DESCRIPTION

TITLE OF THE INVENTION: METHOD, DEVICE, STORAGE MEDIUM, AND ELECTRONIC DEVICE FOR PREDICTING AUTO LOAN RISK

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] This application claims priority to Chinese patent application with the filing No. 2025102181777, filed with the Chinese Patent Office on February 26, 2025, and entitled "METHOD, DEVICE, STORAGE MEDIUM, AND ELECTRONIC DEVICE FOR PREDICTING AUTO LOAN RISK", the entire contents of which are incorporated by reference in this application.

TECHNICAL FIELD

[0002] The present disclosure relates to the field of machine learning, and more specifically, to a method, a device, a storage medium, and an electronic device for predicting auto loan risks.

BACKGROUND ART

[0003] In modern financial risk management, predicting risk is a crucial task. Traditional risk prediction models are mainly made based on historical data and fixed risk characteristics, and then these models are used to predict future risks. However, this method has some obvious disadvantages. Since this method usually assumes that risk characteristics are static, it ignores the fact that risk characteristics may change over time. Even though some technologies have tried to improve the model by adapting to changes in risk characteristics, these improved methods are still not sensitive enough to sudden risks.

SUMMARY

[0004] In order to overcome at least one of the shortcomings in the prior art, the present disclosure provides a method, device, a storage medium, and an electronic device for predicting auto loan risks, specifically including:

[0005] In the first aspect, the present disclosure provides a method for predicting auto loan risks, the method including:

[0006] obtaining overdue risk characteristics of a borrower in a current repayment cycle;

[0007] processing the overdue risk characteristics through a risk assessment model of a neural network architecture to obtain a first risk score of the borrower in the current repayment cycle;

[0008] processing the overdue risk characteristics through a pre-fitted autoregressive moving average model to obtain a second risk score of the borrower in the current repayment cycle; and

[0009] obtaining a comprehensive risk score of the borrower according to the first risk score and the second risk score.

[0010] In the second aspect, the present disclosure provides a device for predicting auto loan risks, the device including:

[0011] a risk feature module, wherein the risk feature module is configured to obtain overdue risk features of a borrower in a current repayment cycle;

[0012] a risk score module, wherein the risk score module is configured to process the overdue risk features through a risk assessment model of a neural network architecture to obtain a first risk score of the borrower in the current repayment cycle, and

[0013] the risk score module is further configured to process the overdue risk features through a pre-fitted autoregressive moving average model to obtain a second risk score of the borrower in the current repayment cycle; and

[0014] a risk comprehensive module, wherein the risk comprehensive module is configured to obtain a comprehensive risk score of the borrower according to the first risk score and the second risk score.

[0015] In the third aspect, the present disclosure provides a storage medium, wherein the storage medium stores a computer program, and the computer program is processed by a processor to implement the method for predicting auto loan risks.

[0016] In the fourth aspect, the present disclosure provides an electronic device, wherein the electronic device includes a processor and a memory; the memory stores a computer program; and the computer program is processed by the processor to implement the method for predicting auto loan risks.

[0017] Compared to the prior art, the present disclosure has the following beneficial effects.

[0018] The present disclosure provides a method, device, a storage medium, and an electronic device for predicting auto loan risks. The electronic device obtains the overdue risk characteristics of the borrower in the current repayment cycle; the overdue risk characteristics are processed by the risk assessment model of the neural network architecture to obtain the first risk score of the borrower in the current repayment cycle; the overdue risk characteristics are

processed by the pre-fitted autoregressive moving average model to obtain the second risk score of the borrower in the current repayment cycle; according to the first risk score and the second risk score, the comprehensive risk score of the borrower is obtained. In this way, since the risk assessment model of the neural network architecture can better capture the impact of sudden events, it makes up for the defect that the autoregressive moving average model is insensitive to sudden events, and improves the prediction accuracy of overdue risk.

BRIEF DESCRIPTION OF DRAWINGS

[0019] In order to more clearly illustrate the technical solution of the embodiment of the present disclosure, the following is a brief introduction to the drawings required for use in the embodiment. It should be understood that the following drawings only show certain embodiments of the present disclosure, and therefore should not be regarded as limiting the scope. For those ordinary skills in the art, other relevant drawings can also be obtained based on these drawings without creative work.

[0020] Figure 1 is a flow chart of the method for predicting auto loan risks provided in the embodiment of the present disclosure;

[0021] Figure 2 is one of the detailed flow charts of the method for predicting auto loan risks provided in the embodiment of the present disclosure;

[0022] Figure 3 is a schematic diagram of a characteristic change information provided in the embodiment of the present disclosure;

[0023] Figure 4 is another detailed flow chart of the method for predicting auto loan risks provided in the embodiment of the present disclosure;

[0024] Figure 5 is another detailed flow chart of the method for predicting auto loan risks provided in the embodiment of the present disclosure;

[0025] Figure 6 is a structural schematic diagram of the device for predicting auto loan risks provided in the embodiment of the present disclosure; and

[0026] Figure 7 is a structural schematic diagram of the electronic device provided in the embodiment of the present disclosure.

DETAILED DESCRIPTION OF EMBODIMENTS

[0027] In order to make the purpose, technical solution, and advantages of the embodiment of the present disclosure clear, the technical solution in the embodiment of the present disclosure will be clearly and completely described below in combination with the drawings in the embodiment of the present disclosure. Obviously, the described embodiments are a part of

the embodiments of the present disclosure, not all of the embodiments. The components of the embodiment of the present disclosure generally described and shown in present drawings can be arranged and designed in various different configurations.

[0028] Therefore, the following detailed description of the embodiment of the present disclosure provided in the drawings is not intended to limit the scope of protection claimed of the present disclosure, but only represents the selected embodiment of the present disclosure. Based on the embodiments in the present disclosure, all other embodiments obtained by those ordinarily skilled in the art without creative work are within the scope of protection of the present disclosure.

[0029] It should be noted that similar numbers and letters represent similar items in the following drawings. Therefore, when an item is defined in one drawing, it does not need to be further defined and explained in the subsequent drawings.

[0030] In the description of the present disclosure, the terms “first”, “second”, “third”, etc. are only used to distinguish the description and cannot be understood as indicating or implying relative importance. In addition, the terms “include”, “comprise”, or any other variants thereof are intended to cover non-exclusive inclusion, so that a process, method, article, or device including a series of elements includes not only those elements, but also other elements not explicitly listed, or also includes elements inherent to such process, method, article, or device. In the absence of further restrictions, an element defined by the sentence “includes one...” does not exclude the presence of other identical elements in the process, method, article, or device including the element.

[0031] Based on the above statement, as introduced in the background art, even if some technologies have tried to improve the model by adapting to changes in risk characteristics, these improved methods are still not sensitive enough to sudden risks.

[0032] For example, take the Autoregressive Integrated Moving Average Model (ARIMA) as an example (hereinafter referred to as the ARIMA model). The ARIMA model is a commonly used time series prediction method that combines the autoregressive model (AR) and the moving average model (MA). The basic idea of the ARIMA model is to identify patterns and trends in the historical data of the time series by analyzing them, and to use these patterns to predict future values. To achieve this goal, the ARIMA model contains three components: autoregressive term (AR), difference term (I), and moving average term (MA). The autoregressive term represents the linear relationship between the current value and the value of several periods in the past; the difference term is used to make the time series stable; and the moving average term is used to capture the autocorrelation of the error term. Through

the combination of these three components, the ARIMA model can effectively capture short-term fluctuations and long-term trends in the time series.

[0033] However, although the ARIMA model performs well in processing stable time series data, the model is not sensitive enough to sudden risks. This is mainly because the ARIMA model mainly relies on patterns and trends in historical data for prediction. When sudden events (such as economic crises, and natural disasters) occur, these events often have no precedents and cannot be predicted by historical data. Therefore, the ARIMA model may not be able to adjust its prediction model in time to cope with these sudden changes, resulting in inaccurate predictions.

[0034] Based on the discovery of the above technical problems, the inventors have proposed the following technical solutions through creative work to solve or improve the above problems. It should be noted that the defects in the above-mentioned solutions in the prior art are the results obtained by the inventor after practice and careful study. Therefore, the discovery process of the above-mentioned problems and the solutions proposed in the embodiments of the present disclosure for the above-mentioned problems below should all be the contributions made by the inventor to the present disclosure in the process of invention and creation, and should not be understood as the technical content known to those skilled in the art.

[0035] In view of the above-mentioned problems, the present embodiment provides a method for predicting auto loan risks. As shown in Figure 1, the method includes the following steps:

[0036] S1, obtaining the overdue risk characteristics of the borrower in the current repayment cycle;

[0037] S2, processing the overdue risk characteristics through the risk assessment model of the neural network architecture to obtain the first risk score of the borrower in the current repayment cycle;

[0038] S3, processing the overdue risk characteristics through the pre-fitted autoregressive moving average model to obtain the second risk score of the borrower in the current repayment cycle; and

[0039] S4, obtaining the comprehensive risk score of the borrower according to the first risk score and the second risk score.

[0040] In this way, since the risk assessment model of the neural network architecture can better capture the impact of sudden events, it makes up for the defect that the autoregressive moving average model is insensitive to sudden events, and improves the prediction accuracy of overdue risks.

[0041] It is worth noting that for the scheme involved in the present disclosure, the data related to user privacy is explicitly notified before being collected and generated during the execution of the embodiment of the present disclosure, and the authorization of the user is obtained. At the same time, for the personal information involved in the embodiment of present disclosure, the providing position of the storage device is in accordance with the legal and regulatory requirements of the country/region where the above-mentioned data-related behaviors occur, and the related behaviors include but are not limited to: authorization, generation, use, storage, etc. It can be understood that implementing the overdue risk characteristics used in this scheme, the providing position of its storage device is in accordance with the legal and regulatory requirements of the country/region where the above-mentioned data-related behaviors occur, and the related behaviors include but are not limited to: authorization, generation, use, storage, etc.

[0042] In addition, it should be understood that for the auto loan risk prediction method of this embodiment, the electronic device implementing the method can be, but not limited to, a mobile terminal, a tablet computer, a laptop computer, a desktop computer, and a server. The server can be a single server or a server group. The server group can be centralized or distributed (for example, the server can be a distributed system). In some embodiments, the server can be local or remote relative to the user terminal. In some embodiments, the server can be implemented on a cloud platform; and as an example only, the cloud platform can include a private cloud, a public cloud, a hybrid cloud, a community cloud, a distributed cloud, an inter-cloud, a multi-cloud, etc., or any combination thereof. In some embodiments, the server can be implemented on an electronic device having one or more components.

[0043] To make the solution provided in this embodiment clear, the following is a detailed description of each step in the method shown in Figure 1, taking the server as an electronic device for implementing the method. However, it should be understood that the operations of the flowchart can be implemented out of sequence, and steps without logical contextual relationships can be in reversed sequences or implemented simultaneously. In addition, under the guidance of the content of present disclosure, those skilled in the art can add one or more other operations to the flowchart, or remove one or more operations from the flowchart. Therefore, continuing to refer to Figure 1, the method includes steps S1~S4.

[0044] S1, obtaining the overdue risk characteristics of the borrower in the current repayment cycle.

[0045] In this embodiment, the above-mentioned multiple overdue sub-features include dynamic features and static features that can reflect whether the borrower will be overdue. For

example, the multiple overdue sub-features may include borrower credit history features, income stability features, vehicle-related features, economic environment risk features, user personal features, and vehicle location information. These features are described in detail below.

[0046] (1) Borrower credit history features include credit card overdraft records, repayment records of other loans, credit scores, overdue repayment records, and default records.

[0047] Credit card overdraft records reflect the borrower use of credit cards, including whether there is overdraft behavior and the frequency and amount of overdrafts. If the borrower often overdrafts and fails to repay on time, this indicates that his financial management ability is poor and he may default in the process of repaying the auto loan.

[0048] Repayment records of other loans include repayment records of all previous loans of the borrower (such as housing loans, consumer loans). If the borrower has repeatedly overdue repayments or defaults on loans, this indicates that his willingness to repay is low and he is more likely to default in the future during the repayment of auto loans.

[0049] Credit score is a quantitative indicator used to evaluate the credit status of the borrower, which is usually calculated comprehensively by a credit scoring agency based on the borrower historical repayment record, overdraft situation, etc. The higher the credit score is, the better the borrower credit is and the lower the default risk is; or conversely, a lower credit score means a higher default risk.

[0050] Default record. This feature focuses on whether the borrower has defaulted in previous loans. For example, a customer has overdue credit card payments for [X] times in total in the two years before applying for an auto loan, with the longest consecutive overdue payment being [X] months. Based on this, the financial institution can preliminarily determine that the customer has a very high risk of default during the auto loan repayment process.

[0051] Therefore, a comprehensive assessment of the borrower historical repayment record, overdraft situation, credit score, etc. can effectively identify potential default risks.

[0052] (2) Income stability feature. This is another important component of the auto loan risk assessment in this embodiment. It is mainly used to examine the borrower occupation type, years of work, income source, and other factors to determine the stability and reliability of their income.

[0053] Occupation type. There are significant differences in income stability and reliability of different occupations. For example, public officials, state-owned enterprise employees, and formal employees of large enterprises have relatively lower default risks than freelancers, self-employed individuals, or small and micro business owners due to their job stability and income

reliability. Such occupations usually have fixed wages and benefits, which reduces the risk of default due to unstable income.

[0054] Years of work. Borrowers with longer years of work usually have higher income stability and job security. In contrast, borrowers with shorter years of work may face greater income fluctuations and uncertainty. For example, borrowers with more than [X] years of work have significantly higher income stability than borrowers with less than [X] years of work.

[0055] Source of income. In addition to occupation type and years of work, source of income is also an important factor in measuring income stability. For example, borrowers with multiple stable sources of income (such as fixed salary, rental income, investment income) have higher income stability than borrowers with only a single source of income. Diversified sources of income can effectively mitigate the risks brought by a single source of income.

[0056] Trend of income change. By analyzing the trend of the borrower income change in the past few years, we can further understand the stability of his income. If the borrower income has been rising or stable in the past few years, this indicates that his income stability and repayment ability are strong; or conversely, if the income is on a downward trend, the risk of default is higher.

[0057] Career prospects. Some industries have better career prospects and greater income growth potential. For example, high-tech industries and financial industries usually have good career development prospects and high-income levels. Therefore, borrowers engaged in these industries usually have high income stability and repayment ability.

[0058] Therefore, this embodiment can effectively identify the income stability and repayment ability of borrowers by comprehensively evaluating the borrower occupation type, years of work, income source, income change trend, career prospects, and so on.

[0059] (3) Vehicle-related characteristics are an important part of auto loan risk assessment, mainly involving information such as the value, purpose, and purchase channel of the vehicle, which can assess the value and reliability of the vehicle as collateral.

[0060] Vehicle value. The market value of the vehicle is one of the key factors in determining the amount and loan ratio of the auto loan. Studies have found that the higher the market value of the vehicle is, the higher its security as collateral is. Financial institutions usually refer to the vehicle valuation report provided by a third-party appraisal agency to determine the actual value of the vehicle. In addition, the residual value rate of the vehicle is also an important consideration. Vehicles with a high residual value rate are more likely to obtain a higher recovery value when they are disposed of in the future.

[0061] Vehicle use. The use of the vehicle can be divided into two main categories: commercial and personal use. Vehicles for personal use usually have higher stability and lower depreciation rate, while commercial vehicles depreciate faster due to frequent use and high wear and tear. Therefore, the risk of vehicles for personal use as collateral is relatively low, while commercial vehicles require more cautious evaluation.

[0062] Vehicle brand and model. Vehicles of different brands and models have different value retention and liquidity in the market. Well-known brands and high-end models usually have higher market recognition and stronger value retention, while some niche brands or low-end models have relatively weaker value retention. Therefore, in the evaluation of auto loans, the brand and model of the vehicle will also be taken into consideration.

[0063] Purchase channel. The purchase channel of the vehicle will also affect its value and reliability as collateral. Vehicles purchased through formal channels usually have complete procedures and high transparency, while vehicles purchased through informal channels may have problems such as incomplete procedures and unclear ownership, which increase the risk of vehicle disposal. Therefore, financial institutions are more inclined to accept vehicles purchased through formal channels as collateral.

[0064] Vehicle mileage. The mileage of a vehicle is an important indicator to measure the use of the vehicle. Vehicles with lower mileage are usually in better condition and have higher residual values, while vehicles with higher mileage may have higher maintenance costs and lower residual values. Therefore, the mileage of the vehicle is also one of the critical factors that need to be considered in the assessment of auto loans.

[0065] Vehicle insurance status. The insurance status of the vehicle is also an important factor in assessing its risk. Comprehensive vehicle insurance can not only reduce the loss of the vehicle after an accident, but also improve the overall safety of the vehicle. Therefore, the vehicle insurance report provided by the insurance company is also one of the important bases for financial institutions to assess the risk of auto loans.

[0066] Therefore, vehicle-related characteristics can effectively identify the risk of the vehicle as collateral by comprehensively evaluating the value, use, brand and model, purchase channel, mileage, and insurance status of the vehicle. These characteristics can not only reflect the basic condition of the vehicle, but also help financial institutions more accurately predict future repayment risks, so as to take appropriate measures to manage and reduce auto loan risks.

[0067] (4) Economic environment risk is also an important part of auto loan risk assessment, mainly involving the impact of macroeconomic factors and market conditions on the borrower repayment ability. Specifically, these factors include the following aspects.

[0068] Macroeconomic conditions. Macroeconomic conditions directly affect the borrower employment opportunities, income level, and overall financial status. For example, slower economic growth will lead to higher unemployment and lower income, which will increase the risk of borrowers defaulting. On the contrary, strong economic growth will help increase borrower income levels and employment stability, and reduce the risk of default.

[0069] Interest rate changes. Changes in interest rates have a direct impact on borrower repayment pressure. When interest rates rise, borrower repayment burden increases, which may cause some borrowers to be unable to repay their loans on time, thereby increasing the risk of default. Conversely, falling interest rates can reduce borrower repayment pressure and improve their repayment ability.

[0070] Inflation rate. A high inflation rate will decrease borrower real income, reduce their purchasing power, and thus affect their repayment ability. A high inflation rate will also cause borrowers to pay more interest and principal when repaying their loans, increasing their financial pressure. On the contrary, a low inflation rate helps maintain borrower purchasing power and income levels, reducing default risk.

[0071] Regional economic conditions. Differences in regional economic conditions will also affect the repayment ability of borrowers. Economically developed regions have more job opportunities, higher income levels, and stronger borrower repayment ability. In economically underdeveloped regions, there are fewer job opportunities, lower income levels, weaker borrower repayment ability, and higher default risks.

[0072] Changes in policies and regulations. Changes in policies and regulations may also have an impact on borrower repayment ability. For example, tax policies and credit policies issued by the government may directly affect borrower income and expenditure. In addition, changes in regulatory policies, such as strengthening credit review and increasing down payment ratios, will also have an impact on borrower repayment ability.

[0073] Market competition conditions. Market competition conditions will also affect borrower repayment ability. In a highly competitive market environment, borrowers may face greater economic pressure, thereby increasing the risk of default. In a relatively stable market environment, borrower repayment ability is usually more stable.

[0074] Therefore, economic environment risk can effectively identify borrower repayment risks under changing economic environments through a comprehensive assessment in aspects of macroeconomic conditions, interest rate changes, inflation rates, regional economic conditions, policy and regulation changes, and market competition conditions.

[0075] (5) User personal characteristics are a key component in the risk assessment of auto loans, mainly involving factors such as the borrower personal information, credit record, repayment willingness, and behavior, in order to assess their reliability and risk level as a borrower.

[0076] Age and occupation. Studies have found that the borrower age and occupation have a great impact on their repayment ability and stability. Young borrowers who are at the beginning of their careers may lack stable work experience and high-income levels, while older borrowers with stable occupations usually have higher incomes and good career prospects. In addition, whether the borrower has a stable occupation, such as civil servants, teachers, doctors, these occupations usually have higher income stability and repayment ability.

[0077] Credit record. The borrower credit record is an important basis for assessing his or her credit status. A good credit record indicates that the borrower has a good repayment history and reputation, while a bad credit record means that the borrower may have overdue repayments or other credit problems. Financial institutions usually refer to the borrower credit report to assess his or her credit score and historical repayment behavior.

[0078] Income and debt situation. The borrower income level and debt situation are important factors in assessing his or her repayment ability. The higher the borrower income and the less debt are, the stronger his repayment ability and the lower the risk of default are. Financial institutions will evaluate the stability of his income and the proportion of debt through the income certificate, bank flow, and other materials provided by the borrower.

[0079] Asset status. The asset status of the borrower is also an important factor in evaluating his repayment ability. Having higher-value fixed assets (such as real estate, stocks, deposits) can serve as additional repayment guarantees. Financial institutions will understand the borrower financial stability and potential sources of repayment by evaluating the borrower asset status.

[0080] Repayment willingness and behavior. The borrower repayment willingness and historical behavior are also important indicators for assessing his credit risk. Whether the borrower has good repayment habits, such as repaying on time and repaying in advance, reflects his serious attitude towards debt. In addition, whether the borrower has a record of using other loans or credit cards, and whether these records are good, will also affect his credit score.

[0081] Educational background. The borrower educational background also reflects his repayment ability and credit quality to a certain extent. Borrowers with higher education

usually have higher professionalism and repayment ability, while borrowers with lower education levels may face greater financial pressure and repayment difficulties.

[0082] Family status. The family status of the borrower, such as the number of family members, marital status, will also affect their repayment ability and stability. Borrowers from single-parent families or those with heavy family burdens may face greater financial pressure, while borrowers with fewer family members, stable marriages, and smaller financial burdens usually have higher repayment ability.

[0083] Therefore, user personal characteristics can effectively identify the credit risk and repayment ability of borrowers by comprehensively evaluating the borrower age and occupation, credit record, income and debt situation, asset status, repayment willingness and behavior, educational background, family status, and so on.

[0084] (6) Vehicle positioning information, through which the information such as vehicle driving trajectory, speed, mileage, can be obtained, and this information helps to more accurately grasp the borrower vehicle usage and detect abnormal behavior in a timely manner, thereby improving the accuracy of risk prediction.

[0085] As an optional embodiment, in order to inform the risk assessment model which dynamic features are more important and which are relatively less important, the overdue risk characteristics of the current repayment cycle include multiple overdue sub-features and preset weights are assigned to each overdue sub-feature. In this regard, it can be understood that when conducting risk assessment, the overdue risk characteristics of the borrower in the current repayment cycle will be subdivided into multiple specific sub-features, and a pre-set weight will be assigned to each sub-feature. This design is to ensure that the impact of different characteristics on the overall risk can be reasonably quantified and reflected during the risk assessment process.

[0086] For example, the server can group various dynamic characteristics according to different time levels, such as daily level changes, weekly level changes, monthly level changes, and annual level changes; and then, the non-numerical characteristics in each group are encoded for further processing and calculation. When assigning weights, the server can assign weights to each sub-feature from the aspects of cycle change frequency, intention level, policy sensitivity, influence, economic indicators, etc.

[0087] For cycle change frequency, the server can analyze the cycle change frequency of each dynamic feature and assign different weights according to the frequency. For example, if a feature changes every day, it will be assigned a higher weight; conversely, or if the feature changes less, it will be assigned a lower weight.

[0088] For the intention level, the server can assign different weights according to the impact of the features on the degree of intention to buy a car, change a car, or take out a loan in different time periods. For example, in February, users have a greater intention to take out loans, so the relevant features of that month will be given a higher weight.

[0089] For policy sensitivity, the server can analyze dynamic features that have a greater impact on policy sensitivity, such as the new energy replacement subsidy policy, and assign different weights according to the sensitivity high or low. If a policy change has a greater impact on risk characteristics, then the policy-related features will be given a higher weight.

[0090] For influence, the server can consider factors such as the country vehicle management, production, and monetary policy this year, and assign different weights according to the degree of impact of these factors on dynamic features. For example, if the GDP of a region grows faster, it will affect the local loan demand and repayment ability, so the characteristics of the region will be given a higher weight.

[0091] For economic indicators, the server can weight the affected dynamic features based on factors such as national and provincial GDP and per capita income to reflect the impact of the economic environment on risk characteristics. For example, if the per capita income of a province is higher, the loan risk characteristics of the province will be given a lower weight.

[0092] Based on the description of the borrower risk characteristics in the above implementation, the following continues to explain step S2 in Figure 1.

[0093] S2, processing the overdue risk characteristics through the risk assessment model of the neural network architecture to obtain the first risk score of the borrower in the current repayment cycle.

[0094] In this embodiment, the risk assessment model of the neural network architecture above-mentioned can be a fine-tuned large language model. Because the model has learned how to understand and process complex text information through a large amount of training data, and can capture the correlation and potential patterns between different risk characteristics. Therefore, when the risk characteristics of the above borrower are input into the risk assessment model in text form, the risk model will first parse and understand the input text to identify the key risk characteristics and their weights. Then, the model will use its internal neural network structure to analyze how these characteristics work together on the overall risk through a series of calculations and reasoning processes. Finally, the model outputs a comprehensive first risk score, which reflects the model prediction of the borrower overdue risk in the current repayment cycle.

[0095] Therefore, in this way, the fine-tuned large language model can not only efficiently process diverse input data, but also provide more accurate and reliable risk assessment results. Moreover, the model has learned how to quickly adapt to and understand new information or changes through additional training data and fine-tuning processes. When faced with unexpected events, the model can quickly parse relevant text data and identify key information and anomalies. For example, when conducting risk assessment, if there is a sudden major fluctuation in the market or the news reports an important event that affects the borrower credit status, the fine-tuned large language model can capture this information in a timely manner and adjust the risk assessment results accordingly.

[0096] Exemplarily, the large language model can be Qwen-14B. The model has undergone deep learning with large-scale training and has strong text understanding and generation capabilities. Therefore, after fine-tuning Qwen-14B, it can be used to predict the risk of borrower overdue.

[0097] Based on the above embodiment, the first risk score acquisition method is described, and step S3 in Figure 1 is further described below.

[0098] S3, processing the overdue risk characteristics by the pre-fitted autoregressive moving average model to obtain the second risk score of the borrower in the current repayment cycle.

[0099] It should be understood that the ARMA model, as a commonly used time series analysis tool, can capture the trend and seasonal components in the data and smooth them. In this application, the model first fits the collected historical repayment data of the borrower to determine the model parameters. Then, using these parameters, the model can process and predict the overdue risk characteristics of the borrower. To achieve this goal, the ARMA model can identify and quantify the time series characteristics of various risk factors, and then calculate the second risk score of the borrower in the current repayment cycle.

[0100] Compared with the large language model, the ARMA model relies on numerical input to perform calculations and analysis, so it cannot directly process non-numerical data. In order for the ARMA model to work effectively, the input risk sub-features must be converted into quantitative form, that is, converted into numerical values by a certain method. For example, some qualitative characteristics of the borrower (such as credit record, repayment behavior) may need to be quantified by scoring or coding. These quantified data can better represent the changing trends and patterns of risk characteristics, so that the ARMA model can capture the time series characteristics of these characteristics and perform trend analysis and prediction.

[0101] In some embodiments, it can be understood that when faced with sudden events, since the risk assessment model of the neural network architecture can quickly parse the relevant text

data and identify the key information and abnormal situations therein, the above-mentioned first risk score can characterize the impact of the sudden information in the feature change information on the repayment risk of the borrower in the current repayment cycle.

[0102] In some embodiments, since the autoregressive moving average model can identify and quantify the time series characteristics of various risk factors, and calculate the second risk score of the borrower in the current repayment cycle based on this, the second risk score can characterize the impact of the non-sudden information in the feature change information on the repayment risk of the borrower in the current repayment cycle.

[0103] Based on the description of the second risk score acquisition way in the above embodiment, the following continues to explain step S4 in Figure 1.

[0104] S4, obtaining the comprehensive risk score of the borrower based on the first risk score and the second risk score.

[0105] In this way, by combining the first risk score generated by the risk assessment model and the second risk score generated by the ARIMA model, the advantages of the two models can be comprehensively utilized to improve the accuracy of the overall prediction.

[0106] In this embodiment, the above-mentioned first risk score and the second risk score are both values between 0 and 1, and the larger the value is, the higher the risk of overdue is. Therefore, as an optional embodiment, the first risk score and the second risk score can be weighted and summed using a preset weight to obtain a comprehensive risk score.

[0107] Optionally, the above-mentioned obtaining the comprehensive risk score of the borrower based on the first risk score and the second risk score includes:

[0108] calculating the comprehensive risk score of the borrower based on the first risk score, the second risk score, and respective weights of the first risk score and the second risk score.

[0109] Optionally, the weight of the first risk score and the weight of the second risk score can be preset weights, or can be obtained by real-time prediction based on the weight model, which is not limited herein.

[0110] In some embodiments, when the difference between the first risk score and the second risk score is smaller, the preset weight can be selected for calculation, so that when no sudden information occurs, the advantages of the two models can be comprehensively utilized to improve the accuracy of the overall prediction; and when the difference between the first risk score and the second risk score is larger, the prediction weight obtained by real-time prediction based on the weight model is used to calculate, so that when sudden information occurs, the accuracy of the overall prediction can be guaranteed.

[0111] Optionally, the weight model can be a pre-trained machine learning model, such as a neural network or a regression model, which can automatically learn and adjust the weights of each risk score according to the optimized feature change information.

[0112] However, it is found in practice that when the difference between the first risk score and the second risk score is larger, it means that the recognition results of the two models have a larger difference, which is often caused by the ARIMA model insensitivity to sudden information. Therefore, the preset weight cannot adapt to the above situation. In this regard, as shown in Figure 2, this embodiment provides the following embodiments S4-1 of step S4.

[0113] S4-1, obtaining the feature change information between the overdue risk characteristics of the previous repayment cycle and the overdue risk characteristics of the current repayment cycle.

[0114] Optionally, the overdue risk characteristics include: multiple risk sub-features, and the above-mentioned obtaining the feature change information between the overdue risk characteristics of the previous repayment cycle and the overdue risk characteristics of the current repayment cycle includes:

[0115] calculating the feature change information according to each risk sub-feature in the overdue risk characteristics of the previous repayment cycle and each risk sub-feature in the overdue risk characteristics of the current repayment cycle.

[0116] The feature change information includes multiple change sub-information corresponding to multiple risk sub-features.

[0117] Optionally, for each risk sub-feature, if the change sub-information corresponding to the risk sub-feature meets the preset requirements, the change sub-information corresponding to the risk sub-feature is determined to be sudden information. If the change sub-information corresponding to the risk sub-feature does not meet the preset requirements, the change sub-information corresponding to the risk sub-feature is determined to be non-sudden information.

[0118] In this embodiment, the server can subtract each risk sub-feature in the overdue risk feature of the previous repayment cycle with each risk sub-feature in the overdue risk feature of the current repayment cycle to obtain feature change information. If the change value of a risk sub-feature is larger, it indicates that the change may be sudden information, reflecting the new risk factors that have recently appeared in the borrower; or on the contrary, if the change value is smaller, it may belong to non-sudden information, that is, the normal fluctuation of the borrower risk characteristics. In this way, sudden information and non-sudden information can be distinguished more accurately.

[0119] For example, as shown in Figure 3, 5 risk sub-features of the previous repayment cycle and 5 risk sub-features of the current repayment cycle are shown. Figure 3 shows 5 risk sub-features of the previous repayment cycle and 5 risk sub-features of the current repayment cycle. The corresponding feature values are shown in the following table.

Risk sub-feature	A	B	C	D	E
Previous repayment cycle	20	31	11.9	23.5	0.9
Current repayment cycle	10	20	8	25	1.3
Feature change information	10	11	3.9	1.5	0.4

[0120] As can be easily seen from the feature change information in Figure 3, the change range of risk sub-feature A and risk sub-feature B in two adjacent repayment cycles increases, while the change range of other risk sub-features is smaller. It should be understood that the above implementation is only an example listed for the convenience of explaining the feature change information. The features and values in the example will not change with the actual sub-features.

[0121] Based on the description of the feature change information in the above implementation, continue to refer to Figure 2. After step S4-1, step S4 also includes:

[0122] S4-2, optimizing the feature change information to obtain optimized feature change information.

[0123] The optimized feature change information enhances the sudden information in the feature change information and suppresses the non-sudden information in the feature change information. It should be understood that, as shown in Figure 3, for different risk sub-features, the range of their feature values is obviously different, so it cannot be directly used to measure the degree of change of the event. In this regard, this embodiment proposes an optimization way that integrates the difference between the first risk score the second risk score, and the feature change information, which is used to enhance the sudden information in the feature change information and suppress the non-sudden information. As shown in Figure 4, step S4-2 may include:

[0124] S4-2-2, obtaining the divergence index between the risk assessment model and the autoregressive moving average model according to the first risk score and the second risk score, and

[0125] S4-2-3, optimizing the feature change information using the divergence index to obtain the optimized feature change information.

[0126] As shown in Figure 3, the feature change information includes multiple change sub-information. Therefore, in a specific embodiment, for each change sub-information, the server may perform a power operation on the change sub-information and the divergence index to obtain the optimized change sub-information, wherein the reciprocal of the change sub-information is the exponent and the divergence index is the base. The corresponding mathematical expression is:

[0127] $y = x^n$,

[0128] where y represents the optimized change sub-information, x represents the divergence index, and n represents the reciprocal of the change sub-information.

[0129] In this embodiment, the divergence index may be the ratio or difference between the first risk score and the second risk score. In other words, in some embodiments, the divergence index between the risk assessment model and the autoregressive moving average model can be determined according to the ratio or difference between the first risk score and the second risk score.

[0130] When the divergence index is the difference between the two, the divergence index is also a value ranging between 0 and 1. Through the above expression, if the change sub-information is less than 1, it will be further reduced, and if the change sub-information is greater than 1, it will be further enhanced. Moreover, the value range of the optimized change sub-information is constrained between 0 and 1, which is conducive to the processing of the subsequent weight model.

[0131] In this way, the problem of different value ranges of different risk sub-feature values can be effectively solved, ensuring that all feature change information is compared and processed at the same scale. Secondly, the power operation optimization using the divergence index can flexibly enlarge or reduce the amplitude of the change sub-information, so as to more accurately distinguish between sudden information and non-sudden information. In particular, for the case where the change sub-information is less than 1, the optimization will further reduce its influence, and for the case where the change sub-information is greater than 1, its influence will be further enhanced, so that the model can capture the key change points more sensitively.

[0132] Based on the above embodiment, the optimization way of the feature change information is explained. Continuing to refer to Figure 2 or Figure 4, after step S4-2, step S4 also includes:

[0133] S4-3, processing the optimized feature change information by a pre-trained weight model to obtain the prediction weights of the first risk score and the second risk score, and

[0134] S4-4, obtaining the comprehensive risk score according to the respective prediction weights of the first risk score and the second risk score.

[0135] In this way, the weight model determines the importance of each risk score in the overall assessment by processing the optimized feature change information. After training, the weight model can capture key change points more sensitively and automatically adjust the weights of each risk score to more accurately reflect its ability to predict future risks. In addition, the weight model can be a pre-trained machine learning model, such as a neural network or a regression model, the model can automatically learn and adjust the weights of each risk score according to the optimized feature change information. Specifically, the model can adopt a supervised learning method and be trained with a large amount of data, so that the model can identify which feature change information is more important for predicting the first risk score and the second risk score. During the training process, the model will continuously adjust its internal parameters to minimize the prediction error, and finally obtain a model that can predict the prediction weight of each risk score.

[0136] As described in the above embodiment, when the difference between the first risk score and the second risk score is larger, it means that the recognition results of the two models have a large difference, which is often caused by the insensitivity of the ARIMA model to sudden information. Therefore, it is not necessary to use the above weight model to generate the prediction weights of the first risk score and the second risk score in an adaptive manner every time, but it is necessary to rely on the divergence index between the first risk score and the second risk. Therefore, as shown in Figure 5, based on Figure 4, step S4-2 in Figure 4 also includes:

[0137] S4-2-1, determining whether the divergence index is greater than the divergence threshold. If it is yes, it executes step 4-2-2 in Figure 5; or otherwise, it executes sub-step S4-5 of step S4 in Figure 5.

[0138] S4-5, obtaining a comprehensive risk score according to the respective preset weights of the first risk score and the second risk score.

[0139] It can be understood that the server calculates the divergence index between the first risk score and the second risk score and compares it with a pre-set divergence threshold. If the divergence index does not exceed the threshold, the results of the two models are considered acceptable. At this time, the respective preset weights can be used directly to calculate the comprehensive risk score. In this way, not only can inaccurate weight distribution be avoided

in high divergence situations, but also the calculation process can be simplified in low divergence situations, thereby improving the efficiency and robustness of the overall system.

[0140] For the above-mentioned risk assessment model and autoregressive moving average model, this embodiment proposes a new model training method that can greatly improve the training efficiency of the model. The following takes the risk assessment model as an example to explain the training method of the risk assessment model in detail. Before explaining, it should be understood that hyperparameters are crucial in model training and determine the learning process and final performance of the model. Appropriate hyperparameter settings can control the complexity of the model, prevent overfitting or underfitting, and thus ensure effective model learning; and at the same time, they affect the convergence speed of the model, and the training process can be accelerated through reasonable selection. In addition, hyperparameters also affect the selection and efficiency of the optimization algorithm, thereby indirectly affecting the generalization ability of the model.

[0141] In view of this, the server can also call a third-party large language model to generate the current hyperparameters for the network model to be trained; use the current hyperparameters to initialize the network model to be trained; train the initialized network model to be trained through training samples to obtain the candidate model trained by the network model to be trained and the training effect; continue to call the third-party large language model to process the current hyperparameters and training effect to obtain new hyperparameters; according to the new hyperparameters, return to the step of initializing the network model to be trained using the current hyperparameters until the iteration stop condition is met, and select the model with the best training effect from multiple candidate models as the risk assessment model.

[0142] It can be understood that in the above training method, the server generates hyperparameters for the network model to be trained with the help of the reasoning ability of the third-party large language model, and adjusts the hyperparameters according to the feedback training effect, so as to continuously optimize the provided hyperparameters.

[0143] For example, it is assumed that the third-party large language model is Qwen72b and the network model to be trained is Qwen14b. In the early stage of training, a series of hyperparameter restriction conditions are provided in advance to optimize the training effect of the model. First, it is to take {initial weight/500, initial weight*500} as its initial weight range, set the learning rate to the interval of [0.001, 0.1], and adjust it with a step size of 0.001, and set the batch size to the interval of [16, 128] with a step size of 16; and finally, it is to set

the number of hidden layer nodes according to the model complexity, ranging from [32, 256], with a step size of 32.

[0144] Based on the above restrictions, the third-party large language model generates hyperparameters within the range of the above restrictions. To achieve this process, the server calls the third-party large language model Qwen72b to generate a set of initial hyperparameters for the network model Qwen14b to be trained. These hyperparameters are used to initialize the Qwen14b model. Then, the initialized Qwen14b model is trained using training samples to obtain a candidate model and its training effect. Subsequently, the server calls Qwen72b again, and takes the current hyperparameters and training effects as input, so that Qwen72b performs reasoning based on the context of the call and the current hyperparameters and training effects to obtain new hyperparameters. Based on the new hyperparameters, the server reinitializes the Qwen14b model and repeats the above training and hyperparameter adjustment process until the iteration stop condition is met (for example, the loss value of the candidate model tends to be stable). Throughout the process, the server uses the reasoning ability of Qwen72b and the feedback training effect to adjust the hyperparameters and gradually optimize the model. Finally, one of the candidate models with the best training effect is selected as the final risk assessment model. In this way, the scheme effectively utilizes the reasoning ability of Qwen72b and realizes efficient training and optimization of the Qwen14b model.

[0145] The same optimization method can be adopted for the ARIMA model to optimize it, and this embodiment will not be repeated.

[0146] Based on the same inventive concept as the auto loan risk prediction method provided in this embodiment, this embodiment also provides a device for predicting auto loan risks, and the device includes at least one software function module that can be stored in a memory or solidified in an electronic device in the form of software. The processor in the electronic device is used to execute the executable module stored in the memory. For example, the software function module computer program, and so on are included in the device. Please refer to Figure 6, from the functional point of view, the device may include:

[0147] a risk feature module 11, configured to obtain the overdue risk features of the borrower in the current repayment cycle;

[0148] a risk score module 12, configured to process the overdue risk features through the risk assessment model of the neural network architecture, and obtain the first risk score of the borrower in the current repayment cycle;

[0149] a risk score module 12, further configured to process the overdue risk features through the pre-fitted autoregressive moving average model, and obtain the second risk score of the borrower in the current repayment cycle; and

[0150] a risk comprehensive module 13, configured to obtain the comprehensive risk score of the borrower based on the first risk score and the second risk score.

[0151] In this embodiment, the risk feature module 11 is used to implement step S1 in Figure 1, the risk score module 12 is used to implement steps S2 and S3 in Figure 1, and the risk comprehensive module 13 is also used to implement step S4 in Figure 1. Therefore, the detailed description of each of the above modules can refer to the specific embodiment of the corresponding steps, and this embodiment will not be repeated.

[0152] Since having the same concept as the above-mentioned auto loan risk prediction method, the device for predicting auto loan risks can also implement other steps or sub-steps of the method through the above-mentioned module.

[0153] Optionally, the risk comprehensive module 13 is also specifically used for:

[0154] obtaining the feature change information between the overdue risk characteristics of the previous repayment cycle and the overdue risk characteristics of the current repayment cycle;

[0155] optimizing the feature change information to obtain optimized feature change information, wherein the optimized feature change information enhances the sudden information in the feature change information and suppresses the non-sudden information in the feature change information;

[0156] processing the optimized feature change information through the pre-trained weight model to obtain the respective prediction weights of the first risk score and the second risk score; and

[0157] obtaining a comprehensive risk score according to the respective prediction weights of the first risk score and the second risk score.

[0158] Optionally, the risk comprehensive module 13 is also specifically used for:

[0159] obtaining the divergence index between the risk assessment model and the autoregressive moving average model according to the first risk score and the second risk score; and

[0160] using the divergence index to optimize the feature change information to obtain the optimized feature change information.

[0161] Optionally, the feature change information includes multiple change sub-information, and the optimized feature change information includes multiple optimized change sub-information; and the risk comprehensive module 13 is also specifically used for:

[0162] for each change sub-information, performing a power operation between the change sub-information and a divergence index to obtain the optimized change sub-information, wherein the reciprocal of the change sub-information is the exponent and the divergence index is the base.

[0163] Optionally, after obtaining the divergence index between the risk assessment model and the autoregressive moving average model according to the first risk score and the second risk score, the risk comprehensive module 13 is also specifically used for:

[0164] determining whether the divergence index is greater than the divergence threshold.

[0165] If it is greater than the divergence threshold, the step of optimizing the feature change information using the divergence index to obtain the optimized feature change information is performed.

[0166] Optionally, the overdue risk feature of the current repayment cycle includes multiple overdue sub-features and a preset weight assigned to each overdue sub-feature.

[0167] Optionally, the device for predicting auto loan risks also includes a model training module, which is used for:

[0168] calling a third-party large language model to generate current hyperparameters for the network model to be trained;

[0169] using the current hyperparameters to initialize the network model to be trained;

[0170] training the initialized network model to be trained through training samples to obtain candidate models trained by the network model to be trained and training effects;

[0171] continuing to call the third-party large language model to process the current hyperparameters and training effects to obtain new hyperparameters; and

[0172] according to the new hyperparameters, returning to the step of initializing the network model to be trained using the current hyperparameters until the iteration stop condition is met, and selecting the model with the best training effect from multiple candidate models as the risk assessment model.

[0173] In addition, the functional modules in various embodiments of the present disclosure can be integrated together to form an independent part, or each module can exist separately, or two or more modules can be integrated to form an independent part.

[0174] It should also be understood that if the above embodiment is implemented in the form of a software functional module and sold or used as an independent product, it can be stored in

a computer-readable storage medium. Based on this understanding, the technical solution of the present disclosure can be essentially embodied in the form of a software product, or the part the technical solution of the present disclosure that contributes to the prior art or the part of the technical solution can be embodied in the form of a software product. The computer software product is stored in a storage medium and includes several instructions for a computer device (which can be a personal computer, a server, or a network device, etc.) to execute all or part of the steps of the method described in each embodiment of present disclosure.

[0175] Therefore, this embodiment also provides a storage medium, and the storage medium is a computer-readable storage medium. The storage medium stores a computer program, and when the computer program is executed by the processor, the auto loan risk prediction method provided in this embodiment is implemented. The storage medium can be a USB flash drive, a mobile hard disk, a read-only memory (ROM), a random access memory (RAM), disk or CD, and other media that can store program codes.

[0176] This embodiment provides an electronic device for implementing an auto loan risk prediction method. As shown in Figure 7, the electronic device may include a processor 22 and a memory 21. In addition, the memory 21 stores a computer program, and the processor implements the auto loan risk prediction method provided in this embodiment by reading and executing the computer program corresponding to the above embodiment in the memory 21.

[0177] Continuing to refer to Figure 7, the electronic device also includes a communication unit 23. The memory 21, the processor 22, and the communication unit 23 are electrically connected to each other directly or indirectly through the system bus 24 to realize data transmission or interaction.

[0178] The memory 21 can be an information recording device based on any electronic, magnetic, optical, or other physical principles, used to record execution instructions, data, etc. In some embodiments, the memory 21 can be, but not limited to, a volatile memory, a non-volatile memory, a storage drive, etc.

[0179] In some embodiments, the volatile memory may be a random access memory (RAM). In some embodiments, the non-volatile memory may be a read-only memory (ROM), a programmable read-only memory (PROM), an erasable programmable read-only memory (EPROM), an electrically erasable read-only memory (EEPROM), a flash memory, etc. In some embodiments, the storage drive may be a disk drive, a solid state drive, any type of storage disk (such as an optical disk, a DVD), a similar storage medium, or a combination thereof, etc.

[0180] The communication unit 23 is used to send and receive data through a network. In some embodiments, the network may include a wired network, a wireless network, a fiber optic

network, a telecommunications network, an intranet, the Internet, a local area network (LAN), a wide area network (WAN), a wireless local area network (WLAN), a metropolitan area network (MAN), a wide area network (WAN), a public switched telephone network (PSTN), a Bluetooth network, a ZigBee network, or a near field communication (NFC) network, or any combination thereof. In some embodiments, the network may include one or more network access points. For example, the network may include a wired or wireless network access point, such as a base station and/or a network switching node, through which one or more components of the service request processing system may be connected to the network to exchange data and/or information.

[0181] The processor 22 may be an integrated circuit chip having a signal processing capability, and the processor may include one or more processing cores (e.g., a single-core processor or a multi-core processor). As an example only, the above processor may include a central processing unit (CPU), an application specific integrated circuit (ASIC), an application specific instruction set processor (ASIP), a graphics processing unit (GPU), a physical processing unit (PPU), a digital signal processor (DSP), a field programmable gate array (FPGA), a programmable logic device (PLD), a controller, a microcontroller unit, a reduced instruction set computing (RISC), or a microprocessor, or any combination thereof.

[0182] It is understood that the structure shown in FIG. 7 is only for illustration. The electronic device may also have more or fewer components than those shown in FIG. 7, or have a different configuration than that shown in FIG. 7. The components shown in FIG. 7 may be implemented by hardware, software, or a combination thereof.

[0183] It should be understood that the apparatus and method disclosed in the above embodiments may also be implemented in other ways. The device embodiments described above are merely illustrative. For example, the flowcharts and block diagrams in the drawings show the possible architectures, functions, and operations of the devices, methods, and computer program products according to the various embodiments of the present disclosure. In this regard, each block in the flowchart or block diagram may represent a module, a program segment, or a portion of a code, and the module, the program segment, or the portion of a code contains one or more executable instructions for implementing the specified logical functions. It should also be noted that in some alternative implementations, the functions marked in the boxes may also occur in an order different from that marked in the drawings. For example, two consecutive blocks can actually be executed substantially in parallel, and they may sometimes be executed in the opposite order, depending on the functions involved. It should also be noted that each block in the block diagram and/or flowchart, and the combination of blocks in the

block diagram and/or flowchart, can be implemented with a dedicated hardware-based system that performs the specified functions or actions, or can be implemented with a combination of dedicated hardware and computer instructions.

[0184] The above are only various implementation methods of the present disclosure, but the protection scope of the present disclosure is not limited thereto. Any technician familiar with the technical field can easily think of changes or substitutions within the technical scope disclosed in the present disclosure, which should be covered within the protection scope of the present disclosure. Therefore, the protection scope of the present disclosure shall be subject to the protection scope of the claims.

INDUSTRIAL APPLICABILITY

[0185] Using the above solution, the risk assessment model of the neural network architecture can better capture the impact of sudden events, thereby compensating for the defect that the autoregressive moving average model is insensitive to sudden events and improving the prediction accuracy of overdue risks.

CLAIMS

Claim 1: A method for predicting auto loan risks, wherein the method comprises:

obtaining overdue risk characteristics of a borrower in a current repayment cycle;

processing the overdue risk characteristics through a risk assessment model of a neural network architecture to obtain a first risk score of the borrower in the current repayment cycle;

processing the overdue risk characteristics through a pre-fitted autoregressive moving average model to obtain a second risk score of the borrower in the current repayment cycle; and

obtaining a comprehensive risk score of the borrower according to the first risk score and the second risk score.

Claim 2: The method for predicting auto loan risks according to claim 1, wherein a step of obtaining the comprehensive risk score of the borrower according to the first risk score and the second risk score comprises:

calculating the comprehensive risk score of the borrower according to the first risk score, the second risk score, and respective weights of the first risk score and the second risk score.

Claim 3: The method for predicting auto loan risks according to claim 1 or 2, wherein the step of obtaining the comprehensive risk score of the borrower according to the first risk score and the second risk score comprises:

obtaining feature change information between the overdue risk characteristics of a previous repayment cycle and the overdue risk characteristics of the current repayment cycle;

optimizing the feature change information to obtain the optimized feature change information, wherein the optimized feature change information enhances sudden information in the feature change information and suppresses non-sudden information in the feature change information;

processing the optimized feature change information through a pre-trained weight model to obtain respective prediction weights of the first risk score and the second risk score; and

obtaining the comprehensive risk score according to the respective prediction weights of the first risk score and the second risk score.

Claim 4: The method for predicting auto loan risks according to claim 3, wherein a step of optimizing the feature change information to obtain the optimized feature change information comprises:

obtaining a divergence index between the risk assessment model and the autoregressive moving average model according to the first risk score and the second risk score; and

using the divergence index to optimize the feature change information to obtain the optimized feature change information.

Claim 5: The method for predicting auto loan risks according to claim 3 or 4, wherein the overdue risk feature comprises: multiple risk sub-features, and a step of obtaining the feature change information between the overdue risk characteristics of the previous repayment cycle and the overdue risk characteristics of the current repayment cycle comprises:

calculating the feature change information according to each risk sub-feature in the overdue risk feature of the previous repayment cycle and each risk sub-feature in the overdue risk feature of the current repayment cycle, wherein the feature change information comprises multiple change sub-information corresponding to multiple risk sub-features.

Claim 6: The method for predicting auto loan risks according to claim 5, wherein for each risk sub-feature, if the change sub-information corresponding to the risk sub-feature meets the preset requirements, the change sub-information corresponding to the risk sub-feature is determined to be sudden information; and

if the change sub-information corresponding to the risk sub-feature does not meet the preset requirements, the change sub-information corresponding to the risk sub-feature is determined to be non-sudden information.

Claim 7: The method for predicting auto loan risks according to claim 4, wherein a step of obtaining the divergence index between the risk assessment model and

the autoregressive moving average model according to the first risk score and the second risk score comprises:

determining the divergence index between the risk assessment model and the autoregressive moving average model according to a ratio or difference between the first risk score and the second risk score.

Claim 8: The method for predicting auto loan risks according to claim 4, wherein the optimized feature change information comprises a plurality of optimized change sub-information; and

a step of using the divergence index to optimize the feature change information to obtain the optimized feature change information comprises:

for each of the change sub-information, the change sub-information is subjected to a power operation with the divergence index to obtain the optimized change sub-information, wherein a reciprocal of the change sub-information is an exponent and the divergence index is a base.

Claim 9: The method for predicting auto loan risks according to claim 4 or 7, wherein after obtaining the divergence index between the risk assessment model and the autoregressive moving average model according to the first risk score and the second risk score, the method further comprises:

determining whether the divergence index is greater than a divergence threshold;

if it is greater than the divergence threshold, performing the step of using the divergence index to optimize the feature change information to obtain the optimized feature change information.

Claim 10: The method for predicting auto loan risks according to any one of claims 1 to 9, wherein the overdue risk feature of the current repayment cycle comprises multiple overdue sub-features and a preset weight assigned to each of the overdue sub-features.

Claim 11: The method for predicting auto loan risks according to any one of claims 1 to 10, wherein the method further comprises a training method for the risk assessment model, the training method comprising:

calling a third-party large language model to generate current hyperparameters for a network model to be trained;

using the current hyperparameters to initialize the network model to be trained;

training the initialized network model to be trained through training samples to obtain candidate models trained by the network model to be trained and a training effect;

continuing to call the third-party large language model to process the current hyperparameters and the training effect to obtain new hyperparameters; and

according to the new hyperparameters, returning to the step of using the current hyperparameters to initialize the network model to be trained until an iteration stop condition is met, and selecting the one with a best training effect from the multiple candidate models as the risk assessment model.

Claim 12: A device for predicting auto loan risks, wherein the device comprises:

a risk feature module, wherein the risk feature module is configured to obtain overdue risk features of a borrower in a current repayment cycle;

a risk score module, wherein the risk score module is configured to process the overdue risk features through a risk assessment model of a neural network architecture to obtain a first risk score of the borrower in the current repayment cycle, and

the risk score module is further configured to process the overdue risk features through a pre-fitted autoregressive moving average model to obtain a second risk score of the borrower in the current repayment cycle; and

a risk comprehensive module, wherein the risk comprehensive module is configured to obtain a comprehensive risk score of the borrower according to the first risk score and the second risk score.

Claim 13: A storage medium, wherein the storage medium stores a computer program, and the computer program is processed by a processor to implement a method for predicting auto loan risks according to any one of claims 1 to 11.

Claim 14: An electronic device, wherein the electronic device comprises a processor and a memory; the memory stores a computer program; and the computer program is processed by the processor to implement a method for predicting auto loan risks according to any one of claims 1 to 11.