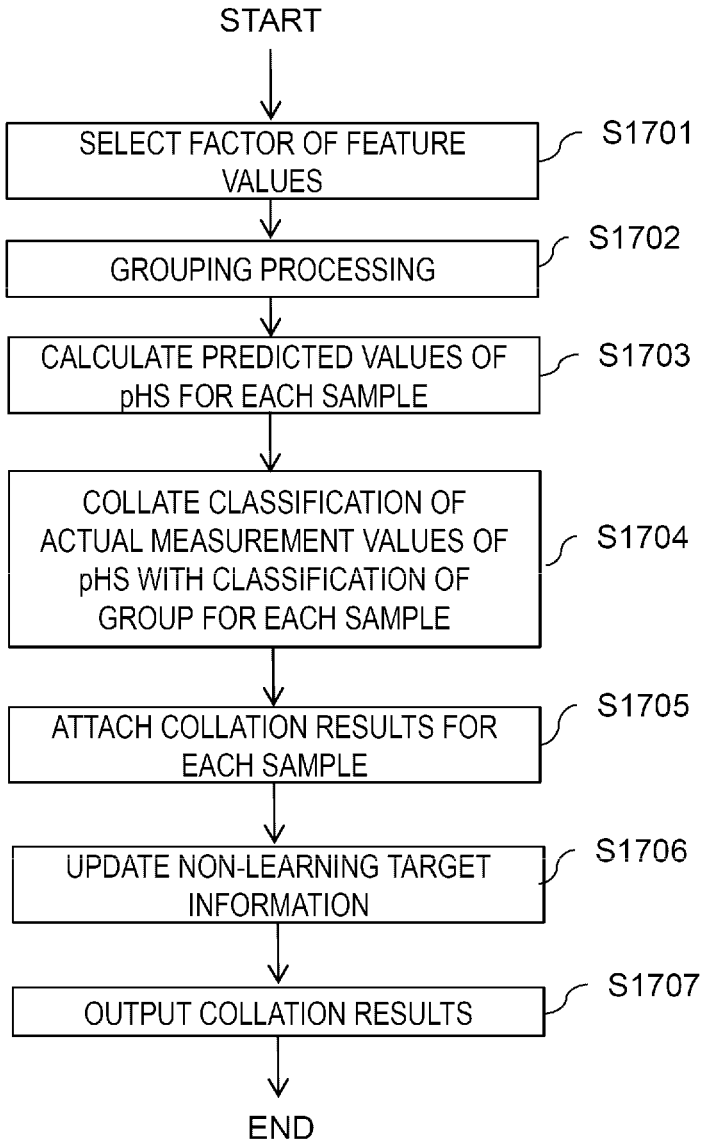

1600
200
180
160
140
120
100
80
60
40
20
0
0
500
1000
1500
2000
2500
BELONGING GROUP
DANGER
104
pH VALUE
7.1

FIG. 17


START
SELECT FACTOR OF FEATURE VALUES
S1701
GROUPING PROCESSING
S1702
CALCULATE PREDICTED VALUES OF pHS FOR EACH SAMPLE
S1703
COLLATE CLASSIFICATION OF ACTUAL MEASUREMENT VALUES OF pHS WITH CLASSIFICATION OF GROUP FOR EACH SAMPLE
S1704
ATTACH COLLATION RESULTS FOR EACH SAMPLE
S1705
UPDATE NON-LEARNING TARGET INFORMATION
S1706
OUTPUT COLLATION RESULTS
S1707
END

COLLATION APPARATUS, COLLATION METHOD, AND COLLATION PROGRAM

CLAIM OF PRIORITY

[0001] The present application claims priority from Japanese patent application JP 2022-015123 filed on Feb. 2, 2022, the content of which is hereby incorporated by reference into this application.

BACKGROUND OF THE INVENTION

1. Field of the Invention

[0002] The present invention relates to a collation apparatus, a collation method, and a collation program for collating data.

2. Description of the Related Art

[0003] Cardio toco gram (CTG) is a waveform showing temporal changes in fetal heart rate and a tocogram (uterine contraction) obtained from a fetal heart rate monitor and an external tocodynamometer, respectively, and is used to evaluate well-being of a fetus. The CTG is an essential test for evaluating the fetus during delivery. The CTG is useful for early detection of low oxygen and acidosis of the fetus that may occur during delivery, and for reducing hypoxic encephalopathy and cerebral palsy in an unborn fetus.

[0004] A doctor performs an evaluation of the CTG according to a level classification in which an evaluation is executed based on a baseline of a fetal heart rate and a pattern of bradycardia. However, the waveform of the CTG is complicated and depends on experiences of a medical worker who makes a determination. Ramanujam, E., et al. "Prediction of Fetal Distress Using Linear and Non-linear Features of CTG Signals." International Conference On Computational Vision and Bio Inspired Computing. Springer, Cham, 2019 (Non-Patent Literature 1) discloses a technique for predicting a fetal state based on a fetal heart rate signal.

[0005] However, a prediction method presented in Non-Patent Literature 1 described above is a technique of predicting a fetal state by extracting feature data from waveforms of the fetal heart rate and the uterine contraction using annotated data of a doctor, and the method requires well-organized annotated data. Since an annotation of data depends on experiences of the doctor, there is a variation in reliability. In addition, the annotation performed by the doctor can be only classified into several categories (for example, safety or danger), and a pH value cannot be predicted according to the annotation alone.

SUMMARY OF THE INVENTION

[0006] An object of the invention is to improve reliability of an annotation.

[0007] A collation apparatus according to an aspect of the invention disclosed in the present application includes: a grouping processing unit configured to group, based on each explanatory variable of a sample group, the sample group into a first group indicating a first classification and a second group indicating a second classification having a lower evaluation than the first classification; a collation unit configured to collate the classification of the first group and the second group that are obtained by the grouping processing unit with a classification identified by each objective variable of the sample group; and an output unit configured to output a collation result obtained by the collation unit.

[0008] According to a representative embodiment of the invention, reliability of an annotation is improved. Problems, configurations, and effects other than those described above are made clear according to the following description of the embodiments.

BRIEF DESCRIPTION OF THE DRAWINGS

[0009] FIG. **1** is an explanatory diagram showing an example of well-organization of a learning DB.

[0010] FIG. **2** is a block diagram of a hardware configuration example of a collation apparatus.

[0011] FIG. **3** is an explanatory diagram showing an example of the learning DB.

[0012] FIG. **4** is an explanatory diagram showing a measuring factor example 1 included in feature data.

[0013] FIG. **5** is an explanatory diagram showing a measuring factor example 2 included in the feature data.

[0014] FIG. **6** is an explanatory diagram showing an example of a basic information DB.

[0015] FIG. **7** is a block diagram showing a functional configuration example of the collation apparatus.

[0016] FIG. **8** is a flowchart showing an example of a preprocessing procedure performed by a preprocessing unit.

[0017] FIG. **9** is an explanatory diagram showing a display example of a selection screen during learning.

[0018] FIG. **10** is an explanatory diagram showing a display example of a selection screen during prediction.

[0019] FIG. **11** is a flowchart showing an example of a collation processing procedure during learning.

[0020] FIG. **12** is an explanatory diagram showing an example of a feature data selection screen.

[0021] FIG. **13** is an explanatory diagram showing an example of a collation result display screen.

[0022] FIG. **14** is an explanatory diagram showing an example of the collation result display screen.

[0023] FIG. **15** is an explanatory diagram showing an example of the collation result display screen.

[0024] FIG. **16** is an explanatory diagram showing an example of the collation result display screen.

[0025] FIG. **17** is a flowchart showing an example of a collation processing procedure during prediction.

DESCRIPTION OF THE PREFERRED EMBODIMENTS

Example of Well-Organization of Learning DB

[0026] FIG. **1** is an explanatory diagram showing an example of well-organization of a learning DB. A learning DB **100** is a database that stores, as sample data, a combination of feature data serving as an explanatory variable and correct data serving as an objective variable for each sample which is a pregnant woman. The correct data is, for example, an annotation (a fetal state is safe or dangerous) performed by a doctor for a delivered sample during learning, and is an annotation (the fetal state is safe or dangerous) obtained during learning for a pre-delivery sample during pH prediction.

[0027] Each piece of sample data is clustered into a safety group in which the fetal state is safe and a danger group in which the fetal state is dangerous. Clustering is executed in

unsupervised learning that does not use the correct data or supervised learning that uses the correct data. Here, the unsupervised learning that does not use the correct data will be described as an example. In the unsupervised learning that does not use the correct data, a sample data group is clustered into two groups, in which a group having a larger number of pieces of sample data is set as the safety group and a group having a smaller number of pieces of sample data is set as the danger group.

[0028] pH is an umbilical arterial blood gas analysis value immediately after delivery serving as an index of low oxygen or acidosis of a fetus. For example, a pH value is set to 7.2 as a reference. When the pH > 7.2, the fetus is safe, and when the pH ≤ 7.2, the fetus is dangerous. The pH value is an actual measurement value immediately after delivery in the case of the delivered sample, and is a predicted value before delivery in the case of the pre-delivery sample.

[0029] If a collation result **101** indicates that the sample data belongs to the safety group and the pH value is a safety value (both safe), the sample data is stored in the learning DB **100** as a learning target, and an annotation indicating "safety" is attached to the sample data. The annotation indicating "safety" is displayed to a user.

[0030] If a collation result **102** indicates that the sample data belongs to the safety group and the pH value is a danger value (contradiction), the sample data is set as a non-learning target in the learning DB **100** so as not to be used for learning, and a case indicating that an attribute "safety" of the sample and the safety value of the pH are "contradictory" is displayed to a user.

[0031] If a collation result **103** indicates that the sample data belongs to the danger group and the pH value is the safety value (contradiction), the sample data is set as the non-learning target in the learning DB **100** so as not to be used for learning, and a case indicating that an attribute "danger" of the sample and the safety value of the pH are "contradictory" is displayed to a user.

[0032] If a collation result **104** indicates that the sample data belongs to the danger group and the pH value is the danger value (both dangerous), the sample data is set as the non-learning target in the learning DB **100** so as not to be used for learning, and an annotation indicating "danger" is attached to the sample data. The annotation indicating "danger" is displayed to a user.

[0033] In this way, the collation results **101** to **104** indicating "safety", "contradiction", and "danger" are automatically attached as annotations. Accordingly, reliability of the annotations can be improved. In addition, since the sample data to which the collation results **102** to **104** indicating "contradiction" or "danger" are attached as annotations serves as the non-learning target, the sample data to which the collation result **101** indicating "safety" is attached as an annotation remains. Therefore, automatic organization of the learning DB **100** can be implemented. In addition, by generating a learning model using the remaining sample data group, accuracy of a predicted value of the pH can be improved.

Hardware Configuration Example of Collation Apparatus

[0034] FIG. **2** is a block diagram of a hardware configuration example of a collation apparatus. A collation apparatus **200** includes a processor **201**, a storage device **202**, an input device **203**, an output device **204**, and a communication interface (communication IF) **205**. The processor **201**, the storage device **202**, the input device **203**, the output device **204**, and the communication IF **205** are connected by a bus **206**. The processor **201** controls the collation apparatus **200**. The storage device **202** serves as a work area of the processor **201**. The storage device **202** is a non-transitory or transitory recording medium that stores various programs and data. Examples of the storage device **202** include a read only memory (ROM), a random access memory (RAM), a hard disk drive (HDD), and a flash memory. The input device **203** inputs data. Examples of the input device **203** include a keyboard, a mouse, a touch panel, a numeric keypad, a scanner, a microphone, and a sensor. The output device **204** outputs data. Examples of the output device **204** include a display, a printer, and a speaker. The communication IF **205** is connected to a network and transmits and receives the data.

Learning DB **100**

[0035] FIG. **3** is an explanatory diagram showing an example of the learning DB **100**. The learning DB **100** is stored in the storage device **202** or a storage device of another computer accessible to the collation apparatus.

[0036] The learning DB **100** includes, as fields, sample IDs **301**, feature data **302**, pHs **303**, belonging groups **304**, annotations **305**, and non-learning target information **306**. A combination of values of the fields **301** to **306** in the same row defines an entry indicating sample data of one sample. Although the sample represents a pregnant woman, when a heart rate and labor intensity of the same pregnant woman are measured at different dates and times, samples will be different. In FIG. **3**, sample data of m sample or m samples (m is an integer of 1 or more) is registered.

[0037] Each of the sample IDs **301** is identification information that uniquely identifies a sample. The feature data **302** is data indicating features of the sample identified by each of the sample IDs **301**. The feature data **302** includes factors F1 to Fn (n is an integer of 1 or more) including basic factors such as age, the number of weeks of pregnancy, development delay of a fetus, the number of fetuses, a delivery method, medication information, and smoking for a pregnant woman, and measurement factors such as measurement results obtained by a measurement apparatus that measures a heart rate and labor intensity.

[0038] The pHs **303** are the umbilical arterial blood gas analysis values immediately after delivery, and predicted values **331** and actual measurement values **332** are stored therein. Before delivery, only the predicted values **331** are calculated and stored by a calculation unit **703** to be described later. After delivery, the umbilical arterial blood gas analysis values are measured and stored as the actual measurement values **332**.

[0039] Each of the belonging groups **304** is a group to which the sample identified by the sample ID **301** belongs. The group includes the safety group and the danger group. As described with reference to FIG. **1**, when clustering is performed by the unsupervised learning, the group having a larger number of pieces of sample data is set as the safety group and the group having a smaller number of pieces of sample data is set as the danger group.

[0040] On the other hand, the belonging groups **304** of the sample data may be determined by using a pH value = 7.2 as

a reference for the actual measurement values **332**, attaching a correct label indicating safety when the actual measurement values **332** are pH > 7.2, attaching a correct label indicating danger when the actual measurement values **332** are pH ≤ 7.2, and executing the supervised learning.

[0041] Each of the annotations **305** is an evaluation index for a fetus of a sample, and is attached by a doctor or attached as a collation result by a collation unit **704** to be described later.

[0042] The non-learning-target information **306** is information for setting the sample data to be the non-learning target. "0" indicates a default value of the learning target, and "1" indicates the non-learning target. It is noted that the collation apparatus may delete an entry of sample data serving as the non-learning target, without using the non-learning target information **306**.

Feature Data **302**

[0043] FIG. **4** is an explanatory diagram showing a measuring factor example 1 included in the feature data **302**. FIG. **4** shows a histogram **400** obtained based on waveforms of CTG. Factors of the feature data **302** obtained based on the histogram **400** include, for example, a mode, an average value, a median value, variance, a histogram width, a low frequency, and a tendency.

[0044] FIG. **5** is an explanatory diagram showing a measuring factor example 2 included in the feature data **302**. FIG. **5** shows waveforms of CTG. The waveforms include a heart rate waveform **501** and a labor intensity waveform **502**. Factors obtained based on the heart rate waveform **501** include, for example, a baseline, a waveform maximum value, a waveform minimum value, a waveform average value, and waveform variance. Factors obtained based on the labor intensity waveform **502** include, for example, a proportion of labor (total labor time/measurement period). In addition, factors obtained as medical knowledge include, for example, the number of times fetal heart rate drops to 80 [bpm] or less, the number of times the fetal heart rate drops from the baseline by 30 [bpm] or more, duration of the fetal heart rate dropping to 80 [bpm] or less, duration of the fetal heart rate dropping from the baseline by 30 [bpm] or more, and time from the lowest fetal heart rate to birth.

Basic Information DB

[0045] FIG. **6** is an explanatory diagram showing an example of a basic information DB. The basic information DB **600** is stored in the storage device **202** or a storage device of another computer accessible to the collation apparatus.

[0046] The basic information DB **600** stores data used for cleansing the sample data. Specifically, for example, the basic information DB **600** includes conditions **601** related to a basic factor group and data quality conditions **602**. In the conditions **601** related to the basic factor group, for example, the basic factor group such as the age, the number of weeks of pregnancy, the delivery method, the number of fetuses, the development delay of the fetus, the medication information, and the smoking for a pregnant woman who is a sample serves as the non-learning target. For example, in the case of age, if sample data is 45 years old or older, the sample data is set to the non-learning target. In addition, in the case of the number of weeks of pregnancy, sample data of less than 27 weeks or 43 weeks or more is set to the non-learning target. In this way, a condition serving as the non-learning target is set for each factor.

[0047] The data quality conditions **602** are conditions related to quality of values of sample data, which are different from the conditions **601** related to the basic factor group. For example, sample data with a missing value of 20% or more is set to the non-learning target. It is noted that the non-learning target may be, as long as the sample data is not used for learning, a state in which the sample data itself is simply left in the learning DB **100** or a state in which the sample data is deleted from the learning DB **100**. It is noted that even if the sample data is deleted from the learning DB **100**, the sample data may remain in the storage device **202**.

Functional Configuration Example of Collation Apparatus

[0048] FIG. **7** is a block diagram showing a functional configuration example of the collation apparatus **200**. The collation apparatus **200** can access the learning DB **100** and the basic information DB **600**. The collation apparatus **200** includes a preprocessing unit **701**, a grouping processing unit **702**, the calculation unit **703**, the collation unit **704**, an output unit **705**, and a learning unit **706**. Specifically, the preprocessing unit **701**, the grouping processing unit **702**, the calculation unit **703**, the collation unit **704**, the output unit **705**, and the learning unit **706** are implemented by, for example, causing the processor **201** to execute a program stored in the storage device **202** shown in FIG. **2**.

[0049] The preprocessing unit **701** refers to the basic information DB **600**, cleanses the sample data group in the learning DB **100**, and sets unnecessary sample data to the non-learning target.

[0050] The grouping processing unit **702** groups the sample data group in the learning DB **100** into the safety group and the danger group. Specifically, for example, as described above, the grouping processing unit **702** executes, by the unsupervised learning, grouping between the sample data having short distances between the feature data **302** (specifically, for example, a measurement factor group) of the sample data, and executes grouping until the sample data finally converge into two groups. The final two groups are the safety group and the danger group. The group having a larger number of pieces of sample data is the safety group, and the group having a smaller number of pieces of sample data is the danger group.

[0051] The grouping processing unit **702** classifies a combination of the feature data **302** (specifically, the measurement factor group) and a correct label (safety if pH > 7.2, and danger if pH ≤ 7.2) based on the actual measurement values **332** of the pHs **303** as training data into the safety group and the danger group by the supervised learning. Since the actual measurement values **332** of the pHs **303** are used, sample data to be grouped serves as sample data of a delivered pregnant woman.

[0052] The calculation unit **703** calculates the predicted values **331** of the pHs **303** by inputting a specific measurement factor group (a factor group obtained as medical knowledge) of sample data (prediction target sample data) for which the predicted values **331** of the pHs **303** have not been calculated to a learning model generated by the learning unit **706**.

[0053] As shown in FIG. **1**, the collation unit **704** collates the annotations **305** with a safety value (pH > 7.2) or a dan-

ger value (pH ≤ 7.2) obtained based on the pHs **303** for each sample data. As for the pHs **303**, the actual measurement values **332** are used for sample data having the actual measurement values **332**, and the predicted values **331** are used for sample data having no actual measurement values **332**.

[0054] Each of the annotations **305** is an annotation performed by a doctor before the collation executed by the collation unit **704**, and becomes a collation result obtained by the collation unit **704** after the collation executed by the collation unit **704**.

[0055] The output unit **705** outputs a preprocessing result obtained by the preprocessing unit **701** and the collation result obtained by the collation unit **704** in a displayable manner. Specifically, for example, the output unit **705** displays the preprocessing result or the collation result on a display apparatus which is an example of the output device **204**, or transmits the preprocessing result or the collation result to another computer via the communication IF **205** to display the preprocessing result or the collation result on the other computer.

[0056] The learning unit **706** generates a multiple regression model as the learning model using the factor group obtained as medical knowledge of the sample data in the feature data **302** and the actual measurement values **332** of the pHs **303**.

Collation Processing Procedure

[0057] Next, an example of a collation processing procedure performed by the collation apparatus **200** will be described for each function. The collation apparatus **200** executes learning of the learning model and prediction of the pHs **303** using the learning model, and will be described by indicating which of learning and prediction the collation apparatus **200** is applied to in processes performed by functions to be described later.

Example of Preprocessing Procedure

[0058] FIG. **8** is a flowchart showing an example of a preprocessing procedure performed by the preprocessing unit **701**. The preprocessing procedure is performed in both learning and prediction. The preprocessing unit **701** determines whether there is unselected sample data in the learning DB **100** (step S**801**). When there is the unselected sample data (step S**801**: Yes), the preprocessing unit **701** selects one piece of unselected sample data (step S**802**). The preprocessing unit **701** executes preprocessing (cleansing), that is, a process of determining whether selected sample data corresponds to the conditions **601** related to the basic factor group and the data quality conditions **602**, on the selected sample data, using the basic information DB **600** (step S**803**).

[0059] Then, the preprocessing unit **701** outputs a selection screen in the displayable manner (step S**804**). Specifically, for example, the preprocessing unit **701** executes displaying on a display apparatus, which is an example of the output device **204**, or executes displaying on another computer operated by a user.

[0060] FIG. **9** is an explanatory diagram showing a display example of a selection screen during learning. A selection screen **900** displays, as a preprocessing result, a first radio button **901**, a second radio button **902**, an execution button **903**, a first character string **910**, and a second character string **920**.

[0061] The first radio button **901** is a selection button for a user to set the preprocessed selected sample data to the learning target, and a reason thereof is displayed as the first character string **910**. "All conditions" of the first character string **910** are the conditions **601** related to the basic factor group and the data quality conditions **602** in the basic information DB **600**. That is, it is indicated that the selected sample data is the learning target.

[0062] The second radio button **902** is a selection button for a user to set the preprocessed selected sample data to the non-learning target, and a reason thereof is displayed as the second character string **920**. The second character string **920** is, for example, a condition corresponding to the selected sample data among the conditions **601** related to the basic factor group and the data quality conditions **602** in the basic information DB **600**.

[0063] The execution button **903** is a button for checking selection of either the first radio button **901** or the second radio button **902**, and the preprocessing unit **701** receives a signal indicating whether the selected sample data is selected as the learning target or the non-learning target.

[0064] FIG. **10** is an explanatory diagram showing a display example of a selection screen during prediction. A selection screen **1000** displays, as a preprocessing result, a first radio button **1001**, a second radio button **1002**, an execution button **1003**, a first character string **1010**, and a second character string **1020**.

[0065] The first radio button **1001** is a selection button for a user to set the preprocessed selected sample data to the learning target, and a reason thereof is displayed as the first character string **1010**. "All conditions" of the first character string **1010** are the conditions **601** related to the basic factor group and the data quality conditions **602** in the basic information DB **600**. That is, it is indicated that the selected sample data is the learning target.

[0066] The second radio button **1002** is a selection button for a user to set the preprocessed selected sample data to the non-learning target and for prompting the user to recheck mounting of the measurement apparatus, and content for prompting the rechecking is displayed as the second character string **1020**. The execution button **1003** is a button for checking selection of either the first radio button **1001** or the second radio button **1002**, and the preprocessing unit **701** receives a signal indicating whether the selected sample data is selected as the learning target or the non-learning target.

[0067] Referring back to FIG. **8**, when the execution button **903** or the execution button **1003** is pressed, the preprocessing unit **701** receives a selection signal (step S**805**). When the selection signal indicates the learning target (step S**806**: Yes), the process returns to step S**801**. On the other hand, when the selection signal indicates the non-learning target (step S**806**: No), the preprocessing unit **701** sets the non-learning target information **306** of the selected sample data to the non-learning target (step S**807**), and returns to step S**801**. In step S**801**, when there is no unselected sample data, the preprocessing unit **701** ends the preprocessing.

Example of Collation Processing Procedure During Learning

[0068] FIG. **11** is a flowchart showing an example of a collation processing procedure during learning. The group-

ing processing unit **702** selects a factor of the feature data (step S**1101**). Specifically, for example, the grouping processing unit **702** outputs a feature data selection screen at start of collation in the displayable manner.

[0069] FIG. **12** is an explanatory diagram showing an example of the feature data selection screen. A feature data selection screen **1200** includes an automatic selection button **1201**, a number selection button **1202**, a factor group list **1203**, and an execution button **1204**. The automatic selection button **1201** is a button for the collation apparatus **200** to automatically select a factor of the feature data **302**. The number selection button **1202** is a button for selecting any one or more factors from a factor group in the factor group list **1203**. A user selects a radio button (indicated by a circle) of each factor at a left end of the factor group list **1203**. When the execution button **1204** is pressed, the grouping processing unit **702** receives a selection method signal indicating automatic selection or number selection (including a selection number).

[0070] Referring back to FIG. **11**, the grouping processing unit **702** selects the factor of the feature data when receiving the selection method signal. Specifically, for example, in the case of the automatic selection, the grouping processing unit **702** automatically selects a factor of the feature data **302** according to T-test or principal component analysis. In the case of the number selection, the grouping processing unit **702** selects a number-selected factor.

[0071] The grouping processing unit **702** executes a grouping process on the sample data group in the learning DB **100** using the factor selected in step S**1101** as the feature data **302** (step S**1102**). Sample data to be subjected to the grouping process (step S**1102**) is sample data having the actual measurement values **332** of the pHs **303** and having the non-learning target information **306** of "0" (learning target). Accordingly, since defective data is not applied to the grouping process (step S**1102**), accuracy of the grouping process (step S**1102**) during learning is improved.

[0072] During learning, in the grouping process (step S**1102**), the grouping processing unit **702** may execute the supervised learning using selection factors of the sample data and correct data (a correct label obtained based on the actual measurement values **332** of the pHs **303**) as a learning data set, or may execute the unsupervised learning using only the selection factors of the sample data. In any case, the grouping processing unit **702** groups the sample data group into the safety group and the danger group, and sets the belonging groups **304**.

[0073] Next, as shown in FIG. **1**, the collation unit **704** collates a classification (safety or danger) of the actual measurement values **332** of the pHs **303** with a classification (safety or danger) of the belonging groups **304** for each piece of sample data (step S**1103**). The collation unit **704** attaches the collation results **101** to **104** as the annotations **305** (step S**1104**), and updates the non-learning target information **306** based on the collation results **101** to **104** (step S**1105**). Specifically, for example, the collation unit **704** updates the non-learning target information **306** to "1" for the sample data of the collation results **101** to **104**. Then, the output unit **705** outputs the collation results **101** to **104** in the displayable manner (step S**1106**).

[0074] FIG. **13** to FIG. **16** are explanatory diagrams showing examples of collation result display screens. A collation result display screen **1300** displays the collation result **101**, a collation result display screen **1400** displays the collation result **102**, a collation result display screen **1500** displays the collation result **103**, and a collation result display screen **1600** displays the collation result **104**.

[0075] Returning to FIG. **11**, the learning unit **706** executes learning using the learning data set which is a combination of the selection factors of the sample data group and the actual measurement values **332** of the pHs **303** in the collation result **101**, and generates the learning model (for example, the multiple regression model) (step S**1107**). Accordingly, the collation process during learning executed by the grouping processing unit **702**, the collation unit **704**, the output unit **705**, and the learning unit **706** ends.

Example of Collation Processing Procedure During Prediction

[0076] FIG. **17** is a flowchart showing an example of a collation processing procedure during prediction. The grouping processing unit **702** selects a factor of the feature data, as in step S**1101** (step S**1701**). The grouping processing unit **702** executes a grouping process on the sample data group in the learning DB **100** using the factor selected in step S**1701** as the feature data **302** (step S**1702**).

[0077] Sample data to be subjected to the grouping process (step S**1702**) is sample data having no actual measurement values **332** of the pHs **303** and having the non-learning target information **306** of "0" (learning target). Accordingly, since defective data is not applied to the grouping process (step S**1702**), accuracy of the grouping process (step S**1702**) during prediction is improved.

[0078] During learning, in the grouping process (step S**1702**), the grouping processing unit **702** may execute the unsupervised learning using only the selection factors of the sample data, or may execute the supervised learning using the selection factors of the sample data and the correct data as the learning data set.

[0079] In the case of the supervised learning, the correct data is, for example, a classification (a correct label with both safety as "safety" and a correct label with contradiction and both danger as "danger") of the annotations **305** attached in step S**1104**. In any case, the grouping processing unit **702** groups the sample data group into the safety group and the danger group, and sets the belonging groups **304**. By executing the supervised learning using the correct data, the collation result **101** attached as the annotations **305** in step S**1104** can be reflected in the learning model.

[0080] Next, the calculation unit **703** calculates the predicted values **331** of the pHs **303** of the sample data by inputting values of the selection factors of the sample data to the learning model, and stores the predicted values **331** in the learning DB (step S**1703**) .

[0081] Next, as shown in FIG. **1**, the collation unit **704** collates a classification (safety or danger) of the predicted values **331** of the pHs **303** with a classification (safety or danger) of the belonging groups **304** for each piece of sample data (step S**1704**). The collation unit **704** attaches the collation results **101** to **104** as the annotations **305** (step S**1705**), and updates the non-learning target information **306** based on the collation results **101** to **104** (step S**1706**).

[0082] Specifically, for example, the collation unit **704** updates the non-learning target information **306** to "1" for the sample data of the collation results **101** to **104**. Then, the collation unit **704** outputs the collation results **101** to **104** in the displayable manner as shown in FIG. **14** to FIG. **17** (step

S1707). Accordingly, the collation process during prediction executed by the grouping processing unit **702**, the calculation unit **703**, the collation unit **704**, and the output unit **705** ends.

[0083] It is noted that even in a sample having no actual measurement values **332** of the pHs **303** before delivery, the actual measurement values **332** of the pHs **303** are obtained after delivery. In this case, the collation apparatus can update the annotations **305** by executing the collation process during learning shown in FIG. **11** on the actual measurement values **332** of the pHs **303**. In addition, the collation apparatus re-learns the learning model by performing error back-propagation based on differences between the predicted values **331** and the actual measurement values **332** of the pHs **303**. Accordingly, accuracy of the learning model can be improved.

[0084] As described above, since the collation results **101** to **104** indicating "safety", "contradiction", and "danger" are automatically attached as the annotations **305**, reliability of the annotations **305** can be improved. In addition, since the sample data to which the collation results **102** to **104** indicating "contradiction" or "danger" are attached as the annotations **305** serves as the non-learning target, the sample data to which the collation result **101** indicating "safety" is attached as the annotation **305** remains. Therefore, the automatic organization of the learning DB **100** can be implemented. In addition, by generating the learning model using the remaining sample data group, accuracy of the predicted values **331** of the pHs **303** can be improved. Therefore, it is possible to predict a fetal state without increasing data processing cost.

[0085] In the above-described embodiment, two groups of safety and danger are used. However, a classification of groups is not limited to safety and danger, and may be a classification of evaluation indicating a degree such as accuracy or reliability of a sample. In addition, in the above-described embodiment, the sample is a pregnant woman. However, the sample is not limited to a pregnant woman, and various measurement targets such as a person and an apparatus may be used as the sample.

[0086] The invention is not limited to the above embodiment and includes various modifications and equivalent configurations within the spirit of the appended claims. For example, the above-mentioned embodiment is described in detail in order to make the invention easy to understand, and the invention is not necessarily limited to those including all the configurations described above. In addition, a part of the configurations according to one embodiment may be replaced with configurations according to another embodiment. In addition, the configurations according to one embodiment may be added to the configurations according to another embodiment. Furthermore, a part of the configurations according to each embodiment may be added to, deleted from, or replaced with another configuration.

[0087] A part or all of the configurations, functions, processing units, processing methods described above and the like may be implemented by hardware by, for example, designing with an integrated circuit, or may be implemented by software by a processor interpreting and executing a program for implementing each function.

[0088] Information of a program, a table, and a file for implementing each function can be stored in a storage apparatus such as a memory, a hard disk, and a solid state drive (SSD), or a recording medium such as an integrated circuit (IC) card, an SD card, and a digital versatile disc (DVD) .

[0089] Control lines and information lines indicate what is considered necessary for description, and not all control lines and information lines necessary for implementation are necessarily shown. It may be considered that almost all the configurations are actually connected to each other.

What is claimed is:

1. A collation apparatus comprising:

a grouping processing unit configured to group, based on each explanatory variable of a sample group, the sample group into a first group indicating a first classification and a second group indicating a second classification having a lower evaluation than the first classification;

a collation unit configured to collate the classification of the first group and the second group that are obtained by the grouping processing unit with a classification identified by each objective variable of the sample group; and

an output unit configured to output a collation result obtained by the collation unit.

2. The collation apparatus according to claim **1**, wherein

the collation unit attaches an annotation indicating the first classification to the first sample when the classification identified by the objective variable of the first sample belonging to the first group in the sample group is the first classification.

3. The collation apparatus according to claim **1**, wherein

the collation unit attaches an annotation indicating a contradiction to the first sample when the classification identified by the objective variable of the first sample belonging to the first group in the sample group is the second classification.

4. The collation apparatus according to claim **1**, wherein

the collation unit attaches an annotation indicating the second classification to the second sample when the classification identified by the objective variable of the second sample belonging to the second group in the sample group is the second classification.

5. The collation apparatus according to claim **1**, wherein

the collation unit attaches an annotation indicating a contradiction to the second sample when the classification identified by the objective variable of the second sample belonging to the second group in the sample group is the first classification.

6. The collation apparatus according to claim **1**, wherein

the grouping processing unit groups the sample group into the first group and the second group by performing clustering by unsupervised learning using the explanatory variable.

7. The collation apparatus according to claim **1**, wherein

the grouping processing unit groups the sample group into the first group and the second group based on supervised learning according to the explanatory variable and a classification identified by an actual measurement value of the objective variable.

8. The collation apparatus according to claim **2**, further comprising:

a learning unit configured to generate a learning model by learning based on the explanatory variable of the first sample to which an annotation indicating the first classification is attached and an annotation indicating the first classification serving as the objective variable; and

a calculation unit configured to calculate a predicted value of each objective variable of a prediction target sample group by inputting each explanatory variable of the prediction target sample group to the learning model generated by the learning unit.

9. The collation apparatus according to claim **8**, wherein

the grouping processing unit groups the prediction target sample group into the first group and the second group based on each explanatory variable of the prediction target sample group, and

the collation unit collates the classification of the first group and the second group into which the prediction target sample group is grouped by the grouping processing unit with a classification identified by the predicted value calculated by the calculation unit.

10. The collation apparatus according to claim **9**, wherein

when a classification identified by the predicted value of a first prediction target sample belonging to the first group in the prediction target sample group is the first classification, the collation unit attaches the annotation indicating the first classification to the first prediction target sample.

11. The collation apparatus according to claim **9**, wherein

when a classification identified by the predicted value of a first prediction target sample belonging to the first group in the prediction target sample group is the second classification, the collation unit attaches an annotation indicating a contradiction to the first prediction target sample.

12. The collation apparatus according to claim **9**, wherein

when a classification identified by the predicted value of a second prediction target sample belonging to the second group in the prediction target sample group is the second classification, the collation unit attaches an annotation indicating the second classification to the second prediction target sample.

13. The collation apparatus according to claim **9**, wherein

when a classification identified by the predicted value of a second prediction target sample belonging to the second group in the prediction target sample group is the first classification, the collation unit attaches an annotation indicating a contradiction to the second prediction target sample.

14. A collation method executed by a collation apparatus, the collation apparatus including a processor configured to execute a program and a storage device configured to store the program, the collation method comprising:

a grouping process of grouping, by the processor, based on each explanatory variable of a sample group, the sample group into a first group indicating a first classification and a second group indicating a second classification having a lower evaluation than the first classification;

a collation process of collating, by the processor, the classification of the first group and the second group that are obtained by the grouping process with a classification identified by each objective variable of the sample group; and

an output process of outputting, by the processor, a collation result obtained by the collation process.

15. A collation program for causing a processor to execute:

a grouping process of grouping, based on each explanatory variable of a sample group, the sample group into a first group indicating a first classification and a second group indicating a second classification having a lower evaluation than the first classification;

a collation process of collating the classification of the first group and the second group that are obtained by the grouping process with a classification identified by each objective variable of the sample group; and

an output process of outputting a collation result obtained by the collation process.

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