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Development of Infrastructure and Invoices of Web Banking Software Based on Coreless Banking

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Abstract*:* Today, many transaction-based analysis methods are used in non-core banking to evaluate web banking software based on customer data sets. The evaluation of the data set of the web banking software leads to the choice of canceling the customer's loan or rejecting the customer's request. This factoring work mechanism involves in-depth evaluation of the dataset or customer information. The data mining approach is described as the most common method for analyzing web banking software, focusing on different algorithms, such as infrastructure development. This important process includes the collection, analysis and final credit decision of various factors that are used to evaluate transaction-based programs. These sources are credit application forms, interbank data sharing, ledger data and the most key internal bank data. The scoring method in granting facilities is often known as scoring, which is actually a method of evaluating loan applications. At the same time, archives and records of past micro-facilities are evaluated to identify characteristics that have an important effect in discriminating between good and bad web banking software applications.

Keywords: coreless banking, credit scoring, granting facilities methods, internet banking, transaction-based systems, assess applicant credit

1- Introduction

As you know, if the microfinance recipient makes a mistake or is unable to settle it, the lender will have the right to confiscate the property. The two main reasons for needing an expert support system are:

1) Lack of accurate measurement methods

2) Lack of public credit risk review system and web banking software

In many banks. Risk assessment in bank loans should be understood as the importance of risk tolerance [1, 2]. In order to rank customers into good and bad classes, the banking system measures the accuracy of the data set. Customers who are in good classes are more likely to return the money to the bank [3, 4]. Bad class customers are not likely to return the cash to the bank and therefore their subsequent loan requests will not be considered.

A variety of web banking software evaluation methods are used to minimize loan data corruption rates. Since the evaluation of web banking software plays a fundamental role in the banking sector and is very vital, it is essentially a fundamental factor facing banks. Accurate classification of loan information plays a significant role in order to prevent economic loss.

In case of granting a loan from a bank or financial institution, the beneficiary (customer) is obliged to repay the original and future interest within the framework of the contract that he has seen and signed. The most important factor is the borrowed amount and the bank's interest rate. First, when approving a customer's loan request, the bank checks his details and documents. Each bank considers a transaction-based score for each customer, which is expressed in numbers based on the borrower's credit file. The amount of credit department activity in terms of marketing lies in the core of the bank. Another important factor is risk assessment in bank loans, which should be understood as the importance of risk.

1-1 Goal

Risk is one of the functions of the non-core banking system, which is not completely eliminated but reduced by using appropriate and modern methods. One of the main goals in a coreless banking system is to maintain a stable and healthy transaction-based system that begins with credit planning and ends with closing. Web banking software, which is the most essential form of risk for banks, is strongly related to measuring and managing the superiority of this method.

2- Research Bases

Non-core banking factors and infrastructure development on micro-facilities

Creating efficiencies in application delivery pipelines is achieved, at least in part, by IT automation. Automation requires some degree of standardization to overcome excessive compatibility burdens across different application environments. Standardizing IT environments also reduces incompatibilities with third-party components and avoids common developer bottlenecks associated with technology versioning. An open platform with iterative, microservice-based architectures—based on application programming interfaces (APIs), real-time event streams, and loosely coupled modular components—supports the standardization required for an automated application delivery pipeline. This pipeline has the advantage of continuously supporting any environment, without the need to rewrite the code. As a result, development teams can write their code once, run it anywhere, and adopt third-party components from any source, avoiding vendor-imposed restrictions on leading product and service innovation.

Banks always seek to meet the expectations and needs of their customers. By facilitating communication with customers and increasing its speed and effectiveness, information technology provides the basis for improving performance and innovation in service delivery. Failure to pay attention to added value and customer satisfaction will reduce the future visits of customers as well as the loss of customer support for the bank, and ultimately it will not be possible to achieve the bank's goals. But in recent years, the formation and emergence of online banking services has expanded in the world.

Today, societies are increasingly dependent on computers and computer networks, and a suitable interactive environment has been provided for communicating between people. Geographical distance and borders have lost their importance and the spread of new communications and electronic media and the Internet has created a space called virtual space. Virtual space is a global space. Infinite, beyond space and beyond time.

Virtual banking is created in virtual space and with its help, people can benefit from a variety of electronic services, many of which require electronic payment, without going to bank branches and through computers, mobile phones and devices. Buy ATMs can use banking services. In this way, virtual banks are a new generation of banks that offer a variety of banking products and services to the general public using the latest achievements in information and communication technology and without the need for a physical branch.

2-1 research background

Basically, in every two decades, electronic business facilities are provided according to the information technology capabilities of that era. While ATMs and credit cards were introduced in the first twenty years, in the second period, electronic data exchange and the international banking system became possible [5].

The use of internet bank services is one of the new achievements of the information age, it has drastically changed the world trade and changed the business rules and created many advantages in business methods.

Virtual banking is a new field in the virtual space and the world of e-commerce, which provides a very suitable situation for providing banking services. Although e-banking, internet banking and virtual banking coincide in some cases, they differ from each other in some cases.

Scoring programs and algorithms predict an applicant's likelihood of repaying credit in advance and address whether microfacilities are in default at any given moment. The program scorecard is created based on the classification of good or bad in terms of web banking software. Past loan applications are evaluated to identify features that have a significant impact on explaining the differences between good and bad web banking software applications. [6]

In case of granting a loan from the bank, the customer is obliged to repay the principal and future interest of the facility. The most important feature is the loan amount and interest rate. Generally, at first, the bank checks the customer's profile and documents when approving the loan. [7]

This process is referred to as facility evaluation, which requires a time parameter, but is usually a binary decision that results in approval or rejection. The two main reasons for the need for a management and monitoring system are the lack of accurate measurement methods and the lack of a public credit risk system and web banking software in many banks. [8]

Many risks associated with bank loans, for non-core banking and borrowing customers. Risk assessment in bank loans should be understood as the importance of risk. Web banking software is a risk that the loan will not be repaid on time or in full. Liquidity risk is basically a condition that can be withdrawn from deposits too quickly and the bank prohibits the payment of immediate cash. Also, interest rate risk has the risk that the interest rates priced in bank loans are too low to earn enough money in the bank. [9]

In order to rank customers into good and bad classes, the banking system measures the accuracy of the data set. Customers who are in good class are more likely to repay the bank. Bad class registered customers are unlikely to return the cash to the bank, so they will be required to pay fines and possible damages. A variety of web banking software evaluation methods are used to minimize loan data. [10]

The advantages of reliable data collection of web banking software are that credit scoring costs are reduced, high-level decisions take less time, and the risks of non-granting of facilities are avoided. Since the evaluation of web banking software has a fundamental role in the banking sector, the accurate classification of information plays a significant role in preventing the losses of economic enterprises. [11]

As customers increasingly look to their devices to help with their daily lives, financial services businesses must offer simple, relevant and accessible products and services when and where customers need them. . Responsive digital offerings are at the core of this vision, creating a flexible operating model that allows financial services to meet new customer expectations while overcoming the usual challenges associated with integrating cross-business processes and systems. 1) A hybrid implementation of cloud architecture is essential to achieve this business fluidity – the need for a technology foundation that allows legacy and new applications and services to be modular business components that can be Mix, match and recombine in a way that adapts to ever-changing markets. where banks operate, this distributed architecture is described as coreless banking [12].

3- Some definitions in non-core banking and micro-facilities

The proximity of competitiveness and profitability of banks and transaction-based financial institutions is basically the quality of the bank's credit portfolio. By increasing the number of customers who have high credit, the quality of bank loans also increases. Transaction-based scoring is the primary decision-making system (in non-core banking) used to assess applicant credit. Therefore, the scoring of credits and facilities can be defined as a method for modeling the applicant's credit.

In the literature, there are various definitions for credit scoring. The origins of scoring systems can be traced back to the 1930s when some mail order businesses used a scoring system to reduce discrepancies between loan analysts. Web banking software management has been an important issue for companies active in the financial field. Because credit analysts were forced to serve in the military during World War II, resulting in a lack of web banking software specialists. Therefore, companies wanted analysts to write the rules they used to assign credit.

The good evaluation of web applications through transaction-based rating methods has led banks to use transaction-based rating for mortgages and microfinance. The amount of such programs has increased so much that it is economically difficult to use the traditional strategies used in it, and the expert has evaluated the requests one by one. The desire of credit applicants and banks to evaluate applications in a fair moment encourages banks to use credit scoring systems in evaluating received applications.

In order to evaluate facilities by acceptance or rejection, the credit score method uses previous credit records to obtain a quantitative model. Credit evaluation criteria are consistently applied to all loan applications in the credit scoring system. Transaction-based decisions can be made quickly with a credit scoring system. Additionally, credit scoring increases customer satisfaction due to the short time required to complete a loan application. Credit scoring models are considered one of the most effective statistical applications in the field of non-core business and banking. Many quantitative methods have been used for credit scoring purposes in banking and computer sources. Studies comparing statistical methods and machine learning methods to evaluate web banking software show that machine learning techniques are more effective than statistical techniques.

3-1 Coreless Banking

Coreless banking is the provision of banking services that are not dependent on traditional core systems. It is a new way to create a digital customer journey from predefined and modular business services. Unlike integrated applications and services—where all software systems are fully integrated—in coreless banking, there are no dependencies on isolated core banking engines. Each banking service is defined as a single, modular business function that is defined and maintained independently of other functions so that banks and fintech partners can continue to innovate and then incorporate updates.

3-2 Flexibility of business architecture

Many current modernization efforts aim to break down monolithic architectures by separating core system processing from banking service functions. Often, applications and services have been integrated into these core banking engines over decades. Refactoring integrated code bases into smaller, more modular business functions (also known as microservices) results in cloud-native applications and services that are independently scalable. And they can be developed, shared, and maintained across teams – reducing the technical debt barrier that integrated core systems often have in digital business and banking innovation.

An IT platform provides the ability to connect and coordinate these modules across the business, orchestrating combinations and recombinations of business functions (defined in modules) to address different customer journeys. Once standardized across all business functions, an IT platform can be used because of its inherent security and policies that can be consistently applied across the developer role or even tailored specifically to each developer role.

3-3 Problem definition and proposed strategy

Credit scoring models are one of the most effective commercial statistical applications. Many quantitative methods were used for scoring purposes in the literature. There are several statistical methods for evaluating web banking software, although these methods are difficult to model complex economic systems because they are based on fixed characteristics and statistical assumptions. Studies comparing statistical methods and machine learning methods to evaluate web banking software show that machine learning techniques are more effective than statistical techniques. A binary classification technique using Support Vector Machines is presented for the evaluation of quantitative web banking software. The KNN method is used with extensive yet sparse data, where the time range is usually less than the last 90 days and the limited meaning is more than the last 90 days. Comparing the performance of the models shows that using the data Extensive models are better than models generated using sparse data.

Another series of research using KNN to evaluate web banking software along with the selection of development parameters has also been done.

In the next step, the calculation and evaluation of these predicted customer performance results are used as input to the classification and regression tree algorithm. Meanwhile, reports based on customer transactions and demographic information is also used. The results are used to prepare decision guidelines to determine whether credit is granted to the applicant, to determine the loan range, annual percentage rate and other levels of banking products. Based on these results, the researchers concluded that the transaction-based reporting of a record holder has the most explanation for credit scoring and that demographic factors are less important because they are less effective in credit scoring.

3-4 comparison methods

Recent studies have shown that traditional statistical analysis techniques along with artificial intelligence (AI) are usually applied in the selection of features that can increase the accuracy of identification of web banking software. According to traditional statistical techniques, the existing research examines the factors that affect customers' web banking software, which is mainly done with statistical methods such as multiple discriminant analysis, multiple logic regression and Markov chain.

By using proposed models such as NLM, creating a logical regression model, it is possible to check the evaluation indicators of granting facilities. Regular custom regression models have also been used many times to investigate the effective factors in web banking software. Mohaghegh Bai et al. evaluated their validity conditions with the Fuzzy definition technique and the test method (2019) [13]. Researchers Zhang and Chi (2018) performed the analysis of customer transaction-based rank by using genetic algorithm [14]. Petropoulos et al. (2016) also presented a hidden Markov model to predict credit ratings and evaluate more reliable predictive performance [15].

Since most risk characterizations focus on financial indicators or private customer data, macroeconomic variables may be overlooked. Second, most rating systems only focus on classification accuracy but are unable to pick out the main variables that influence customers' willingness to make refunds.

3-5 Types of classification for transaction-based risk analysis

3-5-1 Bayesian classifier

A Bayesian network is a statistical model - a straight or circular graph. Each node in the graph represents a random variable, where the edges represent the functions of the corresponding variable. A Bayesian network is also a ring diagram that represents the joint probability distribution of a random variable. In order to calculate parameters such as mean and variance, another important variable for Naïve Bayes classification is a small amount of data.

3-5-2 Bayesian belief network

A Bayesian belief network is a direct circular graph consisting of several nodes representing variables with a finite set of states and edges. This symbol indicates the dependence of possible causality on the variables. A direct ring diagram represents our dependency structure between nodes. Therefore, the relationship between the variables and the corresponding states includes a quantitative part that includes a conditional probability table. The chain rule states that a Bayesian belief network represents the general distribution of all variables based on a direct circular graph. For each node of the network, there are margin measurements and probability conditions.

3-5-3 decision tree

A decision tree is a model that maps the opinions related to the elements of each branch in order to conclude a target value in the leaves. This method is one of the best monitoring techniques. Each internal node or non-leaf node is specified with an input function in this learning method. Each leaf node also has a possible class or class distribution in the tree.

3-5-4 K - nearest neighbor

The KNN method is a regression-based classification technique, which is a non-parametric method. This method includes a favorable and unfavorable training package. Sometimes it is also called a random algorithm. No data points are used for testing to generalize the algorithm. This function means that the training phase is very fast and all training information is retained. During the test phase, all training data is needed. Meanwhile, the measured distance is used to determine the k items of the training data set. In this method, the most common Euclidean distance is used for the input variable with real value. In KNN regression, the prediction is based on the average of K or more similar cases. The KNN mechanism can be calculated as a class with the highest frequency in most comparable cases when KNN is used for classification.

3-5-5 K-Means

The purpose of this algorithm is to discover groups in information with the number of K groups. This algorithm works to assign a K group to each data point according to the provided features. Randomly selects the node value by means of k for the center of the cluster and assigns the closest data point to the cluster. Method

K-Means are one of the most common clustering algorithms.

3-5-6 Development of infrastructures

The importance of this topic can be examined from several aspects.

1. According to some researchers, virtual banking is basically a type of electronic banking, and according to others, it is an upgraded type of traditional electronic banking.

2. The lack of suitable hardware, software and telecommunication infrastructure has been one of the influential factors in the non-expansion of virtual banking, but the adoption of virtual banking is one of the important issues that can be considered in the competitive environment of banking. .

3. A virtual bank is a computerized bank that is able to do most of the banking tasks that normal banks do, with the difference that there is no need to go to a branch and people can access it from any computer at home. They can do the banking and business they want.

In other words, in virtual banking, all the steps from depositing money to deposit to receiving and transferring money and exchanging bank documents with all the countries of the world are done through computer. Implementation of anti-money laundering laws, high security and transparency of exchanges will be possible with the establishment of these banks.

A group of developing infrastructures connected to weighted nodes forms an artificial neural network. Each node can produce an existing neuron, and the synaptic connections between neurons are the same as the communication between nodes. Neural network consists of three layers, called multilayer perceptron, which are input layer, hidden layer and output layer. In the MLP network, the layers are connected as an input unit layer to a layer of hidden units, which are then connected to an output unit layer.

3-6 Abuses in the financial system

The advancement of technology in various fields has resulted in the production of data in high volume. The amount of data is positively and directly related to the complexity of the relationships between them. According to this issue, data mining is used as a heuristic idea to analyze data with the help of other sciences in which the exploration of hidden and unknown information from a large part of the data is also used. Recently, the issues of telecommunications, e-commerce and the provision of new services have led to fraud in new ways of various dimensions. With the increase in the use of the Internet, new types of abuse have appeared, but with the advent of security systems to prevent abuse, significant progress has not been made due to the lack of appropriate patterns. Abuse of the technical dimension that takes advantage of system weaknesses occurs mostly when new techniques are introduced into the system and the developers are not aware of these weaknesses. In this case, instead of trying to discover the weak points of a financial system, fraudsters use their skills to obtain detailed information about the system and exploit it. In such cases, a two-layer protection system is proposed, in which game theory techniques are used to detect fraud in the second layer. In the first step, the system quantifies transaction anomalies based on historical customer data.

4- Examining non-core banking factors and infrastructure development

The risk of default in microfinance, due to asymmetric information between businesses and small institutions and in non-core banking, remains a fundamental factor that threatens the sustainability of transaction-based financial institutions. Usually, the first application of scoring in microcredit is participation. Various performance metrics such as power-2 mean error, regression rate, true-false classification score are used here to present the results developed with the credit scoring model. Financial institutions and small banks can grant small amounts to middle-class entrepreneurs with high growth potential. However, before participating in a project, these financial institutions face difficulty in assessing the riskiness of the client. One of the ways to control the negative effects of symmetric information and transaction costs of coreless banking is to use transaction-based scoring. Transaction-based scoring involves predicting applicant behavior by examining applicant records from other banks or data in a centralized database (data center). This actually classifies different bank customers in different classes according to their behavior during repayment, and then links the new applicant to one of these classes with the provided data. Although the definitions attributed to credit scoring vary from author to author, it is generally accepted that credit scoring is a risk management tool that aims to predict the probability of default on a new loan using existing loans. Is previous

4-1 Coreless banking and infrastructures

The business of banking is expected to continue to change with technological advancements, regulations still to come, changing customer lifestyles, and more. Banks must be able to quickly adapt their products and services to remain relevant. Increasingly, legacy architectures that have defined banking experiences for decades are holding back the industry's ability to address the expectations of a digital future. Ready-to-use modular capabilities enable banks to reduce time-to-market and accelerate the development and delivery of responsive digital products and services through new channels and integrated fintech offerings.

Banking products and services must integrate security by design, support scalability to meet market needs, and remain relevant to customers. Building an agile technology environment that can meet changing needs requires designing a platform for modular and flexible architecture. A bank's IT platform must be able to adapt to new demands, modern development tools, and industry standards, applying fault tolerance to minimize unplanned downtime and regulatory compliance. An open-source platform - tested against enterprise standards for core-less banking - makes it possible to quickly combine microservices and modular business functions with open connectivity with existing tools as well as new technologies from open-source communities and partners. The rapid creation of new digital experiences also means these programs will better align with changing business conditions, delivering differentiated customer experiences and meeting compliance requirements. This type of flexibility allows banks to create optimized application delivery pipelines that can more effectively meet market needs and take advantage of new customer opportunities.

The data used are the accepted and rejected applicants in financial institution X who used partnership contracts. Here, the ability of the artificial neural network model to predict the credit score of this financial institution is analyzed. In the proposed modeling method, the work steps can be assumed as follows:

1. Credit scoring criteria are defined.

2. Criteria for evaluation and classification of credits are defined.

3. The MLP network is used in credit scoring.

4. The obtained results are compared with other prediction methods.

A part of the dataset used in the comparison of the methods is shown in the table below:

Table 1 - Part of the dataset used in the comparison of methods

age	job	marital	education	default	housing	loan	contact	month
44	blue-collar	married	basic.4y	unknown	yes	no	cellular	aug
53	technician	married	unknown	no	no	no	cellular	nov
28	management	single	university.degree	no	yes	no	cellular	jun
39	services	married	high.school	no	no	no	cellular	apr

age	job	marital	education	default	housing	loan	contact	month
55	retired	married	basic.4y	no	yes	no	cellular	aug
30	management	divorced	basic.4y	no	yes	no	cellular	jul
37	blue-collar	married	basic.4y	no	yes	no	cellular	may
39	blue-collar	divorced	basic.9y	no	yes	no	cellular	may
36	admin.	married	university.degree	no	no	no	cellular	jun
27	blue-collar	single	basic.4y	no	yes	no	cellular	apr
34	housemaid	single	university.degree	no	no	no	telephone	may
41	management	married	university.degree	no	yes	no	cellular	aug
55	management	married	university.degree	no	no	no	cellular	aug

In this comparison, which is treated using the following relationship and based on the Bayesian method, in fact, injection is a compensatory behavior that works for each unit in a neural network layer. This behavior is independent of the input to each layer. Bayesian has the effect of transforming the weighted sum:

$y = \sigma\,(\mathbf{w}^T\,\mathbf{x} + b)$

Whether the weighted sum of the layer's inputs produces an output or not is determined by the activation function above. Classically, three types of activation functions can be considered:

1) Linear

2) Threshold (stage of entering the layer)

3) Sigmoid (soft stage)

Sigmoid function is a special case of predictive function characterized by its S-shaped curve. This mechanism is often used because it adds nonlinearity to the network that can be easily extracted for weight learning.

Based on the output range of sigmoid functions, it is divided as follows:

a) Logarithmic sigmoid, which runs from [0, 1].

b) The hyperbolic contact sigmoid, which is in the range of [-1 and 1].

The operation of the above algorithm and its effect on the weights are shown in the figure below:

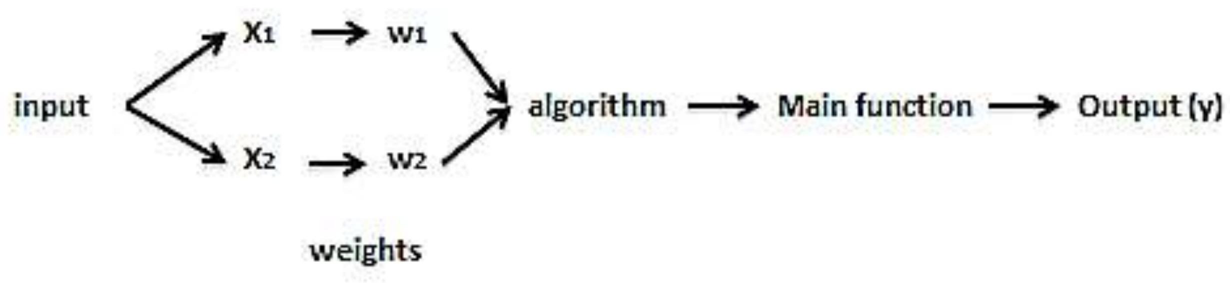

Figure 1 Algorithm performance

For comparative analysis, Development of infrastructure simulation results are compared with participation credit scoring simulation results based on linear regression and discriminant analysis. To evaluate the performance of a scoring model, different performance evaluation criteria are used, such as

- Confusion matrix
- Correct classification rate
- mean square error
- The cost of misclassification

To present the results of the credit rating model of participation and performance evaluation, two regression and classification methods have been used. Also, the error function can evaluate the performance of the neural network during learning. The error function is the learning algorithm's eyes and ears to see if the network is efficient or not (and therefore, how much should be set for its weight values) given the current learning state.

4-2 research methods

Currently, the methods of applying the existing algorithms of coreless banking lead to access to the systematic macrostructures of coreless banking. According to the prediction of the processes used in the learning and testing section, the application of coreless banking algorithms is effective in optimizing the performance of the nearest neighbor according to the performance of the web banking software. The existing challenge is that in the optimization process, in addition to debatable conditions, there are other unpredictable reasons that may affect the progress of the research.

According to the prediction that is obtained as an output, reducing the similarity between the nodes of each cluster can significantly reduce the effect of data clustering. In the intermediate processing section, with the help of KNN and PSO, the nearest neighbor nodes are searched and extracted from the intermediate set.

Analysis of the complexity of the proposed algorithm, in addition to optimal clustering performance, also has performance performance for multifaceted evaluation. The proposed algorithm includes a data clustering stage and a prediction stage. The proposed clustering algorithm by combining KNN and PSO is used to perform data clustering in the first step, and it is designed to deal with web banking software, and it is several times more efficient than the conventional KNN clustering algorithm. The subset of the target cluster is extracted by calculating the similarity between the cluster centers and the test sample.

4-3 processing procedure

• Using loops in the algorithm, especially in the classification training part, which is based on the KNN network.

• Reports points obtained using different classifications.

• Scores indicate better predictions obtained compared to other classifications.

• The results of using two parts, i.e. applying the optimized infrastructure development technique, and then recommending the proposed hybrid network and KNN sets as prediction models for detecting factors.

• A graph formation matrix is formed

• The actual labels of the data items are placed along the rows

• Anticipated labels are placed along the columns

• Many deterministic and stochastic systems are approximated using relatively simple structures

• The resulting chains have the advantage of having important dynamic characteristics of the system

• It is through the examination of these chains that each sample path leads to an approximation of the same transition matrix

4-4 Methodology

As part of the analysis of the extracted data, the most common situations in the reviews were considered in three categories. Top features include checking PSO, Propositional, KNN methods. In general, such modes provide a better visual representation and help to compare between these three categories of output. The more the usage data of a status, the higher its presence in status extraction. From the output of the processes, it is evident that certain features of the class mechanisms in terms of the coreless banking method are used more than the cost-effective mechanisms. However, the sheer amount of variation in the use of this progression does not allow for sufficient conclusions to be drawn about each category of mechanism.

One of the key requirements for understanding the research questions is to understand the parametric status of web banking software hidden in surveys. Cluster analysis helps to better understand this parametric situation by looking at the features that the labeled data use in their analyses. The height of the cluster dendrograms is inversely proportional to the correlation between terms. Highly correlated trends form a cluster at the lower points of the dendrogram. Also, two states at the same altitude, but belonging to different clusters, will have a very distant correlation.

4-5 Analysis of projected data

A simple linear regression was used to test the validity of the hypothesis that this regression model tries to determine whether there is a linear relationship between the ranking of the web banking software and the polarity of the parametric status of the web banking software. The polarity of the method is "proposal" when the above ratio is greater than 1.5, "KNN" when it is between 1 and 1.5, and "PSO" when it is 0 to less than 1. To determine the polarity and parametric status of each cluster, the combination of the optimized KNN algorithm in combination with the optimized multi-factor structure was used in combination with the multi-factor structure against the vocabulary of states. These algorithms were previously trained against a large reservoir of parametric state-based states. It comes as default

The "labeled data type" cluster provides insights into the parametric state and polarities of the parametric state for the mechanisms considered in the sample.

6-4 executive department

In the executive part, according to the way of using the algorithms and the structure of parameters and variables, we examine them in several stages:

First step: The code includes all the libraries and frameworks necessary to run different parts.

The second step: includes token registration and offline dataset to access the dataset.

The third step: includes a brief description of how to execute the current instructions, namely:

"In the first part, first, the data containing the output type, the proposed parametric state of the web banking software, the parametric state of PSO of the web banking software and the parametric state of KNN recorded from the dataset in several data sets in TXT and CSV format are extracted and then This data is analyzed based on the development of the infrastructure and the investigation begins."

The fourth stage: the primary classification and separation of data is based on the triple states and the initial valuation of intermediate variables

The fifth step: In principle, it is the first executive and calculation step that takes the data extracted and separated from the datasets in three separate parts and applies the following to them.

a) For each of the modes and based on the previous separation of the proposed data, it analyzes PSO and KNN and displays the counted and exact number of each

Note: It is necessary for Decker to simplify and increase the speed of processing, the system only evaluates the proposed data, PSO and KNN and considers the number of remaining data as KNN.

b) For the data of step A, it is first processed in the training process and then in the testing process, and the number separated for competence in each type of process and finally displays the accuracy of the system, which is the output of this step in Table 2 below. Come. Different classifiers were compared with the proposed model using the disaggregated data set. Based on this test, the results of the comparison of three methods through API and our proposed method based on the dataset were performed once.

Table 2 - Different classifiers with the proposed model and using the separated data set

Method	Our method-records processed	KNN method-records processed	PSO method-records processed	Learning processed No.	Test processed No.	Accuracy
KNN	3194	2395	3235	5630	1878	85.77
PSO	4041	3030	3245	6275	2093	87.73
Our method	2818	2113	2144	4257	1420	88.66

Data sets were extracted from the information and from the formed networks using probes and API. Then, the extracted data set was sent to the Python environment, which is a platform for proper data analysis and processing. Then the generated data sets were used to build models for classification in various algorithms. The number of features used from the source data set, each one has diverse and different records in terms of the number and factors proposed, PSO and KNN embedding dimensions of the situation to check the parameters and data sets.

In predicting the accuracy of our proposed method, standard classifiers were used for all 3 modes. As can be seen, the accuracy rate of PSO compared to other modes and based on the number of executions in the learning and test phases is significant, i.e. 88.66%.

Labeled data show that it satisfies.

In the next step, the frequency diagram of states is displayed: (Figure 2)

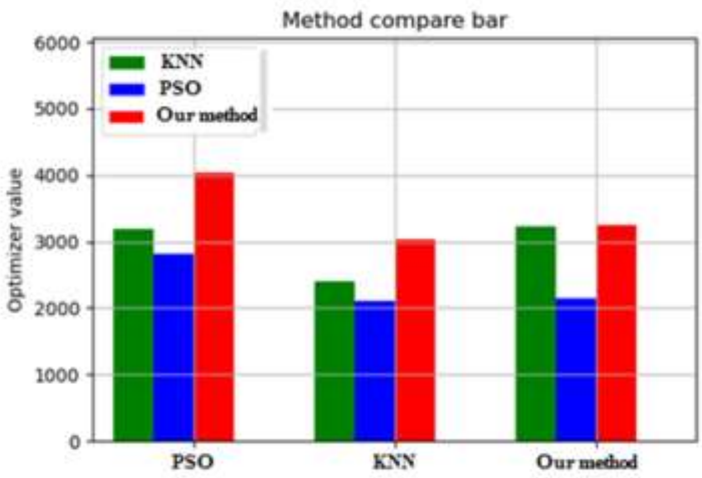

Figure 2 State frequency diagram

It is quite clear that the KNN mode performs significantly better than the other two modes in the two parameters of accuracy and sensitivity (responsiveness) compared to speed. After checking the performance of data based on web banking software by 3 modes, now we are going to analyze these data statistically. The data is grouped into 100 categories and then analyzed separately for each infrastructure development. The best user agent (node) that has the highest score among other nodes is displayed as a member of the group. It should be noted that some data mining algorithms have been used in these calculations. Note: This section may take a few minutes depending on the amount of data. At the beginning of this section, its variables are initialized.

5- Conclusion

As mentioned, the term risk and risk-taking are among the integral functions of the non-core banking system, which cannot be completely eliminated by using appropriate methods, but can be adequately reduced. One of the main goals in a coreless banking system is to maintain a stable and healthy transaction-based system that starts with the credit application and ends with the credit closure. Web banking software, which is the most essential form of risk for banks, is strongly related to measuring and managing the superiority of this method.

Failure of banks to judge transaction-based requests leads to inefficient use of funds. If the bank gives credit to an applicant, it pretends that this loan is not risky, but if the issue is that there is no installment repayment transaction, or because the bank does not intend to create a problem of non-repayment in the future, it grants the credit to the applicant. Does not. This scenario creates a situation for the bank where severe losses are not its main goal.

In the traditional method of credit evaluation, credit is only granted to customers who are not late in repaying the installments of microfinance. In this procedure, due to the mismatch in the transaction-based decision system and the failure to evaluate each applicant with objective variables, due to the use of the subjective judgment of the loan underwriting professional, dissatisfaction is created for the customer.

Using this strategy, the goal is to evaluate transaction-based applications that require greater speed, more efficient processes, and significant accuracy. System speed is related to the objective nature of facility evaluation and decision time. The efficiency and accuracy of the model used in the credit evaluation method relies on the strength and consistency of the prediction. Credit scoring is one of the most important applications of data mining and classification problems, which has attracted more attention during the past decades. The proposed method provides a good classification of applicants by using the development of infrastructures to score participation credit. This research presents a score evaluation model in evaluating credit applications for partnership contracts.

Neural network approach in partnership credit scoring can help financial institutions to reduce their losses significantly. The research shows that the addition of segment partnership criteria using Development of infrastructure in credit scoring gives better results than conventional credit scoring in terms of performance. In addition, the use of Development of infrastructure helps to have a good mean error and reasonable return. Also, the Development of infrastructure model is compared with conventional techniques such as linear regression and discriminant analysis.

Our study can help the coreless banking method to look beyond the ranking of mechanisms to the parametric status of labeled data relative to mechanisms.

From the extracted analysis itself, it is clear that the labeled data have a better parametric condition than the premium mechanisms compared to the cheap mechanisms. The proposed factor has been used in first-class mechanisms more than economical mechanisms. Coreless Banking Method States of mechanisms, confident of their labeled data proposition, should look for ways to improve their labeled data. The ratio of the number of agents proposed to PSO is higher for first-class mechanisms than for cost-effective mechanisms. Coreless banking methods should be careful of such a parametric situation because word of mouth communication has lasting effects on mechanism images. From the regression analysis, we find that the difference in the ranking of the mechanisms is explained by the parametric status of the web banking software to a greater extent in the case of cost-effective mechanisms than in the case of mechanisms considered in the non-core banking method.

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