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APPLICATION OF MACHINE LEARNING IN DETECTING LOAN DELINQUENCY: CASE STUDY OF MICROFINANCE INSTITUTION IN UZBEKISTAN

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The rise of the internet has revolutionized the way we live, work, and communicate. Alongside this digital revolution, a new phenomenon has emerged - big data. Big data refers to the vast amount of structured and unstructured information generated by individuals, organizations, and devices. Big data's emergence has brought about transformative changes across various industries. In particular, big data analytics has enhanced risk management, fraud detection, and personalized banking experiences for customers in the finance industry. The application of the old credit scoring model has been severely constrained by the growth of big data on the Internet, and the original business logic framework has been lost under the new data profiles and business situations.

The modern banks must implement a variety of machine learning (ML) techniques to reduce the manual involvement in the monitoring and testing process and utilize improved automated approaches to deal with increasing number of potential borrowers. Subjective judgement of credit experts on loan advancements is very inefficient and can be dependent on the decision-making ability of those experts. Therefore, application of statistical and machine learning methods can address these problems and might be important tools in credit risk management for several reasons. First, machine learning algorithms have the ability to analyze vast amounts of data and identify patterns that may not be apparent to human analysts.

They can even identify complex relationships and non-linear patterns in data that may not be detectable by human experts. This can lead to more accurate predictions of creditworthiness and a better understanding of the potential risks associated with a particular borrower. Commercial banks can tailor credit offers to individual borrowers' risk profiles, leading to more accurate pricing and better risk management. Moreover, machine learning algorithms can quickly analyze and process large volumes of data in real-time. This enables lenders to make faster and more informed decisions about credit applications, reducing the time and effort required for manual analysis. By automating the credit risk assessment process, machine learning can reduce the need for manual analysis, saving time and resources for lenders. This allows them to process a larger volume of credit applications and improve operational efficiency.

Recent research has examined the use of several machine learning techniques, including decision trees, neural networks, support vector machines, and integration algorithms, in the evaluation of credit. [1] reported that classical logistic regression did not perform as well as the other machine learning methods when there are nonlinear relationships between the variables. However, the logistic regression model offers a significant benefit in terms of variable interpretability and stability, even though prediction accuracy may not be as good as that of the machine learning model.

As a result, some researchers enhanced the logistic regression and used it to forecast borrower default behavior. In [2] personal credit risk assessment was conducted using five famous machine learning methods such as Naïve Bayesian Model, logistic regression model, random forest decision tree and K-Nearest neighbor classifiers. A personal credit evaluation model based on the naive Bayesian classifier was first proposed by [3]. It was tested on German and Australian credit data sets and compared with five neural network models, showing that the naive Bayes classifier has a lower classification error, hence higher accuracy rate. [4] evaluated the P2P online loan borrowers using a neural network model. The results demonstrated that the model was capable of good feature extraction and knowledge discovery.

The borrower evaluation index system can still produce a more accurate assessment of the credit risk of borrowers and has a good capacity to assess and anticipate when virtual information index is present. [5] have used a real social lending platform (Lending Club) dataset with more than 800,000 observations considering different evaluation metrics (i.e. AUC, Sensitivity, Specificity) using random forest, logistic regression and multilayer perceptron. Besides supervised learning techniques, several researches have focused on clustering-launched support vector machine (SVM) models using unsupervised ML algorithms like divisive hierarchical k-means (DHK) and self-organizing maps (SOM) ([6] and [7]).

In this paper, the dataset has been obtained from a micro finance institution (MFI) in Uzbekistan which is well established and has branches in all 14 regions of the country. The dataset contains 12883 individuals (clients) for the period 2019-2022. The summary statistics of the observations are provided in Table 1.

The following statistical method was applied to estimate the probability of being delinquent on the loan payments.

$$\ln(\frac{\pi}{1-p}) = \beta_0 + \beta_1 * Gender + \beta_2 * Age + \beta_3 * Num_{loans} + \beta_4 * Amount + \beta_5 * Interest\ rate + \beta_6 * Age\ squared + \varepsilon$$

Table 1.

Descriptive statistics of the dataset obtained from MFI

	Obs	Mean	SD	Min	Max
NPL	12882	0.12	0.32	0.00	1.00
Gender: male	12882	0.51	0.50	0.00	1.00
Age	12882	42.05	12.33	19.00	84.00
Num loans	12882	0.57	0.55	0.00	5.00
Amount	12882	11,676,434.70	8,416,746.24	500,000.00	50,000,000.00
Interest rate	12882	59.32	1.77	29.20	72.00

The data was split into train (70% of the dataset) and test (30% of the dataset) in order to compute the performance of the model. The train data was used to build the model using the variables provided in Table 1 and the test data was used to predict the probability of being delinquent. Based on the predictions and classification of borrowers into delinquent (when probability of delinquency is higher than 0.5) and not delinquent, the proposed model produced 88% accuracy, 6% sensitivity and 99% specificity. The results of the logistic regression model are provided in Table 2.

Table 2.

The results of logistic regression model

Variable names	*Coefficients*	*Std. Error*
Gender: male	0.3515***	0.0669
Age	-0.0276	0.0175
Age_squared	0.0001	0.0002
num_loans	0.2854***	0.0616
Amount	0.0000***	0.0000
Interest_rate	0.3535***	0.0284

** - significant at 10%, ** - significant at 5%, *** - significant at 1%.*

According to the results, the male borrowers are more likely to be delinquent on the loan payments while holding other variables constant. Age variable and its squared transformation did not show any significant impact on the likelihood of delinquency. Number of loans, amount of the loan and interest rate showed positive relationship with the probability of being delinquent. These findings can have significant implications for policymakers as well as financial professionals in Uzbekistan in tackling issues related to non-performing loans.

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EXPLORING THE CREDIT TRABSFER SYSTEM IN TEACHING ENGLISH FOR ECONOMICS

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The credit module system is a method of teaching languages that is gaining popularity around the world. This system is designed to provide students with a more flexible and personalized approach to language learning. In this article, I will explore the prospects of the credit module system of language teaching, including its benefits and challenges. Firstly, let us understand what the credit module system is and its history background. The credit module system, also known as the credit-based system, is a method of measuring academic achievement based on the number of credits a student earns for completing a particular course or program. The system has been in use for many decades, but its origins can be traced back to the United States in the late 19th century.

The credit hour was initially introduced in 1906 at the University of Chicago by the university's president, William Rainey Harper. He believed that the credit hour would provide a flexible means of measuring academic achievement, enabling students to take courses in a variety of subjects and earn credit towards their degree. The credit hour system quickly became popular among other universities in the United States and was adopted by the Carnegie Foundation in 1910 as a standard unit of academic measurement [3]. Over the years, the credit module system has been refined and adapted to meet the changing needs of higher education. In the 1960s, for example, the system was modified to include the concept of modularization, which allowed students to take individual modules of courses rather than having to complete an entire course to earn credit.

This made it easier for students to design their own courses of study and to tailor their academic programs to their specific needs and interests. In the 1970s and 1980s, the credit module system was further developed to include the idea of credit transfer. This meant that students could transfer credits earned at one