

SPECIFICATION

[TITLE]

LOAN EXPANSION HYPOTHESIS TESTING SYSTEM USING
ARTIFICIAL INTELLIGENCE, AND METHOD USING THE SAME

[TECHNICAL FIELD]

The present disclosure relates to a loan expansion hypothesis testing system using artificial intelligence (AI), and a method using the loan expansion hypothesis testing system. In more particular, the present disclosure relates to a loan expansion hypothesis testing system that uses AI and tests a loan expansion scenario hypothesis for a specific finance account group classified based on respective default probability values of a plurality of finance accounts, by using a sample of the specific finance account group, and a method using the loan expansion hypothesis testing system.

[BACKGROUND ART]

When a loan default risk is significantly low and a loan interest rate is higher than a procurement interest rate, financial institutions handling loan products may always generate profits due to an interest rate difference. Accordingly, financial institutions have a demand to expand loans to specific groups having a low risk of default.

Traditionally, in product design, loan management, etc. performed in financial institutions, policy decision-making and risk prediction management of designed loan products were performed by humans. However, the accuracy of prediction performed by humans was not high, and humans could not quickly respond to unexpected variables. Accordingly, risk management through traditional prediction has some limitations.

As described above, financial institutions always have a demand to expand loans to specific groups having a low risk of default, because, when a loan default risk is significantly low and a loan interest rate is higher than a procurement interest rate, financial institutions handling loan products always generate profits due to an interest rate difference. However, despite such a

demand, it was difficult for traditional forecasting-by-human systems to accurately select a group of customers having a low default risk. In addition, financial institutions should spend more manpower and more money than before in order to more accurately select a group of customers having a low default risk when using a traditional method.

[Prior Art Documents]

[Patent Document]

(Patent document 0001) KR 10-1799395 B1 (November 14, 2017)

[DESCRIPTION OF EMBODIMENTS]

[TECHNICAL PROBLEM]

Provided is a highly-reliable solution to select a loan expansion target from among the clients of a financial institution.

Provided is a testing system capable of confirming the appropriateness of the group selection.

Provided is a testing system capable of analyzing factors that affect a result of a virtual loan expansion policy simulation with respect to the loan expansion target group when the result is predicted as being negative.

In a decision-making process of financial product development, financial product management, and execution and account management, it is intended to perform more accurate decision-making by using an artificial intelligence (AI) prediction model.

It is also intended for financial product managers to simulate a result of easy analysis and prediction through AI technology and reflect a result of the simulation in financial product strategies in real time, without needing to acquire complicated AI technology.

Technical problems of the present disclosure are not limited to the contents mentioned above, and other effects not mentioned will be clearly understood by one of ordinary skill in the art from the following description.

[SOLUTION TO PROBLEM]

According to an aspect of the present disclosure, a loan expansion

hypothesis testing system using artificial intelligence (AI) established based on financial data includes an AI analyzer configured to calculate a default probability value of each of a plurality of finance accounts; a testing segment setter configured to classify the plurality of finance accounts into a plurality of segments, according to a preset criterion and set a specific segment as a testing segment as a testing target, based on the respective default probability values of the plurality of finance accounts calculated by the AI analyzer; a testing group determiner configured to determine a portion of the testing segment to be an experimental group and a comparison group for performing the loan expansion hypothesis testing; and a hypothesis tester configured to perform the loan expansion hypothesis testing with respect to the experimental group and the comparison group.

The AI analyzer may calculate a default probability value of each of a plurality of finance accounts by using a default prediction model generated based on the financial data by using machine learning.

The testing segment setter may set a segment having a minimum average default probability value from among the plurality of segments to be the testing segment.

The preset criterion may be a grade assigned to each of the plurality of finance accounts, based on the respective default probability values of the plurality of finance accounts.

The testing segment setter may combine and set one or more segments from among the plurality of segments as the testing segment in ascending order of the average default probability values of the one or more segments, and may stop the combination when the testing segment approximates to a preset account number.

The testing group determiner may set a preliminary experimental group and a preliminary comparison group by random-sampling the testing segment and performs distribution testing with respect to the preliminary experimental group and the preliminary comparison group, and may determine the preliminary experimental group and the preliminary comparison group to be the experimental group and the comparison group when the testing group determiner determines that the preliminary experimental group and the

preliminary comparison group have passed the distribution testing, and may re-perform the distribution testing by re-sampling the preliminary experimental group and the preliminary comparison group when the testing group determiner determines that the preliminary experimental group and the preliminary comparison group have not passed the distribution testing.

The testing group determiner may determine that the preliminary experimental group and the preliminary comparison group have passed the distribution testing, when a difference between the average default probability values of the preliminary experimental group and the preliminary comparison group is less than or equal to a predetermined value, and may determine that the preliminary experimental group and the preliminary comparison group have not passed the distribution testing, when the difference between the average default probability values of the preliminary experimental group and the preliminary comparison group exceeds the predetermined value.

The hypothesis tester may set, as a hypothesis, that a future default rate of the experimental group is less than a future default rate of the comparison group and may set, as a null hypothesis, that the future default rate of the experimental group is equal to or greater than the future default rate of the comparison group. To test the null hypothesis, the hypothesis tester may apply a loan expansion scenario to the experimental group and an existing loan policy maintaining scenario to the comparison group and may predict respective future default probability values of the plurality of finance accounts included in the experimental group and the comparison group by using the AI analyzer.

The loan expansion scenario may include at least one of a loan amount limit expansion, an interest rate shrinkage, and a new loan permission for each of the plurality of finance accounts, and the existing loan policy maintaining scenario may be continuously maintaining a loan amount limit, an interest rate, and new loan prohibition that are applied to each of the plurality of finance accounts.

The hypothesis tester may determine that the null hypothesis is rejected, when a future average default probability value of the experimental group is less than a future average default probability value of the comparison group, and may measure a loan quality by using the AI analyzer by equally applying the

loan expansion scenario, which has been applied to the experimental group, to all of the finance accounts of the testing segment including the comparison group.

The hypothesis tester may determine that the null hypothesis is rejected, when a future average default probability value of the experimental group is less than a future average default probability value of the comparison group, extract a second experimental group and a second comparison group from the experimental group through the testing group determiner, and set, as a second hypothesis, a future default rate of the second experimental group being lower than a future default rate of the second comparison group and set, as a second null hypothesis, the future default rate of the second experimental group being equal to or higher than the future default rate of the second comparison group. To test the second null hypothesis, the hypothesis tester may apply a second loan expansion scenario having a more expanded loan expansion range than the loan expansion scenario to the second experimental group and the loan expansion scenario to the second comparison group, and predict respective future default probability values for the plurality of finance accounts included in the second experimental group and the second comparison group by using the AI analyzer.

The hypothesis tester may determine that the null hypothesis is adopted, when a future average default probability value of the experimental group is equal to or greater than a future average default probability value of the comparison group, derive a main factor that worsens the future average default rate of the experimental group, through the AI analyzer, exclude one or more finance accounts including the derived main factor, and re-perform loan expansion testing of the loan expansion testing system.

The AI analyzer may include a financing model generator configured to generate a default prediction model through machine learning, based on financial data of each of the plurality of finance accounts; an account manager configured to manage the plurality of finance accounts included in a financial product in order to measure a quality of the financial product; a default probability value calculator configured to calculate the respective default probability values of the plurality of finance accounts included in the account

manager by using the default prediction model; a quality measurer configured to calculate the quality of the financial product, based on the respective default probability values of the plurality of finance accounts calculated by the default probability value calculator; and a factor analyzer configured to analyze a main factor of the finance account that affects the calculated quality of the financial product. According to a result of the factor analyzer, the account manager may select a bank account included in the financial product.

The hypothesis tester may determine that the null hypothesis is adopted, when a future average default probability value of the experimental group is equal to or greater than a future average default probability value of the comparison group, extract a second experimental group and a second comparison group from the experimental group through the testing group determiner, and set, as a second hypothesis, a future default rate of the second experimental group being lower than a future default rate of the second comparison group and set, as a second null hypothesis, the future default rate of the second experimental group being equal to or higher than the future default rate of the second comparison group. To test the second null hypothesis, the hypothesis tester may apply a second loan expansion scenario having a more contracted loan expansion range than the loan expansion scenario to the second experimental group and the loan expansion scenario to the second comparison group, and predict respective future default probability values for the plurality of finance accounts included in the second experimental group and the second comparison group by using the AI analyzer.

According to another aspect of the present disclosure, a loan expansion hypothesis testing method using AI established based on financial data includes an AI analyzing operation of calculating a default probability value of each of a plurality of finance accounts; a testing segment setting operation of classifying the plurality of finance accounts into a plurality of segments, according to a preset criterion and setting a specific segment as a testing segment as a testing target, based on the respective default probability values of the plurality of finance accounts calculated in the AI analyzing operation; a testing group determining operation of determining a portion of the testing segment to be an experimental group and a comparison group for performing the loan expansion

hypothesis testing; and a hypothesis testing operation of performing the loan expansion hypothesis testing with respect to the experimental group and the comparison group.

The AI analyzing operation may include calculating a default probability value of each of a plurality of finance accounts by using a default prediction model generated based on the financial data by using machine learning.

The testing segment setting operation may include setting a segment having a minimum average default probability value from among the plurality of segments to be the testing segment.

The hypothesis testing operation may include setting, as a hypothesis, that a future default rate of the experimental group is less than a future default rate of the comparison group and setting, as a null hypothesis, that the future default rate of the experimental group is equal to or greater than the future default rate of the comparison group, and, to test the null hypothesis, applying a loan expansion scenario to the experimental group and an existing loan policy maintaining scenario to the comparison group and predicting respective future default probability values of the plurality of finance accounts included in the experimental group and the comparison group by re-performing the AI analyzing operation.

The hypothesis testing operation may include determining that the null hypothesis is rejected, when a future average default probability value of the experimental group is less than a future average default probability value of the comparison group, and measuring a loan quality by re-performing the AI analyzing operation by equally applying the loan expansion scenario, which has been applied to the experimental group, to all of the finance accounts of the testing segment including the comparison group.

The hypothesis testing operation may include determining that the null hypothesis is adopted, when a future average default probability value of the experimental group is equal to or greater than a future average default probability value of the comparison group, deriving a main factor that worsens the future average default rate of the experimental group, excluding one or more finance accounts including the derived main factor, and re-performing loan expansion testing of the loan expansion testing system.

[ADVANTAGEOUS EFFECTS OF DISCLOSURE]

In a loan expansion hypothesis testing system and a method using the same, according to an embodiment of the present disclosure, a highly-reliable solution may be provided to select a loan expansion target from among the clients of a financial institution.

The appropriateness of selection of a loan expansion target group may be confirmed.

When a negative result is predicted as a result of a virtual loan expansion policy simulation with respect to the loan expansion target group, factors affecting the negative result may be analyzed.

In a decision-making process of financial product development, financial product management, and execution and account management, more accurate decision-making may be performed using an artificial intelligence (AI) prediction model.

Even though complicated AI technology is not acquired, financial product managers may simulate a result of easy analysis and prediction through AI technology and reflect a result of the simulation in financial product strategies in real time.

Effects of the present disclosure are not limited to the contents mentioned above, and other effects not mentioned will be clearly understood by one of ordinary skill in the art from the following description.

[BRIEF DESCRIPTION OF DRAWINGS]

FIG. 1 is a schematic block diagram of a loan expansion hypothesis testing system according to an embodiment of the present disclosure.

FIG. 2 is a block diagram of a structure of an artificial intelligence (AI) analyzer according to an embodiment of the present disclosure.

FIG. 3 is a graph showing a data map obtained by a data map transformer according to an embodiment of the present disclosure.

FIG. 4 is a diagram illustrating determination and re-prediction of a main factor by an automated financial product management system according to an embodiment of the present disclosure.

FIG. 5 is a block diagram for schematically illustrating operation

concepts of an AI analyzer and a testing segment setter of the loan expansion hypothesis testing system according to an embodiment of the present disclosure.

FIG. 6 is a view schematically illustrating a flow in which a testing group determiner determines an experimental group and a comparison group, according to an embodiment of the present disclosure.

FIG. 7 is a view schematically illustrating a flow in which a hypothesis tester tests a hypothesis, according to an embodiment of the present disclosure.

FIG. 8 is a view schematically illustrating a structure in which a hypothesis tester performs testing when rejecting a null hypothesis, according to an embodiment of the present disclosure.

FIG. 9 is a view schematically illustrating a structure in which a hypothesis tester performs testing when adopting a null hypothesis, according to an embodiment of the present disclosure.

FIG. 10 is a flowchart of a loan expansion hypothesis testing method according to an embodiment of the present disclosure.

[DETAILED DESCRIPTION OF DISCLOSURE]

Embodiments of the disclosure are described in detail herein with reference to the accompanying drawings so that this disclosure may be easily performed by one of ordinary skill in the art to which the disclosure pertains. The disclosure may, however, be embodied in many different forms and should not be construed as being limited to the embodiments set forth herein. In the drawings, parts irrelevant to the description are omitted for simplicity of explanation.

The terms used in the disclosure are merely used to describe particular embodiments, and are not intended to limit the scope of the disclosure. An expression used in the singular may encompass the expression of the plural, unless it has a clearly different meaning in the context.

In the present specification, it is to be understood that the terms such as "including," "having," and "comprising" are intended to indicate the existence of the features, numbers, steps, actions, components, parts, or combinations thereof disclosed in the specification, and are not intended to preclude the

possibility that one or more other features, numbers, steps, actions, components, parts, or combinations thereof may exist or may be added.

In addition, the components shown in the embodiments of the present disclosure are shown independently to indicate different characteristic functions, and thus do not mean that each component is composed of separate hardware or one software component unit. In other words, for convenience of description, each component is listed as each component, and at least two components may be combined to form one component, or one component may be divided into a plurality of components to perform a function. An embodiment in which at least two components may be combined to form one component, and an embodiment in which one component is divided into a plurality of components are also included in the scope of the present disclosure without departing from the essence of the present disclosure.

The following embodiments are provided to be more clearly explained to those of ordinary skill in the art, and thus the shapes and sizes of elements in the drawings may be exaggerated for more clear explanation.

Embodiments of the present disclosure will now be described more fully with reference to the accompanying drawings.

FIG. 1 is a schematic block diagram of a loan expansion hypothesis testing system 10 according to an embodiment of the present disclosure.

Referring to FIG. 1, according to an embodiment of the present disclosure, the loan expansion hypothesis testing system 10 using artificial intelligence (AI) established based on financial data may include an AI analyzer 100, a testing segment setter 200, a testing group determiner 300, and a hypothesis tester 400.

The financial data may be data related with clients who use a financial institution. For example, the financial data may be personal information, credit information, overdue payment information, and the like of the clients.

The AI analyzer 100 may calculate a default probability value of each of a plurality of finance accounts by using a default prediction model generated based on the financial data by using machine learning. The default prediction model may output, as a result value, a probability of overdue payment or default on repayment of a loan product used by clients. Herein, the default probability

value refers not only to 'default' as a dictionary definition, but also to an overdue payment on loan repayment. Because the default prediction model may calculate an overdue payment probability value, the default prediction model may be an overdue payment prediction model. However, for convenience of explanation, the overdue payment prediction model may be collectively referred to as a 'default prediction model'. Therefore, the default probability model in the claims and specification of the present disclosure is able to calculate a default probability value or overdue payment probability value of each of a plurality of finance accounts, and thus embodiments are not limited to only 'default'. In addition, an 'overdue payment rate', which will be described later, is referred to as a 'default rate' for convenience, but may also include an 'overdue payment rate' by definition.

The testing segment setter 200 may classify the plurality of finance accounts into a plurality of segments, according to a preset criterion, and may set a specific segment to be a testing segment as a testing target, based on the respective default probability values of the plurality of finance accounts calculated by the AI analyzer 100.

The testing group determiner 300 may determine a portion of the testing segment to be an experimental group and a comparison group for performing the loan expansion hypothesis testing.

The hypothesis tester 400 may perform the loan expansion hypothesis testing with respect to the experimental group and the comparison group.

FIG. 2 is a block diagram of a structure of the AI analyzer 100 according to an embodiment of the present disclosure.

Referring to FIG. 2, the AI analyzer 100 may include a financing model generator 110, an account manager 120, a default probability value calculator 130, a quality measurer 140, and a factor analyzer 150. The AI analyzer 100 may further include a data map transformer 160.

The AI analyzer 100 may automatically manage a financial product based on financial data 121 for each of the plurality of finance accounts. The financial data 121 may include internal data 121a collected from the financial institution or external data 121b collected from outside the financial institution.

The internal data 121a may include at least one of personal information,

credit information, overdue payment information, interest rate information, loan information, income information, debt information, deposit information, and financial transaction information of each bank account registered in the financial institution. The personal information may include a name, an age, a residence, a family relation, a gender, an income, a work, a working period, asset status information, and the like, and the credit information may include a credit-rating agency rating, an internal credit rating, an ability to repay, and the like. The overdue payment information may include overdue payment information, default information, and debt information for financial institutions in the past, and may also include product information such as loan products, loan execution amounts, spreads, interest payment amounts, and balances.

The external data 121b refers to data not generated internally in the bank, and may be collected in a manner such as alliance or scraping. For example, the external data 121b may be information on a telecommunications company, a card use history, a retailer's consumption pattern, economic indicators, an SNS, an interest rate, a standard interest rate, and a channel via which a behavior of a financial product occurs. The external data 121b may also include pieces of information such as a grade managed by each securities company and the variability of stocks during a past specific period.

The financing model generator 110 may generate a default prediction model 111 through machine learning, based on the financial data 121 for each of the plurality of finance accounts.

The machine learning may use at least one of a Deep Neural Network (DNN), a Convolution Neural Network (CNN), a Recurrent Neural Network (RNN), a Restricted Boltzmann Machine (RBM), and a Deep Brief Network (DBN).

The account manager 120 may manage a plurality of finance accounts that are input to the default prediction model 111. The account manager 120 may manage financial data input to the default prediction model 111, in units of bank accounts, and may adjust input bank accounts. The financial data 121, which is input to the default prediction model 111, may be managed by the account manager 120 in units of bank accounts, and may be input by the quality measurer 140. While prediction is being repeated, the account manager 120

may restrict or expand an input range by adjusting the bank account that are input to the default prediction model 111. The bank account may be a bank account corresponding to one nominee, and information included in the bank account may be classified by a category-type variable and have detailed information. Examples of the category may include a nominee, an address, a gender, a repayment method, a housing type, a balance, a loan interest rate, and credit information.

The default probability value calculator 130 may calculate the respective default probability values of the plurality of finance accounts included in the account manager 120 by using the default prediction model 111 generated by the financing model generator 110. The default probability values calculated by the AI analyzer 100 may be result values of the calculation performed by the default probability value calculator 130.

The quality measurer 140 may input financial data for each of the plurality of finance accounts belonging to the financial product, and thus may calculate the quality of the financial product based on the default prediction model 111.

The factor analyzer 150 may analyze a main factor of a finance account that affects the quality of the financial product calculated by the quality measurer 140. For example, when the risk of an overdue-default rate of a credit loan product with a 5% interest rate is managed to no more than 2%, an overdue-default rate prediction result of a future portfolio through an overdue-default rate prediction model may be expected to rise up to 3% if risk management is not performed. In this case, the factor analyzer 150 may analyze what main factor needs to be adjusted to reach less than 2%, which is a target value. Here, the main factor may be a category-type variable included in the bank account. According to a result of the factor analyzer 150, the account manager 120 may select a bank account included in the financial product.

The data map transformer 160 may visualize an output value of the financing model generator 110 or an output value of the quality measurer 140 into a Vintage Chart or a NetFlow Chart. The Vintage Chart or the NetFlow Chart may be referred to as a data map. The data map may be in the form of a

graph or table that can be read by humans or machines. The form of the data map may vary according to a business type that is applied to the AI analyzer 100. For example, the data map transformer 160 may visualize a business type, such as a retail banking, into a data map such as a Vintage Chart or a NetFlow Chart, and may visualize business types, such as a securities company and a credit card, into other types of data maps.

FIG. 3 is a graph showing a data map obtained by the data map transformer 160 according to an embodiment of the present disclosure.

Referring to FIG. 3, the output value of the quality measurer 140 may be visualized to a Vintage Chart or a NetFlow Chart. The Vintage chart is an analysis index created to compare portfolios executed in a specific duration (January, February, etc., 2017), and is similar to an index that manages the quality of wine for each vintage. The chart in FIG. 3 is a chart accumulating and showing bank accounts that are expected to be an Ever 5+, i.e., to be overdue for at least 5 days even at least once.

Referring to FIG. 3, for example, a rate (L1) of bank accounts predicted to be overdue for at least 5 days even at least once for 25 months after a loan is executed, among 12,423 bank accounts executed in January 2017, is about 25%, namely, 3,106 bank accounts. This prediction data may be accumulated and displayed over time, and a plot of each executed monthly portfolio may be drawn. When the plot of the monthly portfolio is referred to as a quality, a chart obtained by the data map transformer 160 may include a target quality L0. When a quality L1 predicted at the same time point is similar to the value of the target quality L0, the quality of a predicted loan portfolio may be evaluated as being good. Such a quality may include at least one of an income rate, a default rate, or a prepayment rate.

The type of data map that may be generated by the data map transformer 160 and the type of a graph visualizing a combination of the type of the data map with a prediction model may be generated in various categories, and not only a two-dimensional graph but also a multidimensional graph having a plurality of variable axes may be included.

For example, 50 bank accounts from among 1,000 bank accounts are being overdue. When 2,000 additional bank accounts execute a new loan next

month, an overdue payment rate may be lowered to 50/3000 because there is no overdue payment for the 2,000 additional bank accounts that have executed the new loan. As such, the overdue payment rate may not be judged by only one indicator, and thus may be indicated using a multi-dimensional axis.

The factor analyzer 150 determines whether the predicted quality L1 is better or worse than the target quality L0. It may be determined that the quality is good, when a difference $d1$ between the quality L1 predicted at the same time point and the target quality L0 is less than or equal to a certain reference. When it is determined that the predicted quality L1 is not good, the factor analyzer 150 may determine a main factor capable of reducing the difference $d1$ between the predicted quality L1 and the target quality L0 and may analyze the influence of the main factor.

The main factor may bring about the most change in the difference $d1$ when a figure among the detailed information of the categories included in a bank account, which is input data of the default prediction model 111 generated by the financing model generator 110, is limited or a bank account containing the detailed information of any category is included in or limited to loan execution.

For example, a first bank account, a second bank account, and a third bank account may be input to the default prediction model 111. The first bank account, the second bank account, and the third bank account may be accounts on which a loan has been performed at a time point 'A'. The categories of each bank account may include an 'overdue payment history'. The 'overdue payment history' refers to overdue payment for at least five days before the corresponding time point, and detailed information of the category of the 'overdue payment history' may be a count of histories that each bank account was overdue in the past according to the above criterion. When detailed information of the category of the 'overdue payment history' of the second bank account is actually '3' or more, the factor analyzer 150 may again input a bank account except for a bank account having a value of '1' or more in the category of the 'overdue payment history' to the default prediction model 111, and, when the difference $d1$ is reduced, may determine that the 'overdue payment history' is the main factor.

FIG. 4 is a diagram illustrating determination and re-prediction of a main factor by an automated financial product management system according to an embodiment of the present disclosure.

Referring to FIG. 4, the factor analyzer 150 may determine not only the above-described 'overdue payment history' but also may determine the main factor very variously and duplicatedly. One model may not be generated as the default prediction model 111, but various models having different output values according to different purposes may be generated as the default prediction model 111. The factor analyzer 150 may calculate various prediction graphs by using a value obtained by a prediction by the single default prediction model 111. FIG. 4 illustrates that the default prediction model 111 predicts a monthly overdue payment rate for each input bank account and the quality measurer 140 calculates a cumulative default rate according to the predicted monthly overdue payment rate and calculates a ratio of bank accounts dishonored within three months to classify the input bank accounts into grade 1 to grade 10.

Referring to FIGS. 3 and 4, when the factor analyzer 150 determines that a main factor reducing the difference $d1$ between the predicted quality $L1$ and the target quality $L0$ is an 'overdue payment history', the account manager 120 may exclude a bank account having the 'overdue payment history' from input bank account data. The quality measurer 140 may calculate a default rate by using the default prediction model 111 to which bank accounts excluding the bank account having the 'overdue payment history' have been re-input, and the data map transformer 160 may again output a cumulative default rate, based on a calculated value of the factor analyzer 150. At this time, a difference $d2$ between a predicted quality $L2$ and the target quality $L0$ may be re-analyzed. When it is not determined that the quality is good, the factor analyzer 150 may again analyze the main factor. When the factor analyzer 150 determines that a bank account having assigned grade 10 at a rate of default bank accounts within three months is a main factor, the account manager 120 may again exclude the bank account classified into grade 10 from the bank accounts input to the default prediction model 111, and may input a result of the exclusion to the default prediction model 111. The AI analyzer 100 may perform this process and may calculate a predicted quality $L3$ determined to be good.

The account manager 120 may extract one or more bank accounts satisfying a criterion for the major factor from a plurality of pieces of bank account information, and may include a post action unit that recommends an action to be taken to the holders of the bank accounts and a pre-action unit that prohibiting loans from being executed on another bank account that satisfies the criterion for the major factor.

Here, the action is an action taken by a user, and, when the main factor is determined to be grade 10, the user may take an action, such as telephone dunning, mailing, or seizure of assets, to the nominee of a bank account classified as grade 10. The post action unit may recommend this action. The pre-action unit may exclude a bank account similar to the bank account classified into grade 10, as the main factor, from loan candidate bank accounts that are to execute loans in the future.

FIG. 5 is a block diagram for schematically illustrating operation concepts of the AI analyzer 100 and the testing segment setter 200 of the loan expansion hypothesis testing system 10 according to an embodiment of the present disclosure.

Referring to FIG. 5, according to an embodiment of the present disclosure, the AI analyzer 100 may calculate a default probability value for finance account data 122. The finance account data 122 may be group data including a plurality of pieces of finance account data. As described above with reference to FIG. 2, the AI analyzer 100 may calculate respective default probability values for the plurality of pieces of finance accounts data included in the finance account data 122 by using the default prediction model 111 generated by machine-learning the financial data 121.

The testing segment setter 200 may divide the finance account data 122 into a plurality of segments 123 according to a preset criterion, and may set a specific segment as a testing segment 124 as a testing target, based on the respective default probability values of the plurality of pieces of finance account data calculated by the AI analyzer 100. The testing segment setter 200 may calculate an average default probability value of each of the plurality of segments 123, and may set a segment having a minimum average default probability value from among the calculated average default probability values

to be the testing segment 124.

In more detail, the testing segment setter 200 may assign a grade to each of the plurality of pieces of finance account data, based on the respective default probability values of the plurality of pieces of finance account data. For example, the default probability values may be sorted in the order of magnitude, and thus a low grade may be assigned to follow an even distribution or a normal distribution. For example, grade 1 may be assigned at 0% to 10%, grade 2 may be assigned at 11% to 20%, and grade 3 may be assigned at 21% to 30%. In this case, grades 1 to 10 may be assigned. The testing segment setter 200 may classify the plurality of segments 123 according to grades, and may set a segment in a lowest grade, namely, a segment having a minimum average default probability value, to be the testing segment 124. The preset criterion may be a grade assigned to each of the plurality of pieces of finance account data.

According to an embodiment, the preset criterion may be [types (A/B/C) of loan product], [age groups (20s/30s/40s/50s/60s)], [gender (male/female)], or the like. The preset criterion may not be specified as one criterion, and may be changed according to a designation of a user. Not only one preset criterion may be applied, but also one or more preset criteria may be applied. For example, the preset criterion may be designated as [type of loan product & age group (A&30s)] or [type of loan product & age group & gender (B&40s&female)]. The testing segment setter 200 may calculate the respective average default probability values of the plurality of segments 123 classified according to the preset criterion, based on the respective default probability values of the plurality of pieces of finance account data, and may set a segment 123 having a lowest average default probability value as the testing segment 124.

The testing segment setter 200 may classify the plurality of segments 123 according to the above-described all possible preset criteria. In other words, the testing segment setter 200 may classify the plurality of segments 123 according to all labels included in the finance account data. For example, the testing segment setter 200 may classify the plurality of segments 123 according to gender, age, loan product, and region, which are all criteria that enables division.

In this case, the testing segment setter 200 may set a segment 123 having a lowest average default probability value from among the classified segments 123 as the testing segment 124, or may combine one or more segments 123 in ascending order of the average default probability values of the plurality of segments 123, may stop the combination when the number of finance accounts included in a combined segment 123 reaches or approaches a preset account number, and may set the combined segment 123 as the testing segment 124. For example, when there are 100 bank accounts in a single segment 123 on average and the preset account number is 1,000, the testing segment setter 200 may set a plurality of segments 123 as the testing segment 124 in ascending order of the average default probabilities to approximate to 1,000 bank accounts.

FIG. 6 is a view schematically illustrating a flow in which the testing group determiner 300 determines an experimental group and a comparison group, according to an embodiment of the present disclosure.

Referring to FIG. 6, the testing group determiner 300 may extract an experimental group and a comparison group for testing a hypothesis for the testing segment 124. The testing group determiner 300 may extract a preliminary experimental group 125 and a preliminary comparison group 126 from the set testing segment 124 via random sampling. The testing group determiner 300 may perform distribution testing with respect to the preliminary experimental group 125 and the preliminary comparison group 126. The distribution testing may be a Mann-Whitney Test. When the testing group determiner 300 determines that the preliminary experimental group 125 and the preliminary comparison group 126 have passed the distribution testing, the testing group determiner 300 may determine the preliminary experimental group 125 and the preliminary comparison group 126 to be a determined experimental group 127 and a determined comparison group 128. When the testing group determiner 300 determines that the preliminary experimental group 125 and the preliminary comparison group 126 have not passed the distribution testing, the testing group determiner 300 may re-set the preliminary experimental group 125 and the preliminary comparison group 126 via random sampling, and thus may re-perform the distribution testing. A criterion of passing the distribution testing

may be used to determine that the preliminary experimental group 125 and the preliminary comparison group 126 have passed the distribution testing, when a difference between the average default probability values of the preliminary experimental group and the preliminary comparison group is less than or equal to a predetermined value, and determine that the preliminary experimental group 125 and the preliminary comparison group 126 have not passed the distribution testing, when the difference between the average default probability values of the preliminary experimental group and the preliminary comparison group exceeds the predetermined value.

FIG. 7 is a view schematically illustrating a flow in which the hypothesis tester 400 tests a hypothesis, according to an embodiment of the present disclosure.

Referring to FIG. 7, according to an embodiment of the present disclosure, the hypothesis tester 400 may set, as a hypothesis, that a future default rate of an experimental group is less than that of a comparison group, and may set, as a null hypothesis, that the future default rate of the experimental group is equal to or greater than that of the comparison group. The experimental group or the comparison group is the same as a determined experimental group 127 or a determined comparison group 128 determined by the testing group determiner 300 of FIG. 6. Hereinafter, the experimental group or the comparison group for hypothesis testing is described as the determined experimental group 127 or the determined comparison group 128. The hypothesis tested by the hypothesis tester 400 may be inspecting the above-described null hypothesis that the future default rate of the determined experimental group 127 is equal to or greater than that of the determined comparison group 128. The term 'hypothesis rejection' or 'hypothesis adoption' due to the testing by the hypothesis tester 400 refers to 'rejecting' or 'adopting' a null hypothesis.

To test the null hypothesis, the hypothesis tester 400 may apply a loan expansion scenario to the experimental group and an existing loan policy maintaining scenario to the comparison group and thus may predict respective future default probability values for the plurality of finance accounts included in the determined experimental group 127 and the determined comparison group

128 by using the AI analyzer 100.

The loan expansion scenario may include at least one of a loan amount limit expansion, an interest rate shrinkage, and a new loan permission for each of the plurality of finance accounts, and the existing loan policy maintaining scenario may be continuously maintaining a loan amount limit, an interest rate, and new loan prohibition that are applied to each of the plurality of finance accounts.

The hypothesis tester 400 may determine that the null hypothesis is rejected, when a future average default probability value of the determined experimental group 127 is less than that of the determined comparison group 128, and may determine that the null hypothesis is adopted, when the future average default probability value of the determined experimental group 127 is equal to or greater than that of the determined comparison group 128. At this time, the hypothesis tester 400 may perform testing through a Z-Test.

In more detail, given that a sample rate defined by a probability sample having a size of n_1 from a binomial parent population having a parent rate (parent default rate) of p_1 is $\hat{P}_1$ and, independently therefrom, a sample rate defined by a probability sample having a size of n_2 from a binomial parent population having a parent rate (parent default rate) of p_2 is $\hat{P}_2$, when the sample sizes n_1 and n_2 are sufficiently large, a testing statistic Z for a hypothesis may be expressed as Equation 1.

[Equation 1]

$$Z = \frac{\hat{P}_1 - \hat{P}_2}{\sqrt{\hat{P}(1 - \hat{P})\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$$

Here, $\hat{P}$ of Equation 1 is equal to Equation 2.

[Equation 2]

$$\hat{P} = \frac{n_1\hat{P}_1 + n_2\hat{P}_2}{n_1 + n_2}$$

According to an embodiment of the present disclosure, n_1 may be the number of samples of the determined experimental group 127, n_2 may be the number of samples of the determined comparison group 128, p_1 may be a parent rate (parent default rate) of the determined experimental group 127, p_2 may be a parent rate (parent default rate) of the determined comparison group

128, $\hat{p}_1$ may be a sample rate (sample default rate) of the determined experimental group 127, and $\hat{p}_2$ may be a sample rate (sample default rate) of the determined comparison group 128.

The null hypothesis may be Equation 3.

[Equation 3]

$$H_0 : p_1 \geq p_2,$$

where H_0 may be the null hypothesis in which the future default rate of the determined experimental group 127 is equal to or greater than that of the determined comparison group 128. In other words, the determined experimental group 127 may be a default rate becoming worse in the loan expansion scenario.

An approximate critical region of the the null hypothesis may be Equation 4.

[Equation 4]

$$R : Z < -z_\alpha,$$

where R may be a critical region, and, when a distribution of the testing statistic Z follows $N(0,1)$, z_α may be a value satisfying $P(Z > z_\alpha) = \alpha$, with respect to a given significance level α . When Equation 4 is satisfied, the hypothesis tester 400 may determine that the null hypothesis is rejected.

A user may check a simulation result of the determined experimental group 127 and the determined comparison group 128 through a visual material 161 provided by the data map transformer 160 of the AI analyzer 100. Accordingly, the user may check a change in risk by not only checking the value of the result but also checking a time-sequential default rate progress.

FIG. 8 is a view schematically illustrating a structure in which the hypothesis tester 400 performs testing when rejecting a null hypothesis, according to an embodiment of the present disclosure.

Referring to FIG. 8(a), according to an embodiment of the present disclosure, when the hypothesis tester 400 determines that the null hypothesis is rejected, the hypothesis tester 400 may equally apply the loan expansion scenario, which has been applied to the determined experimental group 127, to a testing segment including the determined comparison group 128. Because the fact that the hypothesis tester 400 rejected the null hypothesis means that a

loan quality of the determined experimental group 127 was better than the determined comparison group 128, the hypothesis tester 400 may widen the application range of the loan expansion scenario and check a progress thereof.

Referring to FIG. 8(b), when the hypothesis tester 400 determines that the null hypothesis is rejected, the hypothesis tester 400 may extract a second determined experimental group 127a and a second determined comparison group 128a from the determined experimental group 127 through the testing group determiner 300. The hypothesis tester 400 may apply a second loan expansion scenario having a more expanded loan expansion range than the loan expansion scenario to the second determined experimental group 127a, and may apply the existing loan expansion scenario to the second determined comparison group 128a. At this time, the hypothesis tester 400 may set, as a second hypothesis, a future default rate of the second determined experimental group 127a being lower than that of the second determined comparison group 128a, set, as a second null hypothesis, the future default rate of the second determined experimental group 127a being equal to or higher than that of the second determined comparison group 128a, and re-perform hypothesis testing with respect to the second null hypothesis. When re-performing the hypothesis testing with respect to the second null hypothesis, the hypothesis tester 400 may predict respective future default probability values of the plurality of finance accounts of the second experimental group and the second comparison group by using the AI analyzer 100 and may utilize a result of the prediction. The hypothesis tester 400 may re-classify an experimental group and a comparison group from a restricted experimental group and test a hypothesis by applying a more expanded loan expansion scenario, in order to determine a maximum point where loan expansion is possible. The hypothesis tester 400 may re-perform hypothesis testing until the maximum point is able to be determined. For example, when there is a stage where the hypothesis is adopted during repetition of hypothesis testing, the hypothesis tester 400 may determine this stage as the maximum point where loan expansion is possible.

FIG. 9 is a view schematically illustrating a structure in which the hypothesis tester 400 performs testing when adopting a null hypothesis, according to an embodiment of the present disclosure.

Referring to FIG. 9(a), according to an embodiment of the present disclosure, when the hypothesis tester 400 determines that the null hypothesis is adopted, the hypothesis tester 400 may derive a main factor that worsens the future average default rate of the experimental group, through the AI analyzer 100. The hypothesis tester 400 may exclude the one or more finance accounts including the derived main factor and may re-perform loan expansion testing of the loan expansion testing system. In other words, the AI analyzer 100 may determine that a trained default prediction model is wrong. The AI analyzer 100 may re-generate a default prediction model by changing a hyper parameter or excluding the one or more finance account including the derived main factor from learning data. Thereafter, the loan expansion hypothesis testing system may re-perform analysis from the beginning by using a new default prediction model.

Referring to FIG. 9(b), according to an embodiment of the present disclosure, when the hypothesis tester 400 determines that the null hypothesis is adopted, the hypothesis tester 400 may extract a second determined experimental group 127b and a second determined comparison group 128b from the determined experimental group 127 through the testing group determiner 300. The hypothesis tester 400 may apply a second loan expansion scenario having a more contracted loan expansion range than the loan expansion scenario to the second determined experimental group 127b, and may apply the existing loan policy maintaining scenario to the second determined comparison group 128b. At this time, the hypothesis tester 400 may set, as a second hypothesis, a future default rate of the second determined experimental group 127b being lower than that of the second determined comparison group 128b, may set, as a second null hypothesis, the future default rate of the second determined experimental group 127b being equal to or higher than that of the second determined comparison group 128b, and may re-perform hypothesis testing with respect to the second null hypothesis. When re-performing the hypothesis testing with respect to the second null hypothesis, the hypothesis tester 400 may predict respective future default probability values of the plurality of finance accounts of the second determined experimental group 127b and the second determined comparison group 128b

by using the AI analyzer 100 and may utilize a result of the prediction. Testing a hypothesis by classifying an experimental group and a comparison group from a restricted experimental group and applying the contracted loan expansion scenario may be performed to determine a maximum point where loan expansion is possible, by determining that the default prediction model generated by the AI analyzer 100 through learning seems appropriate but a loan expansion range of the loan expansion scenario is big. Accordingly, the hypothesis tester 400 may re-perform hypothesis testing until the maximum point is able to be determined. For example, when there is a stage where the hypothesis is adopted during repetition of hypothesis testing, the hypothesis tester 400 may determine this stage as the maximum point where loan expansion is possible.

The loan expansion hypothesis testing system according to an embodiment of the present disclosure may ascertain a client standard group appropriate to use a loan product and a main factor, before applying the loan product in the actual market. The loan expansion hypothesis testing system according to an embodiment of the present disclosure may also ascertain a risk in advance through a virtual simulation and may check a progress of a time-sequential risk change, thereby facilitating risk control. The loan expansion hypothesis testing system according to an embodiment of the present disclosure may prevent mistakes and errors from being generated when a person performs hypothesis testing, and may significantly reduce performing costs thereof. Therefore, financial institutions may more accurately and quickly make a decision of handing a loan product.

FIG. 10 is a flowchart of a loan expansion hypothesis testing method according to an embodiment of the present disclosure.

Referring to FIG. 10, according to an embodiment of the present disclosure, the loan expansion hypothesis testing method may include an artificial intelligence (AI) analyzing operation S100, a testing segment setting operation S200, a testing group determining operation S300, and a hypothesis testing operation S400.

In the AI analyzing operation S100, a default probability value of each of a plurality of finance accounts may be calculated.

In the testing segment setting operation S200, the plurality of finance accounts may be classified into a plurality of segments, according to a preset criterion, and a specific segment may be set as a testing segment as a testing target, based on the respective default probability values of the plurality of finance accounts calculated in the AI analyzing operation S100.

In the testing group determining operation S300, a portion of the testing segment may be determined as an experimental group and a comparison group for performing the loan expansion hypothesis testing.

In the hypothesis testing operation S400, the loan expansion hypothesis testing may be performed with respect to the experimental group and the comparison group. In the AI analyzing operation S100, a default probability value of each of a plurality of finance accounts may be calculated using a default prediction model generated based on the financial data by using machine learning.

In the testing segment setting operation S200, a segment having a minimum average default probability value from among the plurality of segments may be set as the testing segment.

In the hypothesis testing operation S400, a future default rate of an experimental group being less than that of a comparison group may be set as a hypothesis, and the future default rate of the experimental group being equal to or greater than that of the comparison group may be set as a null hypothesis. To test the null hypothesis, the AI analyzing operation S100 may be re-performed by applying a loan expansion scenario to the experimental group and an existing loan policy maintaining scenario to the comparison group, and thus respective future default probability values for the plurality of finance accounts included in the experimental group and the comparison group may be predicted.

In the hypothesis testing operation S400, when a future average default probability value of the experimental group is less than that of the comparison group, it may be determined that the null hypothesis is rejected. The AI analyzing operation S100 may be re-performed by equally applying the loan expansion scenario, which has been applied to the experimental group, to all of the finance accounts of the testing segment including the comparison group.

In the hypothesis testing operation S400, when a future average default

probability value of the experimental group is equal to or greater than that of the comparison group, it may be determined that the null hypothesis is adopted. A main factor that worsens the future average default rate of the experimental group may be derived, the one or more finance accounts including the derived main factor may be excluded, and loan expansion testing of the loan expansion testing method may be re-performed.

Various embodiments described in the specification may be implemented by hardware, middleware, a microcode, software and/or combinations thereof. For example, various embodiments may be implemented in one or more on-demand semiconductors (ASICs), digital signal processors (DSPs), digital signal processing devices (DSPDs), programmable logic devices (PLDs), field programmable gate arrays (FPGAs), processors, controllers, microcontrollers, microprocessors, other electronic units designed to perform the functions presented herein, or combinations thereof.

For example, various embodiments may be recorded or encoded in a computer-readable medium including commands. The commands recorded or encoded on the computer-readable medium may cause a programmable processor or other processors to perform a method, for example, when the commands are executed. Computer-readable media include both computer storage media and communication media including any medium that facilitates transfer of a computer program from one place to another place. Storage media may be any available media that can be accessed by a computer. For example, such computer-readable media may include RAM, ROM, EEPROM, CD-ROM or other optical disk storage media, magnetic disk storage media, other magnetic storage devices, or any other medium that can be used to transport or store a desired program code in the form of structures commands or data structures accessible by a computer.

Such hardware, software, firmware, and the like may be implemented within the same device or within separate devices to support various operations and functions described herein. Additionally, the elements, units, modules, components, and the like described as "~er (or)" in the present disclosure may be implemented together or may be individually implemented as individual but interoperable logic devices. Depiction of different features for modules, units,

etc. is intended to highlight different functional embodiments, and does not necessarily mean that they must be realized by individual hardware or software components. Rather, functions associated with one or more modules or units may be performed by separate hardware or software components or may be incorporated within common or separate hardware or software components.

Although operations are shown in the drawings in a specific order, it should not be understood that these operations are performed in the specific order or in a sequential order to achieve a desired result, or that all the illustrated operations should be performed. In any environment, multitasking and parallel processing may be advantageous. Moreover, division of various components in the above-described embodiments should not be understood as being needed in all embodiments, and the described components will generally be understood as being integrated together into a single software product or packaged into multiple software products.

While the present disclosure has been particularly shown and described with reference to exemplary embodiments thereof, it will be understood by one of ordinary skill in the art that various changes in form and details may be made therein without departing from the spirit and scope as defined by the following claims.

[Description of reference numerals]

- 10: loan expansion hypothesis testing system
- 100: AI analyzer
- 110: financing model generator
- 120: account manager
- 130: default probability value calculator
- 140: quality measurer
- 150: factor analyzer
- 160: data map transformer
- 200: testing segment setter
- 300: testing group determiner
- 400: hypothesis tester

CLAIMS

1. A loan expansion hypothesis testing system using artificial intelligence (AI) established based on financial data, the loan expansion hypothesis testing system comprising:

an AI analyzer configured to calculate a default probability value of each of a plurality of finance accounts;

a testing segment setter configured to classify the plurality of finance accounts into a plurality of segments, according to a preset criterion, and set a specific segment as a testing segment as a testing target, based on the respective default probability values of the plurality of finance accounts calculated by the AI analyzer;

a testing group determiner configured to determine a portion of the testing segment to be an experimental group and a comparison group for performing loan expansion hypothesis testing; and

a hypothesis tester configured to perform the loan expansion hypothesis testing with respect to the experimental group and the comparison group.

2. The loan expansion hypothesis testing system of claim 1, wherein the AI analyzer calculates the respective default probability values of the plurality of finance accounts by using a default prediction model generated based on the financial data by using machine learning.

3. The loan expansion hypothesis testing system of claim 1, wherein the testing segment setter sets a segment having a minimum average default probability value from among the plurality of segments to be the testing segment.

4. The loan expansion hypothesis testing system of claim 3, wherein the preset criterion is a grade assigned to each of the plurality of finance accounts, based on the respective default probability values of the plurality of finance accounts.

5. The loan expansion hypothesis testing system of claim 1, wherein the testing segment setter
combines and sets one or more segments from among the plurality of segments as the testing segment in ascending order of the average default probability values of the one or more segments, and
stops the combination when the testing segment approximates to a preset account number.

6. The loan expansion hypothesis testing system of claim 1, wherein the testing group determiner
sets a preliminary experimental group and a preliminary comparison group by random-sampling the testing segment and performs distribution testing with respect to the preliminary experimental group and the preliminary comparison group, and determines the preliminary experimental group and the preliminary comparison group to be the experimental group and the comparison group when the testing group determiner determines that the preliminary experimental group and the preliminary comparison group have passed the distribution testing, and
re-performs the distribution testing by re-sampling the preliminary experimental group and the preliminary comparison group when the testing group determiner determines that the preliminary experimental group and the preliminary comparison group have not passed the distribution testing.

7. The loan expansion hypothesis testing system of claim 6, wherein the testing group determiner
determines that the preliminary experimental group and the preliminary comparison group have passed the distribution testing, when a difference between respective average default probability values of the preliminary experimental group and the preliminary comparison group is less than or equal to a pre-determined value, and
determines that the preliminary experimental group and the preliminary comparison group have not passed the distribution testing, when the difference between respective average default probability values of the preliminary

experimental group and the preliminary comparison group exceeds the pre-determined value.

8. The loan expansion hypothesis testing system of claim 1, wherein the hypothesis tester
sets, as a hypothesis, that a future default rate of the experimental group is less than a future default rate of the comparison group and sets, as a null hypothesis, that the future default rate of the experimental group is equal to or greater than the future default rate of the comparison group, and
to test the null hypothesis, applies a loan expansion scenario to the experimental group and an existing loan policy maintaining scenario to the comparison group and predicts respective future default probability values of the plurality of finance accounts included in the experimental group and the comparison group by using the AI analyzer.

9. The loan expansion hypothesis testing system of claim 8, wherein
the loan expansion scenario comprises at least one of a loan amount limit expansion, an interest rate shrinkage, and a new loan permission for each of the plurality of finance accounts, and
the loan policy maintaining scenario is continuously maintaining a loan amount limit, an interest rate, and new loan prohibition that are applied to each of the plurality of finance accounts.

10. The loan expansion hypothesis testing system of claim 8, wherein the hypothesis tester
determines that the null hypothesis is rejected, when a future average default probability value of the experimental group is less than a future average default probability value of the comparison group, and
measures a loan quality by using the AI analyzer by equally applying the loan expansion scenario, which has been applied to the experimental group, to all of the finance accounts of the testing segment including the comparison group.

11. The loan expansion hypothesis testing system of claim 8, wherein the hypothesis tester

- determines that the null hypothesis is rejected, when a future average default probability value of the experimental group is less than a future average default probability value of the comparison group,
- extracts a second experimental group and a second comparison group from the experimental group through the testing group determiner, and sets, as a second hypothesis, a future default rate of the second experimental group being lower than a future default rate of the second comparison group and sets, as a second null hypothesis, the future default rate of the second experimental group being equal to or higher than the future default rate of the second comparison group, and
- to test the second null hypothesis, applies a second loan expansion scenario having a more expanded loan expansion range than the loan expansion scenario to the second experimental group and the loan expansion scenario to the second comparison group, and predicts respective future default probability values for the plurality of finance accounts included in the second experimental group and the second comparison group by using the AI analyzer.

12. The loan expansion hypothesis testing system of claim 8, wherein the hypothesis tester

- determines that the null hypothesis is adopted, when a future average default probability value of the experimental group is equal to or greater than a future average default probability value of the comparison group, and
- derives a main factor that worsens the future average default rate of the experimental group, through the AI analyzer, excludes one or more finance accounts including the derived main factor, and re-performs loan expansion testing of the loan expansion testing system.

13. The loan expansion hypothesis testing system of claim 12, wherein

- the AI analyzer comprises:
 - a financing model generator configured to generate a default

prediction model through machine learning, based on financial data of each of the plurality of finance accounts;

an account manager configured to manage the plurality of finance accounts included in a financial product in order to measure a quality of the financial product;

a default probability value calculator configured to calculate the respective default probability values of the plurality of finance accounts included in the account manager by using the default prediction model;

a quality measurer configured to calculate the quality of the financial product, based on the respective default probability values of the plurality of finance accounts calculated by the default probability value calculator; and

a factor analyzer configured to analyze a main factor of the finance account that affects the calculated quality of the financial product,

wherein, according to a result of the factor analyzer, the account manager selects a bank account included in the financial product.

14. The loan expansion hypothesis testing system of claim 8, wherein the hypothesis tester

determines that the null hypothesis is adopted, when a future average default probability value of the experimental group is equal to or greater than a future average default probability value of the comparison group,

extracts a second experimental group and a second comparison group from the experimental group through the testing group determiner, and sets, as a second hypothesis, a future default rate of the second experimental group being lower than a future default rate of the second comparison group and sets, as a second null hypothesis, the future default rate of the second experimental group being equal to or higher than the future default rate of the second comparison group, and

to test the second null hypothesis, applies a second loan expansion scenario having a more contracted loan expansion range than the loan expansion scenario to the second experimental group and the loan expansion scenario to the second comparison group, and predicts respective future default

probability values for the plurality of finance accounts included in the second experimental group and the second comparison group by using the AI analyzer.

15. A loan expansion hypothesis testing method using artificial intelligence (AI) established based on financial data, the loan expansion hypothesis testing method comprising:

- an AI analyzing operation of calculating a default probability value of each of a plurality of finance accounts;

- a testing segment setting operation of classifying the plurality of finance accounts into a plurality of segments, according to a preset criterion and setting a specific segment as a testing segment as a testing target, based on the respective default probability values of the plurality of finance accounts calculated in the AI analyzing operation;

- a testing group determining operation of determining a portion of the testing segment to be an experimental group and a comparison group for performing the loan expansion hypothesis testing; and

- a hypothesis testing operation of performing the loan expansion hypothesis testing with respect to the experimental group and the comparison group.

16. The loan expansion hypothesis testing method of claim 15, wherein the AI analyzing operation comprises calculating the respective default probability values of the plurality of finance accounts by using a default prediction model generated based on the financial data by using machine learning.

17. The loan expansion hypothesis testing method of claim 15, wherein the testing segment setting operation comprises setting a segment having a minimum average default probability value from among the plurality of segments to be the testing segment.

18. The loan expansion hypothesis testing method of claim 15, wherein the hypothesis testing operation comprises:

- setting, as a hypothesis, that a future default rate of the experimental

group is less than a future default rate of the comparison group and setting, as a null hypothesis, that the future default rate of the experimental group is equal to or greater than the future default rate of the comparison group, and

to test the null hypothesis, applying a loan expansion scenario to the experimental group and an existing loan policy maintaining scenario to the comparison group and predicting respective future default probability values of the plurality of finance accounts included in the experimental group and the comparison group by re-performing the AI analyzing operation.

19. The loan expansion hypothesis testing method of claim 18, wherein the hypothesis testing operation comprises:

determining that the null hypothesis is rejected, when a future average default probability value of the experimental group is less than a future average default probability value of the comparison group, and

equally applying the loan expansion scenario, which has been applied to the experimental group, to all of the finance accounts of the testing segment including the comparison group, and measuring a loan quality by using the AI analyzer by re-performing the AI analyzing operation.

20. The loan expansion hypothesis testing method of claim 18, wherein the hypothesis testing operation comprises:

determining that the null hypothesis is adopted, when a future average default probability value of the experimental group is equal to or greater than a future average default probability value of the comparison group, and

deriving a main factor that worsens the future average default rate of the experimental group, excluding one or more finance accounts including the derived main factor, and re-performing loan expansion testing of the loan expansion testing method.