# MACHINE LEARNING BASED METHOD AND DEVICE FOR INFANT DEVELOPMENT PREDICTION, STORAGE MEDIUM, AND ELECTRONIC DEVICE

## CROSS-REFERENCE TO RELATED APPLICATION(S)

**[0001]** This application claims priority to Chinese Patent Application No. 201910346364.8, filed April 26, 2019, entitled "MACHINE LEARNING BASED METHOD AND DEVICE FOR INFANT DEVELOPMENT PREDICTION, STORAGE MEDIUM, AND ELECTRONIC DEVICE", the entire disclosure of which is hereby incorporated by reference.

## TECHNICAL FIELD

**[0002]** This disclosure relates to the technical field of computer programs, and particularly to a machine learning based method and device for infant development prediction, a storage medium, and an electronic device.

## BACKGROUND

**[0003]** In the related art, a definite diagnosis can be made on whether an infant has developmental retardation only after the infant is older than 2 years old. However, at this time, intervention on the infant with developmental retardation is relatively late, which is not conducive to recovery of the infant with developmental retardation. Therefore, there is a need for a method for infant development prediction, so as to provide a basis for early intervention on the recovery of the infant with developmental retardation.

## SUMMARY

**[0004]** In view of the above, this application provides a machine learning based method and device for infant development prediction, a storage medium, and an electronic device, which can predict development of an infant, to further get a possibility of developmental retardation of the infant. In this way, a reliable basis can be provided for early intervention on developmental retardation of infants and more practical application can be achieved.

**[0005]** To achieve a first purpose, the technical solution of the machine learning based method for infant development prediction of this application is as follows.

**[0006]** Data of a single limb-movement and corresponding month age data of a sample to-be-tested are acquired. The data of the single limb-movement of the sample to-be-tested is processed, to obtain a feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data. A preset number of feature values of single limb-movements of the sample to-be-tested and corresponding month age data are input into a mathematical model of a stacked extreme learning machine, to perform a logical operation. An output result of the logical operation of the stacked extreme learning machine is used as a basis for "normal development" or "developmental retardation" of the sample to-be-tested, to obtain a prediction result of infant development.

**[0007]** The machine learning based method for infant development prediction of this application can be further implemented by adopting the following technical measures.

**[0008]** In at least one implementation, construction of the mathematical model of the stacked extreme learning machine includes the following.

**[0009]** Data of a single limb-movement and corresponding month age data of a training sample are acquired, where infant development of the training sample is known.

**[0010]** The data of the single limb-movement of the training sample is processed, to obtain a feature value of the single limb-movement of the training sample corresponding to the month age data of the training sample.

**[0011]** The feature value of the single limb-movement of the training sample corresponding to the month age data of the training sample is input into a logical operation formula: $\sum_{i=1}^{L}\beta_i g(W_i \times X_j + b_i) = o_j$, where multiple expressions based on the logical operation formula are obtained when there are multiple training samples, where

$L$ denotes the number of nodes of a neural network with a single hidden layer,

$g(x)$ denotes an activation function,

$W_i=[w_{i1}, w_{i2}, \ldots, w_{in}]^T$ denotes an input weight of the $i$-th hidden layer unit,

$b_i$ denotes a bias of the $i$-th hidden layer unit,

$\beta_i=[\beta_{i1}, \beta_{i2}, \ldots, \beta_{im}]^T$ denotes an output weight of the $i$-th hidden layer unit, and

$o_j$ denotes an output result of a logical operation after the stacked extreme learning machine is applied to the training sample for classification, where the output result of the logical operation includes two major classes of "normal development" and "developmental retardation".

**[0012]** An expression of the activation function $g(x)$, the input weight $W_i$ of the $i$-th hidden layer unit, the bias $b_i$ of the $i$-th hidden layer unit, and the output weight $\beta_i$ of the $i$-th

hidden layer unit are determined according to the plurality of expressions based on the logical operation formula.

**[0013]** The determined expression of the activation function $g(x)$, input weight $W_i$ of the $i$-th hidden layer unit, bias $b_i$ of the $i$-th hidden layer unit, and output weight $\beta_i$ of the $i$-th hidden layer unit are substituted into the logical operation formula, to obtain the mathematical model of the stacked extreme learning machine.

**[0014]** In at least one implementation, the data of the single limb-movement includes: a start time $T_{i0}$, an end time $T_{i1}$, an average acceleration $a_v$, a peak acceleration $a_m$, a left leg movement type $S_L$, and a right leg movement type $S_R$ of the single limb-movement, where a duration $t_i$ of the single limb-movement is a difference $T_{i1}$-$T_{i0}$ between the end time of the single limb-movement and the start time $T_{i0}$ of the single limb-movement.

**[0015]** In at least one implementation, the data of the single limb-movement of the sample to-be-tested is processed to obtain the feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data through one of: univariate feature selection, recursive feature selection, or stepwise feature selection. The data of the single limb-movement of the sample to-be-tested is processed to obtain the feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data as follows.

**[0016]** For the univariate feature selection, the feature value of the single limb-movement is obtained through a statistical measurement method for a single variable of the data of the single limb-movement. For the recursive feature selection, the feature value of the single limb-movement is obtained by normalizing various variables of the data of the single limb-movement. For the stepwise feature selection, the feature value of the single limb-movement is obtained by selecting a single variable of the data of the single limb-movement in turn and normalizing various variables of the data of the single limb-movement.

**[0017]** In at least one implementation, the “normal development” in the output result of the logical operation is classified into different grades according to the mathematical model of the stacked extreme learning machine. Alternatively, the “developmental retardation” in the output result of the logical operation is classified into different grades according to the mathematical model of the stacked extreme learning machine.

**[0018]** To achieve a second purpose, the technical solution of the machine learning based device for infant development prediction of this application is as follows.

**[0019]** The machine learning based device for infant development prediction of this application includes a data acquiring unit, a data processing unit, an operation unit, and a

prediction result outputting unit.

**[0020]** The data acquiring unit is configured to acquire data of a single limb-movement and corresponding month age data of a sample to-be-tested.

**[0021]** The data processing unit is configured to process the data of the single limb-movement of the sample to-be-tested, to obtain a feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data.

**[0022]** The operation unit is configured to input a preset number of feature values of single limb-movements of the sample to-be-tested and corresponding month age data into a mathematical model of a stacked extreme learning machine, to perform a logical operation.

**[0023]** The prediction result outputting unit is configured to use an output result of the logical operation of the stacked extreme learning machine as a basis for "normal development" or "developmental retardation" of the sample to-be-tested, to obtain a prediction result of infant development.

**[0024]** To achieve a third purpose, the technical solution of the storage medium of this application is as follows. The storage medium is configured to store a machine learning based program for infant development prediction, which when executed by a processor, is configured to implement operations of the machine learning based method for infant development prediction of this application.

**[0025]** To achieve a fourth purpose, the technical solution of the electronic device of this application is as follows.

**[0026]** The electronic device includes a motion sensor, a processor, and a memory configured to store a machine learning based program for infant development prediction, where the program is executable on the processor. The motion sensor is configured to acquire data of a single limb-movement of a sample to-be-tested. The program, when executed by the processor, is configured to implement operations of the machine learning based method for infant development prediction of this application.

**[0027]** According to the machine learning based method and device for infant development prediction, the storage medium, and the electronic device, with the known mathematical model of the stacked extreme learning machine, the data of the single limb-movement and the corresponding month age data of the sample to-be-tested are acquired, the data of the single limb-movement of the sample to-be-tested is then processed to obtain the feature value of the single limb-movement of the sample to-be-tested, and the feature value is input into the mathematical model of the stacked extreme learning machine to perform a logical operation, to obtain the output result, where the output result includes two major

classes of “normal development” and “developmental retardation”. As the month age data of the sample to-be-tested can be obtained according to the date of birth shown on the birth certificate, that is, data to-be-acquired of the method simply includes the data of the single limb-movement, in this case, the data of the single limb-movement can be obtained directly through the motion sensor. Therefore, the method can achieve infant development prediction conveniently. Furthermore, in the construction of the mathematical model of the stacked extreme learning machine of the method, infants at all month ages can be covered, and thus, even if the sample to-be-tested has relatively small month age, a relatively accurate output result can be obtained through the mathematical model of the stacked extreme learning machine. Therefore, a reliable basis can be provided for early intervention on developmental retardation of infants.

## BRIEF DESCRIPTION OF THE DRAWINGS

**[0028]** Through the detailed description of implementations below, various other advantages and benefits will become clear to those of ordinary skill in the art. The drawings are only used for illustrating the implementations and are not considered as a limitation to this application. Furthermore, throughout the drawings, the same reference symbols are used to denote the same components.

**[0029]** FIG. 1 is a schematic structural diagram illustrating a machine learning based device for infant development prediction in a hardware running environment according to solutions of implementations.

**[0030]** FIG. 2 is a schematic flowchart illustrating a machine learning based method for infant development prediction according to solutions of implementations.

**[0031]** FIG. 3 is a schematic flowchart illustrating construction of a mathematical model of a stacked extreme learning machine adopted in a machine learning based method for infant development prediction according to solutions of implementations.

**[0032]** FIG. 4 is a schematic diagram illustrating signal flow among various function modules of a machine learning based device for infant development prediction according to solutions of implementations.

**[0033]** FIG. 5 is a schematic diagram illustrating the principle of a stacked extreme learning machine adopted in a machine learning based method for infant development prediction according to solutions of implementations.

## DETAILED DESCRIPTION

**[0034]** To solve the problem of related art, this application provides a machine learning based method and device for infant development prediction, a storage medium, and an electronic device, which can predict development of an infant, to further get a possibility of developmental retardation of the infant. In this way, a reliable basis can be provided for early intervention on developmental retardation of infants and more practical application can be achieved.

**[0035]** To further explain the technical means and effects adopted by this application to achieve the intended purpose, hereinafter, in conjunction with the accompanying drawings and implementations, specific implementation manners, structures, features, and effects of the machine learning based method and device for infant development prediction, the storage medium, and the electronic device of this application are described in detail as follows. In the following description, different "one implementation" or "an implementation" do not necessarily refer to the same implementation. In addition, features, structures, or characteristics in one or more implementations may be combined in any suitable form.

**[0036]** The term "and/or" herein simply describes relationships of related objects, indicating that there can be three relationships. For example, "A and/or B" can indicate any one of three cases: "A and B", "A", and "B".

**[0037]** FIG. 1 is a schematic structural diagram illustrating a machine learning based device for infant development prediction in a hardware running environment according to solutions of implementations.

**[0038]** As illustrated in FIG. 1, the machine learning based device for infant development prediction includes a processor 1001 such as a central processing unit (CPU), a communication bus 1002, a user interface 1003, a network interface 1004, and a memory 1005. The communication bus 1002 is used to implement connection and communication between these components. The user interface 1003 may include a display and an input unit such as a keyboard. The user interface 1003 may also include a standard wired interface and a wireless interface. The network interface 1004 may include a standard wired interface and a wireless interface (such as a wireless-fidelity (Wi-Fi) interface). The memory 1005 may be a high-speed random access memory (RAM), or a stable non-volatile memory (NVM) such as a disk memory. In an example, the memory 1005 is also a storage device independent of the processor 1001.

**[0039]** Those skilled in the art can understand that, the structure illustrated in FIG. 1 does not constitute any limitation to the machine learning based device for infant development

prediction. The machine learning based device for infant development prediction may include more or fewer components than illustrated or may combine certain components or different components.

**[0040]** As illustrated in FIG. 1, the memory 1005 as a storage medium may include an operating system, a data storage module, a network communication module, a user interface module, and a machine learning based program for infant development prediction.

**[0041]** In the machine learning based device for infant development prediction illustrated in FIG. 1, the network interface 1004 is mainly used for data communication with a network server, and the user interface 1003 is mainly used for data interaction with a user. The processor 1001 and the memory 1005 of the machine learning based device for infant development prediction may be set in the machine learning based device for infant development prediction. The machine learning based device for infant development prediction is configured to use the processor 1001 to invoke the machine learning based program for infant development prediction stored in the memory 1005 and execute the machine learning based method for infant development prediction of the implementations.

**[0042]** First implementation

**[0043]** Referring to FIG. 1, the machine learning based method for infant development prediction of the first implementation begins at 101.

**[0044]** At 101, data of a single limb-movement and corresponding month age data of a sample to-be-tested are acquired.

**[0045]** Herein, the data of the single limb-movement of the sample to-be-tested is acquired through a sensor. The data of the single limb-movement includes: a duration $t_i$, an average acceleration $a_v$, a peak acceleration $a_m$, a left leg movement type $S_L$, and a right leg movement type $S_R$ of the single limb-movement. The duration $t_i$ of the single limb-movement is a difference between an end time $T_{i1}$ of the single limb-movement and a start time $T_{i0}$ of the single limb-movement, that is, $T_{i1}$-$T_{i0}$. The left leg movement type $S_L$ and the right leg movement type $S_R$ can be described through text, for example, kicking, squatting, walking, crawling, bending, etc. Alternatively, a symbol is defined for each movement type, for example, kicking=Q1, squatting=Q2, walking=Q3, crawling=Q4, bending=Q5, and then the left leg movement type $S_L$ and the right leg movement type $S_R$ can be described through the symbol. In addition, infants have a relatively rapid development in limb-movement ability within 24 months, especially within 12 months, sometimes, even in a few days, the limb-movements of the infants can change significantly. Therefore, the month age data Y needs to be accurate to “day”, for example, the month age data can be 2m+1, 8m+10, and so on.

**[0046]** At 102, the data of the single limb-movement of the sample to-be-tested is processed, to obtain a feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data.

**[0047]** The data of the single limb-movement of the sample to-be-tested can be processed through selection manners such as univariate feature selection, recursive feature selection, or stepwise feature selection.

**[0048]** For the univariate feature selection, the feature value $X_j$ of the single limb-movement of the sample to-be-tested is obtained through a statistical measurement method for some single variables. In this case, in a first example, $X_j$= {$T_{i1}$-$T_{i0}$, m}; in a second example, $X_j$={$a_v$, Y}; in a third example, $X_j$={$a_m$, Y}; in a fourth example, $X_j$={$X_L$, $X_R$, Y}.

**[0049]** For the recursive feature selection, the feature value $X_j$ of the single limb-movement of the sample to-be-tested is obtained by normalizing various variables of the data of the single limb-movement. For example, in this case, $X_j$={$y_1(T_{i1}-T_{i0})+y_2a_v+y_3a_m$, $X_L$, $X_R$, Y}, where $y_1$ is a feature coefficient of ($T_{i1}$-$T_{i0}$), $y_2$ is a feature coefficient of $a_v$, $y_3$ is a feature coefficient of $a_m$. In this example, the normalizing is linear normalizing. According to actual needs, the power operation can further be performed on some of the above three features ($T_{i1}$-$T_{i0}$), $a_v$, and $a_m$, to increase their influence levels, or the square root operation can further be performed on some of the above three features ($T_{i1}$-$T_{i0}$), $a_v$, and $a_m$, to decrease their influence levels.

**[0050]** In the stepwise feature selection, for the first selection, $X_j$= {$T_{i1}$-$T_{i0}$, Y}; for the second selection, $X_j$={$a_v$,Y}; for the third selection, $X_j$={$a_m$, Y}; for the fourth selection, $X_j$={$X_L$, $X_R$, Y}; thereafter, for the fifth selection, $X_j$={$y_1(T_{i1}-T_{i0})+y_2a_v+y_3a_m$, $X_L$, $X_R$, Y}.

**[0051]** At 103, a preset number of feature values of single limb-movements of the sample to-be-tested and corresponding month age data are input into a mathematical model of a stacked extreme learning machine, to perform a logical operation.

**[0052]** For example, the feature value $X_j$ of the single limb-movement of the sample to-be-tested is input into the mathematical model of the stacked extreme learning machine, that is, $\sum_{i=1}^{L}\beta_i g(W_i \times X_j + b_i)$, where

$L$ denotes the number of nodes of a neural network with a single hidden layer,

$g(x)$ denotes an activation function,

$W_i=[w_{i1}, w_{i2}, \ldots, w_{in}]^T$ denotes an input weight of the $i$-th hidden layer unit,

$b_i$ denotes a bias of the $i$-th hidden layer unit, and

$\beta_i=[\beta_{i1}, \beta_{i2}, \ldots, \beta_{im}]^T$ denotes an output weight of the $i$-th hidden layer unit.

**[0053]** An expression of the activation function $g(x)$, the input weight $W_i$ of the $i$-th hidden layer unit, the bias $b_i$ of the $i$-th hidden layer unit, and the output weight $\beta_i$ of the $i$-th hidden layer unit are known in the trained mathematical model of the stacked extreme learning machine. Therefore, through the above logical operation, an output result $o_j$ is obtained, which includes two major classes of "normal development" and "developmental retardation".

**[0054]** At 104, the output result of the logical operation of the stacked extreme learning machine is used as a basis for "normal development" or "developmental retardation" of the sample to-be-tested, to obtain a prediction result of infant development.

**[0055]** It is to be noted that, in the same time period, for acquiring the data of the limb-movement of the same sample to-be-tested, at least 5-10 groups of data of limb-movements should be acquired for determination of infant development. During acquisition of the data of the limb-movement of the sample to-be-tested, if only a small number of groups of data of limb-movements are acquired, as the sample to-be-tested may move too fast or too slow due to accidental factors, the result of determination of infant development may be inaccurate. If in the same time period, at least 5-10 groups of data of limb-movements are acquired for determination of infant development, inaccurate result due to accidental factors can be minimized. If a large number of groups of data of limb-movements are acquired, it will take a lot of time to determine infant development, which is of little significance to determine whether the infant is developing normally or stunted. If the sample to-be-tested is determined to be stunted according to 5-10 groups of data of limb-movements, 1-3 times of groups of data of limb-movements can be acquired additionally. With more number of groups of data of limb-movements, a definite diagnosis can be made on whether the infant is stunted.

**[0056]** According to the machine learning based method for infant development prediction of the first implementation, with the known mathematical model of the stacked extreme learning machine, the data of the single limb-movement and the corresponding month age data of the sample to-be-tested are acquired, the data of the single limb-movement of the sample to-be-tested is then processed to obtain the feature value of the single limb-movement of the sample to-be-tested, and the feature value is input into the mathematical model of the stacked extreme learning machine to perform a logical operation, to obtain the output result, where the output result includes two major classes of "normal development" and "developmental retardation". As the month age data of the sample to-be-tested can be obtained according to the date of birth shown on the birth certificate, that is, data to-be-

acquired of the method simply includes the data of the single limb-movement, in this case, the data of the single limb-movement can be obtained directly through the motion sensor. Therefore, the method can achieve infant development prediction conveniently. Furthermore, in the construction of the mathematical model of the stacked extreme learning machine of the method, infants at all month ages can be covered, and thus, even if the month age of the sample to-be-tested is relatively small, a relatively accurate output result can be obtained through the mathematical model of the stacked extreme learning machine. Therefore, a reliable basis can be provided for early intervention on developmental retardation of infants.

**[0057]** Referring to FIG.3 and FIG. 5, construction of the mathematical model of the stacked extreme learning machine includes the following.

**[0058]** At 201, data of a single limb-movement and corresponding month age data of a training sample are acquired, where infant development of the training sample is known.

**[0059]** Herein, the data of the single limb-movement of the training sample is acquired through a sensor. The data of the single limb-movement includes: a duration $t_i$, an average acceleration $a_v$, a peak acceleration $a_m$, a left leg movement type $S_L$, and a right leg movement type $S_R$ of the single limb-movement. The duration $t_i$ of the single limb-movement is a difference between an end time $T_{i1}$ of the single limb-movement and a start time $T_{i0}$ of the single limb-movement, that is, $T_{i1}$-$T_{i0}$. The left leg movement type $S_L$ and the right leg movement type $S_R$ can be described through text, for example, kicking, squatting, walking, crawling, bending, etc. Alternatively, a symbol is defined for each movement type, for example, kicking=Q1, squatting=Q2, walking=Q3, crawling=Q4, bending=Q5, and then the left leg movement type $S_L$ and the right leg movement type $S_R$ can be described through the symbol. In addition, infants have a relatively rapid development in limb-movement ability within 24 months, especially within 12 months, sometimes, even in a few days, the limb-movements of the infants can change significantly. Therefore, the month age data Y needs to be accurate to “day”, for example, the month age data can be 2m+1, 8m+10, and so on.

**[0060]** At 202, the data of the single limb-movement of the training sample is processed, to obtain a feature value of the single limb-movement of the training sample corresponding to the month age data of the training sample.

**[0061]** The data of the single limb-movement of the training sample can be processed through selection manners such as univariate feature selection, recursive feature selection, or stepwise feature selection. The data of the single limb-movement of the sample to-be-tested is processed to obtain the feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data as follows.

**[0062]** For the univariate feature selection, the feature value $X_j$ of the single limb-movement of the training sample is obtained through a statistical measurement method for some single variables. In this case, in a first example, $X_j$= {$T_{i1}$-$T_{i0}$, m}; in a second example, $X_j$={$a_v$, Y}; in a third example, $X_j$={$a_m$, Y}; in a fourth example, $X_j$={$X_L$, $X_R$, Y}.

**[0063]** For the recursive feature selection, the feature value $X_j$ of the single limb-movement of the training sample is obtained by normalizing various variables of the data of the single limb-movement. For example, in this case, $X_j$={$y_1(T_{i1}-T_{i0})+y_2a_v+y_3a_m$, $X_L$, $X_R$, Y}, where $y_1$ is a feature coefficient of ($T_{i1}$-$T_{i0}$), $y_2$ is a feature coefficient of $a_v$, $y_3$ is a feature coefficient of $a_m$. In this example, the normalizing is linear normalizing. According to actual needs, the power operation can further be performed on some of the above three features ($T_{i1}$-$T_{i0}$), $a_v$, and $a_m$, to increase their impact levels, or the square root operation can further be performed on some of the above three features ($T_{i1}$-$T_{i0}$), $a_v$, and $a_m$, to decrease their impact levels.

**[0064]** In the stepwise feature selection, for the first selection, $X_j$= {$T_{i1}$-$T_{i0}$, Y}; for the second selection, $X_j$={$a_v$,Y}; for the third selection, $X_j$={$a_m$, Y}; for the fourth selection, $X_j$={$X_L$, $X_R$, Y}; thereafter, for the fifth selection, $X_j$={$y_1(T_{i1}-T_{i0})+y_2a_v+y_3a_m$, $X_L$, $X_R$, Y}.

**[0065]** At 203, the feature value of the single limb-movement of the training sample corresponding to the month age data of the training sample is input into a logical operation formula: $\sum_{i=1}^{L}\beta_i g(W_i \times X_j + b_i) = o_j$, where multiple expressions based on the logical operation formula are obtained when there are multiple training samples, where

$L$ denotes the number of nodes of a neural network with a single hidden layer,

$g(x)$ denotes an activation function,

$W_i$=$[w_{i1}, w_{i2}, \ldots, w_{in}]^T$ denotes an input weight of the $i$-th hidden layer unit,

$b_i$ denotes a bias of the $i$-th hidden layer unit,

$\beta_i$=$[\beta_{i1}, \beta_{i2}, \ldots, \beta_{im}]^T$ denotes an output weight of the $i$-th hidden layer unit, and

$o_j$ denotes an output result of a logical operation after the stacked extreme learning machine is applied to the training sample for classification, where the output result of the logical operation includes two major classes of "normal development" and "developmental retardation".

**[0066]** It is to be noted that, with respect to the training sample, development of the training sample is known, that is, $o_j$ is known. In general, $o_j$ includes two classes of "normal development" and "developmental retardation".

**[0067]** At 204, an expression of the activation function $g(x)$, the input weight $W_i$ of the $i$-

th hidden layer unit, the bias $b_i$ of the *i*-th hidden layer unit, and the output weight $\beta_i$ of the *i*-th hidden layer unit are determined according to the multiple expressions based on the logical operation formula.

**[0068]** In this case, after the stacked extreme learning is completed, obtain the feature value $X_j$ of the single limb-movement of the sample to-be-tested that is to be input into the stacked extreme learning machine and determine the number of nodes *L* of the neural network with a single hidden layer, and then the logical operation of $o_j$ can be output. That is, as long as the feature value $X_j$ of the single limb-movement of the sample to-be-tested is obtained, the development of the sample to-be-tested can be determined.

**[0069]** At 205, the determined expression of the activation function $g(x)$, input weight $W_i$ of the *i*-th hidden layer unit, bias $b_i$ of the *i*-th hidden layer unit, and output weight $\beta_i$ of the *i*-th hidden layer unit are substituted into the logical operation formula, to obtain the mathematical model of the stacked extreme learning machine.

**[0070]** In this case, the mathematical model of the stacked extreme learning machine can be obtained, that is, $\sum_{i=1}^{L} \beta_i g\left(W_i \times X_j + b_i\right)$, where

*L* denotes the number of nodes of the neural network with a single hidden layer,

$g(x)$ denotes an activation function,

$W_i=[w_{i1}, w_{i2}, \ldots, w_{in}]^T$ denotes an input weight of the *i*-th hidden layer unit,

$b_i$ denotes a bias of the *i*-th hidden layer unit, and

$\beta_i=[\beta_{i1}, \beta_{i2},..., \beta_{im}]^T$ denotes an output weight of the *i*-th hidden layer unit.

**[0071]** For the sample to-be-tested, the output result is unknown. The output result $o_j$ can be obtained through the logical operation according to known expression of the activation function $g(x)$, input weight $W_i$ of the *i*-th hidden layer unit, bias $b_i$ of the *i*-th hidden layer unit, output weight $\beta_i$ of the *i*-th hidden layer unit, and the number of nodes *L* of the neural network with a single hidden layer.

**[0072]** In at least one implementation, the data of the single limb-movement includes: a start time $T_{i0}$, an end time $T_{i1}$, an average acceleration $a_v$, a peak acceleration $a_m$, a left leg movement type $S_L$, and a right leg movement type $S_R$ of the single limb-movement, where a duration $t_i$ of the single limb-movement is a difference $T_{i1}$-$T_{i0}$ between the end time of the single limb-movement and the start time $T_{i0}$ of the single limb-movement.

**[0073]** Herein, the reason why these indicators are selected as the data of the single limb-movement is as follows. Data that the motion sensor is able to acquire needs to be first taken into consideration. In addition, relevance of the data to the infant development also needs to

be considered, where these indicators such as the average acceleration $a_v$, the peak acceleration $a_m$, the left leg movement type $S_L$, and the right leg movement type $S_R$ can represent movement ability of the infant. Therefore, these indicators are used as basic data for acquiring the feature value $X_j$ of the single limb-movement. The data of the single limb-movement of the sample to-be-tested and the data of the single limb-movement of the training sample are measured by the same motion sensor or by at least the same type of sensor produced by the same manufacturer. As such, the determination error due to different sensors can be reduced.

**[0074]** In at least one implementation, the data of the single limb-movement of the sample to-be-tested is processed to obtain the feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data through one of: univariate feature selection, recursive feature selection, or stepwise feature selection.

**[0075]** For the univariate feature selection, the feature value of the single limb-movement is obtained through a statistical measurement method for a single variable of the data of the single limb-movement.

**[0076]** In this case, since the selected feature is a single variable, computing efficiency can be improved. However, since for a single variable, less impact factors are taken into consideration, the possibility of error in the determination result is relatively large.

**[0077]** For the recursive feature selection, the feature value of the single limb-movement is obtained by normalizing various variables of the data of the single limb-movement.

**[0078]** In this case, since the recursive feature selection considers various single variables comprehensively, that is, considers association among various single variables by introducing feature coefficients, the possibility of error in the determination result can be reduced.

**[0079]** For the stepwise feature selection, the feature value of the single limb-movement is obtained by selecting a single variable of the data of the single limb-movement in turn and normalizing various variables of the data of the single limb-movement.

**[0080]** In this case, since various single variables and the normalized variable are comprehensively considered, the possibility of error in the determination result can be further reduced.

**[0081]** In at least one implementation, the “normal development” in the output result of the logical operation is classified into different grades according to the mathematical model of the stacked extreme learning machine. Alternatively, the “developmental retardation” in the output result of the logical operation is classified into different grades according to the mathematical model of the stacked extreme learning machine.

**[0082]** In some cases where sub-classification is required, the "developmental retardation" and the "normal development" can be respectively classified into more specific grades. For example, "developmental retardation-1", "developmental retardation-2", and "developmental retardation-3", where "developmental retardation-1" represents the mildest developmental retardation and "developmental retardation-3" represents the severest developmental retardation; as well as "normal development-excellent", "normal development-good", and "normal development-medium". Based on the determination result $o_j$ of the univariate feature selection, the recursive feature selection, or the stepwise feature selection, reference can be further made to values of data ($T_{i1}$-$T_{i0}$), $a_v$, and $a_m$ and types of data $X_L$ and $X_R$, to further classify each of the "normal development" and the "developmental retardation". In the case that $o_j$ is "normal development", the larger the values of ($T_{i1}$-$T_{i0}$), $a_v$, and $a_m$, the better the "normal development", and in this case, it is possible to further set respective thresholds corresponding to "normal development-excellent", "normal development-good", and "normal development-medium" for ($T_{i1}$-$T_{i0}$), $a_v$, and $a_m$. On the other hand, in the case that $o_j$ is "normal development", the more types of $X_L$ and $X_R$, the better the "normal development", and in this case, it is possible to further set respective thresholds corresponding to "normal development-excellent", "normal development-good", and "normal development-medium" for the types of $X_L$ and $X_R$. In the case that $o_j$ is "developmental retardation", the smaller the values of ($T_{i1}$-$T_{i0}$), $a_v$, and $a_m$, the severer the "developmental retardation", and in this case, it is possible to further set respective thresholds corresponding to "developmental retardation-1", "developmental retardation-2", and "developmental retardation-3" for ($T_{i1}$-$T_{i0}$), $a_v$, and $a_m$. On the other hand, in the case that $o_j$ is "developmental retardation", the less types of $X_L$ and $X_R$, the severer the "developmental retardation", and in this case, it is possible to further set respective thresholds corresponding to "developmental retardation-1", "developmental retardation-2", and "developmental retardation-3" for the types of $X_L$ and $X_R$.

**[0083]** Second implementation

**[0084]** Referring to FIG. 4, the machine learning based device for infant development prediction of the second implementation includes a data acquiring unit 301, a data processing unit 302, an operation unit 303, and a prediction result outputting unit 304.

**[0085]** The data acquiring unit 301 is configured to acquire data of a single limb-movement and corresponding month age data of a sample to-be-tested.

**[0086]** Herein, the data of the single limb-movement of the sample to-be-tested is

acquired through a sensor. The data of the single limb-movement includes: a duration $t_i$, an average acceleration $a_v$, a peak acceleration $a_m$, a left leg movement type $S_L$, and a right leg movement type $S_R$ of the single limb-movement. The duration $t_i$ of the single limb-movement is a difference between an end time $T_{i1}$ of the single limb-movement and a start time $T_{i0}$ of the single limb-movement, that is, $T_{i1}$-$T_{i0}$. The left leg movement type $S_L$ and the right leg movement type $S_R$ can be described through text, for example, kicking, squatting, walking, crawling, bending, etc. Alternatively, a symbol is defined for each movement type, for example, kicking=Q1, squatting=Q2, walking=Q3, crawling=Q4, bending=Q5, and then the left leg movement type $S_L$ and the right leg movement type $S_R$ can be described through the symbol. In addition, infants have a relatively rapid development in limb-movement ability within 24 months, especially within 12 months, sometimes, even in a few days, the limb-movements of the infants can change significantly. Therefore, the month age data Y needs to be accurate to "day", for example, the month age data can be 2m+1, 8m+10, and so on.

**[0087]** The data processing unit 302 is configured to process the data of the single limb-movement of the sample to-be-tested, to obtain a feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data.

**[0088]** The data of the single limb-movement of the sample to-be-tested can be processed through selection manners such as univariate feature selection, recursive feature selection, or stepwise feature selection.

**[0089]** For the univariate feature selection, the feature value $X_j$ of the single limb-movement of the sample to-be-tested is obtained through a statistical measurement method for some single variables. In this case, in a first example, $X_j$= {$T_{i1}$-$T_{i0}$, m}; in a second example, $X_j$={$a_v$, Y}; in a third example, $X_j$={$a_m$, Y}; in a fourth example, $X_j$={$X_L$, $X_R$, Y}.

**[0090]** For the recursive feature selection, the feature value $X_j$ of the single limb-movement of the sample to-be-tested is obtained by normalizing various variables of the data of the single limb-movement. For example, in this case, $X_j$={$y_1(T_{i1}-T_{i0})+y_2a_v+y_3a_m$, $X_L$, $X_R$, Y}, where $y_1$ is a feature coefficient of ($T_{i1}$-$T_{i0}$), $y_2$ is a feature coefficient of $a_v$, $y_3$ is a feature coefficient of $a_m$. In this example, the normalizing is linear normalizing. According to actual needs, the power operation can further be performed on some of the above three features ($T_{i1}$-$T_{i0}$), $a_v$, and $a_m$, to upgrade their influence, or the square root operation can further be performed on some of the above three features ($T_{i1}$-$T_{i0}$), $a_v$, and $a_m$, to degrade their influence.

**[0091]** In the stepwise feature selection, for the first selection, $X_j$= {$T_{i1}$-$T_{i0}$, Y}; for the second selection, $X_j$={$a_v$,Y}; for the third selection, $X_j$={$a_m$, Y}; for the fourth selection, $X_j$={$X_L$, $X_R$, Y}; thereafter, for the fifth selection, $X_j$={$y_1(T_{i1}-T_{i0})+y_2a_v+y_3a_m$, $X_L$, $X_R$, Y}.

**[0092]** The operation unit 303 is configured to input a preset number of feature values of single limb-movements of the sample to-be-tested and corresponding month age data into a mathematical model of a stacked extreme learning machine, to perform a logical operation.

**[0093]** For example, the feature value $X_j$ of the single limb-movement of the sample to-be-tested is input into the mathematical model of the stacked extreme learning machine, that is, $\sum_{i=1}^{L} \beta_i g(W_i \times X_j + b_i)$, where

$L$ denotes the number of nodes of a neural network with a single hidden layer,

$g(x)$ denotes an activation function,

$W_i=[w_{i1}, w_{i2}, \ldots, w_{in}]^T$ denotes an input weight of the $i$-th hidden layer unit,

$b_i$ denotes a bias of the $i$-th hidden layer unit, and

$\beta_i=[\beta_{i1}, \beta_{i2}, \ldots, \beta_{im}]^T$ denotes an output weight of the $i$-th hidden layer unit.

**[0094]** An expression of the activation function $g(x)$, the input weight $W_i$ of the $i$-th hidden layer unit, the bias $b_i$ of the $i$-th hidden layer unit, and the output weight $\beta_i$ of the $i$-th hidden layer unit are known in the trained mathematical model of the stacked extreme learning machine. Therefore, through the above logical operation, an output result $o_j$ is obtained, which includes two major classes of "normal development" and "developmental retardation".

**[0095]** The prediction result outputting unit 304 is configured to use an output result of the logical operation of the stacked extreme learning machine as a basis for "normal development" or "developmental retardation" of the sample to-be-tested, to obtain a prediction result of infant development.

**[0096]** It is to be noted that, in the same time period, for acquiring the data of the limb-movement of the same sample to-be-tested, at least 5-10 groups of data of limb-movements should be acquired for determination of infant development. If during acquisition of the data of the limb-movement of the sample to-be-tested, only a small number of groups of data of limb-movements are acquired, as the sample to-be-tested may move too fast or too slow due to accidental factors, the result of determination of infant development may be inaccurate. If in the same time period, at least 5-10 groups of data of limb-movements are acquired for determination of infant development, inaccurate result due to accidental factors can be minimized. If a large number of groups of data of limb-movements are acquired, it will take a lot of time to determine infant development, which is of little significance to determine whether the infant is developing normally or stunted. If the sample to-be-tested is determined to be stunted according to 5-10 groups of data of limb-movements, 1-3 times of groups of

data of limb-movements can be acquired additionally. With more number of groups of data of limb-movements, a definite diagnosis can be made on whether the infant is stunted.

**[0097]** According to the machine learning based device for infant development prediction of the second implementation, with the known mathematical model of the stacked extreme learning machine, the data of the single limb-movement and the corresponding month age data of the sample to-be-tested are acquired, the data of the single limb-movement of the sample to-be-tested is then processed to obtain the feature value of the single limb-movement of the sample to-be-tested, and the feature value is input into the mathematical model of the stacked extreme learning machine to perform a logical operation, to obtain the output result, where the output result includes two major classes of "normal development" and "developmental retardation". As the month age data of the sample to-be-tested can be obtained according to the date of birth shown on the birth certificate, that is, data to-be-acquired of the method simply includes the data of the single limb-movement, in this case, the data of the single limb-movement can be obtained directly through the motion sensor. Therefore, the method can achieve infant development prediction conveniently. Furthermore, in the construction of the mathematical model of the stacked extreme learning machine of the method, infants at all month ages can be covered, and thus, even if the sample to-be-tested has relatively small month age, a relatively accurate output result can be obtained through the mathematical model of the stacked extreme learning machine. Therefore, a reliable basis can be provided for early intervention on developmental retardation of infants.

**[0098]** Third implementation

**[0099]** The storage medium of the third implementation is configured to store a machine learning based program for infant development prediction, which when executed by a processor, is configured to implement operations of the machine learning based method for infant development prediction of this application.

**[0100]** According to the storage medium of the third implementation, with the known mathematical model of the stacked extreme learning machine, the data of the single limb-movement and the corresponding month age data of the sample to-be-tested are acquired, the data of the single limb-movement of the sample to-be-tested is then processed to obtain the feature value of the single limb-movement of the sample to-be-tested, and the feature value is input into the mathematical model of the stacked extreme learning machine to perform a logical operation, to obtain the output result, where the output result includes two major classes of "normal development" and "developmental retardation". As the month age data of the sample to-be-tested can be obtained according to the date of birth shown on the birth

certificate, that is, data to-be-acquired of the method simply includes the data of the single limb-movement, in this case, the data of the single limb-movement can be obtained directly through the motion sensor. Therefore, the method can achieve infant development prediction conveniently. Furthermore, in the construction of the mathematical model of the stacked extreme learning machine of the method, infants at all month ages can be covered, and thus, even if the month age of the sample to-be-tested is relatively small, a relatively accurate output result can be obtained through the mathematical model of the stacked extreme learning machine. Therefore, a reliable basis can be provided for early intervention on developmental retardation of infants.

**[0101]** Fourth implementation

**[0102]** The electronic device of the fourth implementation includes a motion sensor, a processor, and a memory configured to store a machine learning based program for infant development prediction, where the program is executable on the processor. The motion sensor is configured to acquire data of a single limb-movement of a sample to-be-tested. The program, when executed by the processor, is configured to implement operations of the machine learning based method for infant development prediction of this application.

**[0103]** According to the electronic device of the fourth implementation, with the known mathematical model of the stacked extreme learning machine, the data of the single limb-movement and the corresponding month age data of the sample to-be-tested are acquired, the data of the single limb-movement of the sample to-be-tested is then processed to obtain the feature value of the single limb-movement of the sample to-be-tested, and the feature value is input into the mathematical model of the stacked extreme learning machine to perform a logical operation, to obtain the output result, where the output result includes two major classes of “normal development” and “developmental retardation”. As the month age data of the sample to-be-tested can be obtained according to the date of birth shown on the birth certificate, that is, data to-be-acquired of the method simply includes the data of the single limb-movement, in this case, the data of the single limb-movement can be obtained directly through the motion sensor. Therefore, the method can achieve infant development prediction conveniently. Furthermore, in the construction of the mathematical model of the stacked extreme learning machine of the method, infants at all month ages can be covered, and thus, even if the sample to-be-tested has relatively small month age, a relatively accurate output result can be obtained through the mathematical model of the stacked extreme learning machine. Therefore, a reliable basis can be provided for early intervention on developmental retardation of infants.

**[0104]** Although the implementations of this application have been described, those skilled in the art can make further changes and modifications to the implementations once they learn the basic creative concept. Therefore, the appended claims are intended to be interpreted as including the implementations and all changes and modifications falling within the scope of this application.

**[0105]** Those skilled in the art can make various changes and variations to this application without departing from the spirit and scope of this application. In this way, if these changes and variations of this application fall within the scope of the claims of this application and their equivalent technologies, this application is also intended to include these modifications and variations.

What is claimed is:

1. A machine learning based method for infant development prediction, comprising:

acquiring data of a single limb-movement and corresponding month age data of a sample to-be-tested;

processing the data of the single limb-movement of the sample to-be-tested, to obtain a feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data;

inputting a preset number of feature values of single limb-movements of the sample to-be-tested and corresponding month age data into a mathematical model of a stacked extreme learning machine, to perform a logical operation; and

using an output result of the logical operation of the stacked extreme learning machine as a basis for "normal development" or "developmental retardation" of the sample to-be-tested, to obtain a prediction result of infant development.

2. The method of claim 1, wherein construction of the mathematical model of the stacked extreme learning machine comprises:

acquiring data of a single limb-movement and corresponding month age data of a training sample, wherein infant development of the training sample is known;

processing the data of the single limb-movement of the training sample, to obtain a feature value of the single limb-movement of the training sample corresponding to the month age data of the training sample;

inputting the feature value of the single limb-movement of the training sample corresponding to the month age data of the training sample into a logical operation formula: $\sum_{i=1}^{L} \beta_i g(W_i \times X_j + b_i) = o_j$, wherein a plurality of expressions based on the logical operation formula are obtained when there are a plurality of training samples, wherein

$L$ denotes the number of nodes of a neural network with a single hidden layer,

$g(x)$ denotes an activation function,

$W_i=[w_{i1}, w_{i2}, \ldots, w_{in}]^T$ denotes an input weight of the $i$-th hidden layer unit,

$b_i$ denotes a bias of the $i$-th hidden layer unit,

$\beta_i=[\beta_{i1}, \beta_{i2}, \ldots, \beta_{im}]^T$ denotes an output weight of the $i$-th hidden layer unit, and

$o_j$ denotes an output result of a logical operation after the stacked extreme learning machine is applied to the training sample for classification, wherein the

output result of the logical operation comprises two major classes of "normal development" and "developmental retardation";

determining an expression of the activation function $g(x)$, the input weight $W_i$ of the $i$-th hidden layer unit, the bias $b_i$ of the $i$-th hidden layer unit, and the output weight $\beta_i$ of the $i$-th hidden layer unit according to the plurality of expressions based on the logical operation formula; and

substituting the determined expression of the activation function $g(x)$, input weight $W_i$ of the $i$-th hidden layer unit, bias $b_i$ of the $i$-th hidden layer unit, and output weight $\beta_i$ of the $i$-th hidden layer unit into the logical operation formula, to obtain the mathematical model of the stacked extreme learning machine.

3. The method of claim 1 or 2, wherein the data of the single limb-movement comprises:

a start time $T_{i0}$, an end time $T_{i1}$, an average acceleration $a_v$, a peak acceleration $a_m$, a left leg movement type $S_L$, and a right leg movement type $S_R$ of the single limb-movement, wherein

a duration $t_i$ of the single limb-movement is a difference $T_{i1}$-$T_{i0}$ between the end time of the single limb-movement and the start time $T_{i0}$ of the single limb-movement.

4. The method of claim 1 or 2, wherein the data of the single limb-movement of the sample to-be-tested is processed to obtain the feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data through one of: univariate feature selection, recursive feature selection, or stepwise feature selection;

processing the data of the single limb-movement of the sample to-be-tested to obtain the feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data comprising:

for the univariate feature selection, obtaining the feature value of the single limb-movement through a statistical measurement method for a single variable of the data of the single limb-movement;

for the recursive feature selection, obtaining the feature value of the single limb-movement by normalizing various variables of the data of the single limb-movement; or

for the stepwise feature selection, obtaining the feature value of the single limb-movement by selecting a single variable of the data of the single limb-movement

in turn and normalizing various variables of the data of the single limb-movement.

5. The method of claim 2, further comprising:

classifying the “normal development” in the output result of the logical operation into different grades according to the mathematical model of the stacked extreme learning machine; or

classifying the “developmental retardation” in the output result of the logical operation into different grades according to the mathematical model of the stacked extreme learning machine.

6. A machine learning based device for infant development prediction, comprising:

a data acquiring unit configured to acquire data of a single limb-movement and corresponding month age data of a sample to-be-tested;

a data processing unit configured to process the data of the single limb-movement of the sample to-be-tested, to obtain a feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data;

an operation unit configured to input a preset number of feature values of single limb-movements of the sample to-be-tested and corresponding month age data into a mathematical model of a stacked extreme learning machine, to perform a logical operation; and

a prediction result outputting unit configured to use an output result of the logical operation of the stacked extreme learning machine as a basis for “normal development” or “developmental retardation” of the sample to-be-tested, to obtain a prediction result of infant development.

7. The device of claim 6, wherein the prediction result outputting unit comprises:

a data of single limb-movement acquiring module configured to acquire data of a single limb-movement and corresponding month age data of a training sample, wherein infant development of the training sample is known;

a first data processing module configured to process the data of the single limb-movement of the training sample, to obtain a feature value of the single limb-movement of the training sample corresponding to the month age data of the training sample;

a second data processing module configured to input the feature value of the single limb-movement of the training sample corresponding to the month age data of the training

sample into a logical operation formula: $\sum_{i=1}^{L} \beta_i g(W_i \times X_j + b_i) = o_j$, wherein a plurality of expressions based on the logical operation formula are obtained when there are a plurality of training samples, wherein

$L$ denotes the number of nodes of a neural network with a single hidden layer,

$g(x)$ denotes an activation function,

$W_i=[w_{i1}, w_{i2}, \ldots, w_{in}]^T$ denotes an input weight of the $i$-th hidden layer unit,

$b_i$ denotes a bias of the $i$-th hidden layer unit,

$\beta_i=[\beta_{i1}, \beta_{i2},..., \beta_{im}]^T$ denotes an output weight of the $i$-th hidden layer unit, and

$o_j$ denotes an output result of a logical operation after the stacked extreme learning machine is applied to the training sample for classification, wherein the output result of the logical operation comprises two major classes of "normal development" and "developmental retardation";

an activation function determining module configured to determine an expression of the activation function $g(x)$, the input weight $W_i$ of the $i$-th hidden layer unit, the bias $b_i$ of the $i$-th hidden layer unit, and the output weight $\beta_i$ of the $i$-th hidden layer unit according to the plurality of expressions based on the logical operation formula; and

a third data processing module configured to substitute the determined expression of the activation function $g(x)$, input weight $W_i$ of the $i$-th hidden layer unit, bias $b_i$ of the $i$-th hidden layer unit, and output weight $\beta_i$ of the $i$-th hidden layer unit into the logical operation formula, to obtain the mathematical model of the stacked extreme learning machine.

8. The method of claim 6 or 7, wherein the data of the single limb-movement comprises:

a start time $T_{i0}$, an end time $T_{i1}$, an average acceleration $a_v$, a peak acceleration $a_m$, a left leg movement type $S_L$, and a right leg movement type $S_R$ of the single limb-movement, wherein

a duration $t_i$ of the single limb-movement is a difference $T_{i1}$-$T_{i0}$ between the end time of the single limb-movement and the start time $T_{i0}$ of the single limb-movement.

9. The method of claim 6 or 7, wherein the data of the single limb-movement of the sample to-be-tested is processed to obtain the feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data through one of: univariate feature selection, recursive feature selection, or stepwise feature selection;

processing the data of the single limb-movement of the sample to-be-tested to obtain the feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data comprising:

for the univariate feature selection, obtaining the feature value of the single limb-movement through a statistical measurement method for a single variable of the data of the single limb-movement;

for the recursive feature selection, obtaining the feature value of the single limb-movement by normalizing various variables of the data of the single limb-movement; or

for the stepwise feature selection, obtaining the feature value of the single limb-movement by selecting a single variable of the data of the single limb-movement in turn and normalizing various variables of the data of the single limb-movement.

10. The method of claim 7, further comprising:

classifying the “normal development” in the output result of the logical operation into different grades according to the mathematical model of the stacked extreme learning machine; or

classifying the “developmental retardation” in the output result of the logical operation into different grades according to the mathematical model of the stacked extreme learning machine.

11. A storage medium storing a machine learning based program for infant development prediction, which when executed by a processor, is configured to implement a machine learning based method for infant development prediction, the method comprising:

acquiring data of a single limb-movement and corresponding month age data of a sample to-be-tested;

processing the data of the single limb-movement of the sample to-be-tested, to obtain a feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data;

inputting a preset number of feature values of single limb-movements of the sample to-be-tested and corresponding month age data into a mathematical model of a stacked extreme learning machine, to perform a logical operation; and

using an output result of the logical operation of the stacked extreme learning machine as a basis for “normal development” or “developmental retardation” of the sample

to-be-tested, to obtain a prediction result of infant development.

12. The storage medium of claim 11, wherein construction of the mathematical model of the stacked extreme learning machine comprises:

acquiring data of a single limb-movement and corresponding month age data of a training sample, wherein infant development of the training sample is known;

processing the data of the single limb-movement of the training sample, to obtain a feature value of the single limb-movement of the training sample corresponding to the month age data of the training sample;

inputting the feature value of the single limb-movement of the training sample corresponding to the month age data of the training sample into a logical operation formula: $\sum_{i=1}^{L} \beta_i g(W_i \times X_j + b_i) = o_j$, wherein a plurality of expressions based on the logical operation formula are obtained when there are a plurality of training samples, wherein

$L$ denotes the number of nodes of a neural network with a single hidden layer,

$g(x)$ denotes an activation function,

$W_i=[w_{i1}, w_{i2}, \ldots, w_{in}]^T$ denotes an input weight of the $i$-th hidden layer unit,

$b_i$ denotes a bias of the $i$-th hidden layer unit,

$\beta_i=[\beta_{i1}, \beta_{i2},..., \beta_{im}]^T$ denotes an output weight of the $i$-th hidden layer unit, and

$o_j$ denotes an output result of a logical operation after the stacked extreme learning machine is applied to the training sample for classification, wherein the output result of the logical operation comprises two major classes of "normal development" and "developmental retardation";

determining an expression of the activation function $g(x)$, the input weight $W_i$ of the $i$-th hidden layer unit, the bias $b_i$ of the $i$-th hidden layer unit, and the output weight $\beta_i$ of the $i$-th hidden layer unit according to the plurality of expressions based on the logical operation formula; and

substituting the determined expression of the activation function $g(x)$, input weight $W_i$ of the $i$-th hidden layer unit, bias $b_i$ of the $i$-th hidden layer unit, and output weight $\beta_i$ of the $i$-th hidden layer unit into the logical operation formula, to obtain the mathematical model of the stacked extreme learning machine.

13. The storage medium of claim 11 or 12, wherein the data of the single limb-movement

comprises:

a start time $T_{i0}$, an end time $T_{i1}$, an average acceleration $a_v$, a peak acceleration $a_m$, a left leg movement type $S_L$, and a right leg movement type $S_R$ of the single limb-movement, wherein

a duration $t_i$ of the single limb-movement is a difference $T_{i1}$-$T_{i0}$ between the end time of the single limb-movement and the start time $T_{i0}$ of the single limb-movement.

14. The storage medium of claim 11 or 12, wherein the data of the single limb-movement of the sample to-be-tested is processed to obtain the feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data through one of: univariate feature selection, recursive feature selection, or stepwise feature selection;

processing the data of the single limb-movement of the sample to-be-tested to obtain the feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data comprising:

for the univariate feature selection, obtaining the feature value of the single limb-movement through a statistical measurement method for a single variable of the data of the single limb-movement;

for the recursive feature selection, obtaining the feature value of the single limb-movement by normalizing various variables of the data of the single limb-movement; or

for the stepwise feature selection, obtaining the feature value of the single limb-movement by selecting a single variable of the data of the single limb-movement in turn and normalizing various variables of the data of the single limb-movement.

15. The storage medium of claim 12, the method further comprising:

classifying the “normal development” in the output result of the logical operation into different grades according to the mathematical model of the stacked extreme learning machine; or

classifying the “developmental retardation” in the output result of the logical operation into different grades according to the mathematical model of the stacked extreme learning machine.

16. An electronic device, comprising a motion sensor, a processor, and a memory configured to store a machine learning based program for infant development prediction, the

program being executable on the processor, wherein

the motion sensor is configured to acquire data of a single limb-movement of a sample to-be-tested; and

the program, when executed by the processor, is configured to implement a machine learning based method for infant development prediction, the method comprising:

acquiring the data of the single limb-movement and corresponding month age data of the sample to-be-tested;

processing the data of the single limb-movement of the sample to-be-tested, to obtain a feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data;

inputting a preset number of feature values of single limb-movements of the sample to-be-tested and corresponding month age data into a mathematical model of a stacked extreme learning machine, to perform a logical operation; and

using an output result of the logical operation of the stacked extreme learning machine as a basis for "normal development" or "developmental retardation" of the sample to-be-tested, to obtain a prediction result of infant development.

17. The electronic device of claim 16, wherein construction of the mathematical model of the stacked extreme learning machine comprises:

acquiring data of a single limb-movement and corresponding month age data of a training sample, wherein infant development of the training sample is known;

processing the data of the single limb-movement of the training sample, to obtain a feature value of the single limb-movement of the training sample corresponding to the month age data of the training sample;

inputting the feature value of the single limb-movement of the training sample corresponding to the month age data of the training sample into a logical operation formula: $\sum_{i=1}^{L} \beta_i g(W_i \times X_j + b_i) = o_j$, wherein a plurality of expressions based on the logical operation formula are obtained when there are a plurality of training samples, wherein

$L$ denotes the number of nodes of a neural network with a single hidden layer,

$g(x)$ denotes an activation function,

$W_i$=$[w_{i1}, w_{i2}, \ldots, w_{in}]^T$ denotes an input weight of the $i$-th hidden layer unit,

$b_i$ denotes a bias of the $i$-th hidden layer unit,

$\beta_i$=$[\beta_{i1}, \beta_{i2}, \ldots, \beta_{im}]^T$ denotes an output weight of the $i$-th hidden layer unit,

and

$o_j$ denotes an output result of a logical operation after the stacked extreme learning machine is applied to the training sample for classification, wherein the output result of the logical operation comprises two major classes of "normal development" and "developmental retardation";

determining an expression of the activation function $g(x)$, the input weight $W_i$ of the $i$-th hidden layer unit, the bias $b_i$ of the $i$-th hidden layer unit, and the output weight $\beta_i$ of the $i$-th hidden layer unit according to the plurality of expressions based on the logical operation formula; and

substituting the determined expression of the activation function $g(x)$, input weight $W_i$ of the $i$-th hidden layer unit, bias $b_i$ of the $i$-th hidden layer unit, and output weight $\beta_i$ of the $i$-th hidden layer unit into the logical operation formula, to obtain the mathematical model of the stacked extreme learning machine.

18. The electronic device of claim 16 or 17, wherein the data of the single limb-movement comprises:

a start time $T_{i0}$, an end time $T_{i1}$, an average acceleration $a_v$, a peak acceleration $a_m$, a left leg movement type $S_L$, and a right leg movement type $S_R$ of the single limb-movement, wherein

a duration $t_i$ of the single limb-movement is a difference $T_{i1}$-$T_{i0}$ between the end time of the single limb-movement and the start time $T_{i0}$ of the single limb-movement.

19. The electronic device of claim 16 or 17, wherein the data of the single limb-movement of the sample to-be-tested is processed to obtain the feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data through one of: univariate feature selection, recursive feature selection, or stepwise feature selection;

processing the data of the single limb-movement of the sample to-be-tested to obtain the feature value of the single limb-movement of the sample to-be-tested corresponding to the month age data comprising:

for the univariate feature selection, obtaining the feature value of the single limb-movement through a statistical measurement method for a single variable of the data of the single limb-movement;

for the recursive feature selection, obtaining the feature value of the single

limb-movement by normalizing various variables of the data of the single limb-movement; or

for the stepwise feature selection, obtaining the feature value of the single limb-movement by selecting a single variable of the data of the single limb-movement in turn and normalizing various variables of the data of the single limb-movement.

20. The electronic device of claim 17, the method further comprising:

classifying the “normal development” in the output result of the logical operation into different grades according to the mathematical model of the stacked extreme learning machine; or

classifying the “developmental retardation” in the output result of the logical operation into different grades according to the mathematical model of the stacked extreme learning machine.