

Financial Status Analysis Using Credit Score Rating

¹Shynggys Daulet
Institute of Automation and
Information Technologies
Satbayev University
Kazakhstan

¹D.Shynggys@su.edu.kz

⁴Moldagulova Aiman Nickolayevna
Institute of Automation and
Information Technologies
Satbayev University
Kazakhstan

⁴a.moldagulova@satbayev.university

²Abdul Razaque*
Institute of Automation and
Information Technologies
Satbayev University
Kazakhstan

²r.abdul@satbayev.university

⁵Uskenbayeva Raissa Kabievna
Institute of Automation and
Information Technologies
Satbayev University
Kazakhstan

⁵r.k.uskenbayeva@satbayev.university

³Zhyldyz Kalpeyeva
Institute of Automation and
Information Technologies
Satbayev University
Kazakhstan

³z.kalpeyeva@satbayev.university

⁶Ajmal Khan
Department of Electrical and
Computer Engineering
Ohio Northern University

⁶m-khan.2@onu.edu

Abstract: Credit risk assessment is an essential element of financial stability, impacting banking institutions, governmental financial entities, and individual creditworthiness. This paper presents a machine learning-based credit score model aimed at improving the precision of financial risk evaluations through the use of predictive analytics. The model employs sophisticated algorithms, including Random Forest, XGBoost, and Neural Networks, to categorize individuals into credit risk classifications based on their transaction histories, loan repayment patterns, and income stability. Explainable AI methodologies, such as Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP), enhance transparency in decision-making, hence augmenting trust in credit assessments. The research analyzes the effects of economic volatility and regulatory modifications on credit risk evaluation, specifically in Kazakhstan, where there has been a notable increase in consumer loans. Empirical study and thorough experimentation reveal that machine learning models surpass traditional statistical methods, enhancing predicted accuracy and reducing biases in credit assessment. The proposed approach improves financial inclusion by offering a scalable and transparent method for real-time evaluations of creditworthiness. This research advances the creation of adaptable and robust credit risk models that respond to changing financial environments.

Keywords: Credit scoring, machine learning, predictive analytics, financial risk assessment, data mining, explainable AI, creditworthiness

I. INTRODUCTION

Credit risk evaluation is crucial not just for banks but also for governmental financial institutions and society [1]. It guarantees adherence to International financial reporting standards (IFRS) and enhances the financial stability of institutions [2]. Precise credit risk assessment safeguards competitive advantage by calibrating loan pricing, avoiding overpriced loans that jeopardize market share and underpriced loans that do not offset anticipated losses [3]. Credit risk is essential to the present net value (NPV) of financial instruments and underpins data-driven marketing and recommendation systems [4]. In Kazakhstan, like several nations, credit histories are centrally maintained, enabling citizens and financial institutions to access credit records, hence improving transparency and facilitating informed decision-making [5].

Credit risk assessment solutions have progressed over decades, transitioning from the fundamental “5Cs” model (Character, Capital, Collateral, Capacity, and Condition) to

advanced techniques utilizing Linear Discriminant Analysis (LDA) as proposed by Fisher [6], neural networks, and multi-criteria optimization. Regulatory modifications, including IFRS 9, Basel IV, and the European Central Bank’s Asset Quality Review, have impacted methodology, highlighting the necessity for flexible, resilient models in reaction to economic fluctuations like those experienced during COVID-19. Recent research underscores the superiority of complicated models that tackle prior challenges such as the “reject inference” issue and data quality while using soft computing, advanced data mining, and improved data preparation procedures as noted in [7].

In Kazakhstan, consumer loans have been increasing annually, as seen by data from KazTAG, which shows an increase of around 200 billion tenge in 2021, compared to 4.9 trillion tenge in the preceding year. Furthermore, it is noteworthy that in 2020, the total of late debts reached 1.32 trillion tenge, constituting approximately 37% of all loans, including consumer debts and small business loans, as reported in [8].

This paper aims to investigate essential research inquiries in the field of credit risk. How do legislative changes and economic events influence the development and efficacy of credit risk assessment models? Secondly, what are the hurdles and constraints in using advanced machine learning methodologies for credit risk assessment, especially in varied economic contexts such as Kazakhstan? This study seeks to enhance the evolution of flexible and robust credit risk techniques by addressing these inquiries. Figure 1 depicts schematic representation of credit agreement work.

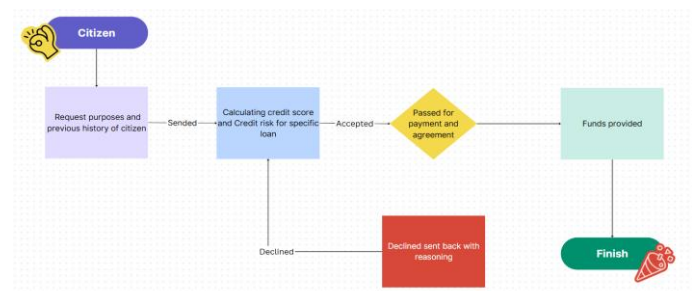


Fig. 1. Schematic representation of credit agreement work

A. Research Contribution

The main contributions of the article are summarized as follows:

- A regressive examination of contemporary data requirements, juxtaposing modern methodologies for resilience under uncertain settings and infrequently observed phenomena. The impact on each citizen's own credit score and financial stability.
- Proposing an alternative methodology for innovative computations and the application of Machine Learning in data analysis.
- Ethical considerations in credit score assessment, highlighting information that may be utilized for computations in particular instances.

This will enable us to get a clearer perspective and develop new dependable solutions on this subject.

B. Problem Identification and Significance

Financial instability continues to pose a significant risk to individuals and communities globally. A multitude of persons encounter challenges in financial management owing to restricted access to financial planning education, volatile employment circumstances, and an incapacity to obtain affordable loans. The increasing intricacy of contemporary financial institutions, particularly the transition to digital platforms, has exacerbated the situation, rendering many susceptible to suboptimal decision-making and manipulation. The above illustrates the annual changes in consumer loans taken by Kazakhstani citizens, reflecting the everyday economic stability and growth at the grassroots level. The importance of financial stability is paramount, as it underpins individual welfare and societal advancement. Financially stable individuals may satisfy their fundamental wants, invest in their futures, and foster the development of their local economies. In contrast, instability induces stress, restricts access to vital services, and sustains cycles of poverty and inequality. Insufficient financial stability obstructs long-term planning, impeding ambitions such as schooling, property, and retirement. It further intensifies economic inequalities, establishing obstacles for underprivileged populations and hindering overall social equity. Moreover, instability among a substantial segment of the population exerts pressure on public services, since an increasing number of persons depend on social safety nets to fulfill fundamental requirements.

C. Paper organization

The organization of the paper is as follows: In Section 2, we examine pertinent research on the issue. Section 3 presents a summary of our proposed methodology. Section 4 presents experimental data and methodology, whereas Section 5 conducts a comprehensive discussion and analysis of our findings. In Section 6, we present conclusions, emphasizing significant observations and proposing avenues for future research.

II. PROPOSED FOR FINANCIAL STATUS ANALYSIS USING CREDIT SCORE RATING

We introduce a machine learning-driven credit scoring approach that uses predictive analytics to assess financial

conditions more accurately. To calculate credit scores, the model uses supervised learning to analyze transaction records, loan payback habits, and income consistency. The system classifies people into credit risk categories using advanced algorithms like Random Forest, XGBoost, and Neural Networks. Explainable AI methods local interpretable model-agnostic explanations (LIME)) and Shapley additive explanations (SHAP) are explainability techniques used to interpret complex models and understand their decision-making process. SHAP and LIME explain credit rating factors, allowing users and financial institutions to understand and trust the model's conclusions. Credit scores are updated in real time using data processing and adaptive learning to improve financial decision-making. A cloud-based API connects banking and lending institutions for instant creditworthiness assessments. A customized financial insights dashboard offers credit rating and debt management advice. By using alternate data sources, this data-centric approach lowers credit scoring biases and increases financial inclusion. The proposed credit evaluation platform is fair, transparent, and scalable, helping financial institutions and clients make better financial decisions.

Hypothesis-1: Credit scoring models that incorporate a variety of financial data improve the precision of loan repayment behavior predictions.

Proof: The premise is validated by adding a greater range of financial characteristics, such assets and payment history, to the credit scoring model: the model becomes more accurate at forecasting loan payback patterns.

Standard credit score formula:

Credit score Z is defined as the formula below.

$$Z = \alpha_1 T + \alpha_2 D_e + \alpha_3 P_a + \sum_{i=1}^n \alpha_i I_e \quad (1)$$

- $\alpha_1, \alpha_2, \alpha_3, \alpha_{1t}$ are weights assigned to each feature,
- T is income,
- D_e is debt,
- P_a is payment history,
- I_e are other financial features (e.g., assets, credit inquiries, etc.).

For calculation of accuracy improvement, we might utilize root mean squared error.

TABLE I. Algorithm

Algorithm 1: Data collection and aggregation for credit scoring using machine learning
Input: $\{ \partial \}$ Output: $\{ \beta: \text{Bank Intelligence System}, C: \text{Credit Scoring}, \gamma: \text{Data Aggregation} \}$ 1. Initialization: $\{ \partial: \text{Bank data}, \beta: \text{Bank intelligence system}, C: \text{Credit scoring}, \gamma: \text{Data aggregation} \}$ 2. Set ∂ 3. Do Process $\partial \in \gamma \rightarrow \gamma$ (Data preparation) 4. Train Machine Learning model using $\gamma \rightarrow C$ (Feature selection and model training) 5. If C achieves acceptable performance metrics (accuracy, AUC, etc.), 6. β successful 7. Else

8. β needs improvement (model tuning, feature engineering)
9. End-else
10. Endif

Here is the basic score for credit score measurement.

$$Z_{basic} = \alpha_1 T + \alpha_2 D_e \quad (2)$$

If we add the accuracy formula here.

$$Accuracy_{basic} = \sqrt{\frac{1}{N} \sum_{i=1}^N (Z_{pred}^{basic} - Z_{true})^2} \quad (3)$$

Here Z_{pred}^{basic} is possible credit score when used basic data.

If we apply the same approach on formula with additional data we will face next results.

$$Z_{extended} = \alpha_1 T + \alpha_2 D_e + \alpha_2 P_a + \sum_{i=1}^n \alpha_i I_e \quad (4)$$

We add the accuracy formula here.

$$Accuracy_{extended} = \sqrt{\frac{1}{N} \sum_{i=1}^N (Z_{pred}^{extended} - Z_{true})^2} \quad (5)$$

We could say more data gathered for prediction improves each model's accuracy quite significantly. In addition, we could rely on the empirical research of Jagtiani and Lemieux [9].

Hypothesis-2: Machine Learning-Driven Credit Scoring Models Yield Higher Predictive Accuracy in Identifying Loan Defaulters Compared to Traditional Statistical Methods

Proof: A well-known credit scoring model mostly prioritizes the use of linear regression or logistic available data like income (I_n), debt (D_e), and payment history (P_a).

$$P_a(z = 1) = \frac{1}{1 + e^{-(i_0 + i_1 I_n + i_2 D_e + i_3 P_a)}} \quad (6)$$

- i_0, i_1, i_2, i_3 are model coefficients,
- I_n, D_e , and P_a are income, debt, and payment history, respectively.

In contrast to fundamental machine learning models, such as "Random Forest," we may illustrate it using the formula below.

$$P_a(z = 1) = \theta(I_n, D_e, P_a, \text{other features}) \quad (7)$$

Here θ represents a specific machine learning model used in this specific case in our example above used "Random Forest".

Empirical studies demonstrate that machine learning models generally outperform classical statistical models, yielding superior accuracy ratings. This is due to the proficiency of machine learning models in identifying nonlinear connections between variables, enabling them to uncover patterns often overlooked by traditional methods. These models incorporate a wide array of variables without requiring human feature engineering, effectively managing complex, high-dimensional datasets. By autonomously recognizing intricate feature correlations, they also provide insights that enhance predictive accuracy and equity.

Lemma 1: Machine Learning Models Improve Credit Score Accuracy via Nonlinear Data Relationships

Proof: Let $z \in \{0,1\}$ represent loan repayment outcomes (default or repayment) and Z be financial.

Machine learning models predict default probabilities using complex, nonlinear functions:

$$F_{ML} = (z = 1|Z) = \delta(Z; \epsilon) \quad (8)$$

here δ includes interactions and transformations.

Traditional linear models predict probabilities as

$$F_{Traditional} = (z = 1|Z) = \frac{1}{1 + e^{-\beta^T x}} \quad (9)$$

Machine learning reduces errors and improves fairness in credit scoring by analyzing broader, richer data features.

Corollary 1: Machine learning promotes fairer credit decisions Through Bias Mitigation Machine learning models reduce bias in credit scoring by incorporating diverse, non-linear data relationships and minimizing reliance on singular demographic variables. Process broader features Z_{ML} including income, spending habits, and credit behavior, while excluding sensitive data.

Use feature importance metrics and bias-detection tools to ensure fairness in predictions:

$$Fairness\ Metric = 1 - \frac{Disparate\ Impact}{Ideal\ proportion} \quad (10)$$

III. EXPERIMENTAL SETUP AND RESULT

This section provides experimental setup, dataset description, and results.

A. Experimental Setup

An Intel Core i5-1250P processor is used in the construction of the suggested intelligent credit scoring system to maximize performance. This CPU is appropriate for a range of data processing activities since it provides a balanced combination of processing power and efficiency. With 16 GB of RAM installed, the system has enough memory to manage moderately complicated data manipulation and machine learning tasks. The system may still take advantage of the integrated graphics and multi-core processing capabilities of the Intel Core i5-1250P for parallel algorithm execution, even though it does not have as many GPU cores as the prior setup. Utilizing a variety of software libraries and frameworks, the system runs on Windows 10. With several built-in libraries like NumPy, Scikit-Learn, and TensorFlow that are essential for data processing, machine learning tasks, and model training, Python continues to be the primary programming language. Scikit-Learn provides a comprehensive toolset for a range of machine learning techniques, while NumPy makes effective numerical operations and dataset manipulation possible. Building, training, and implementing machine learning models with TensorFlow ensures a high degree of system development freedom. The code editor is a Jupyter Notebook environment, which enables real-time code execution and smooth library and framework interaction. The system also makes use of publicly available datasets to guarantee the reproducibility and transparency of its findings. This guarantees that the credit scoring model can be confirmed and validated by the scientific community and is based on excellent research standards.

All things considered, this intelligent credit scoring system's technical features demonstrate its capacity to provide strong performance for machine learning tasks, together with an

effective and adaptable development environment that fosters algorithmic innovation and data-driven decision-making.

Table 1. Parameters and their description for conducting the experiments

TABLE I: Tools and their description

Name of the tools	Description
Programming Language	Python (version 3.12.1, 64 bits)
Development Environment	Jupyter Notebook
Machine Learning Library	Scikit-learn (built on SciPy, NumPy, and matplotlib) Tensorflow

B. Dataset Description

The World Bank and the National Bank of Kazakhstan are two respectable and credible organizations that provided the dataset for this investigation. With its extensive global financial data, the World Bank offers important insights into national economic performance, credit markets, financial inclusion, and macroeconomic indicators. Understanding the economic and worldwide trends that affect credit scoring models is made easier with the help of this data. Concurrently, information from the National Bank of Kazakhstan is combined to offer a regionally focused viewpoint. Also around 2431 row of interest rates, currency rates, the performance of the banking industry, inflation rates, and other national economic indicators are among the vital financial statistics provided by the National Bank. Utilizing this data guarantees that the research is pertinent to Kazakhstan's unique financial and economic circumstances.

This dataset offers a comprehensive picture of the variables affecting credit rating by fusing local economic and financial data from the National Bank of Kazakhstan with worldwide financial data from the World Bank. This deliberate blending of local and international data strengthens the analysis's resilience by giving a thorough and accurate picture of Kazakhstan's financial ecosystem while also taking into consideration more general global economic factors.

C. Results

i. Income distribution

Figure 2 shows the monthly income distribution of the population in Kazakhstan, which is measured in Kazakhstani Tenge (KZT). The histogram displays the number of people who fall under specific income brackets. The y-axis shows frequency, while the x-axis depicts monthly revenue levels that range from 100,000 KZT to 800,000 KZT. The data distribution appears to be uniform, which suggests that the distribution of wages is evenly distributed throughout the population, with only minor differences in frequency among income categories. The density curve is represented by the blue line overlay, which provides a smooth approximation of the shape of the income distribution. This curve reaches its peak between KZT 400,000 and KZT 500,000, which indicates that a significant percentage of people earn money within this area. Although some income categories have somewhat larger or lower numbers, the distribution is still generally the same, and there are variances in frequency. The graphic depiction emphasizes the primary trend of mid-range income levels, providing information about the financial status of the people and demonstrating the diversity of incomes.

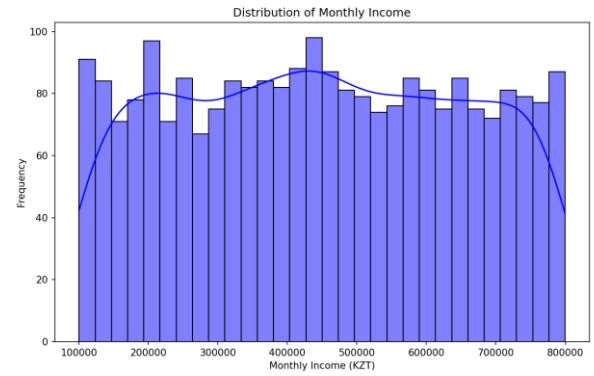


Fig 2. Monthly income distribution

ii. debt-to-income ratio

Figure 3 shows the connection between the debt-to-income ratio and the current credit score. The data points are divided into groups based on default history. The x-axis shows the debt-to-income ratio, which goes from 0 to 50, and the y-axis shows the current credit score, which goes from 660 to 800. The default history of everyone is represented by a different hue. Blue means that the person has never defaulted, while orange means that they have defaulted at some point in the past. Most of the data points are grouped together in the lower debt-to-income ratio range, especially between 0 and 10. This indicates that most people have a relatively modest amount of debt when compared to their income. In this area, there is a higher density of people with higher credit scores (above 750), notably among those with no default history (blue points). As the debt-to-income ratio rises, credit ratings tend to drop, and the data points become more spread out. This trend shows that those with a history of defaults (orange points), who are often found in the lower credit score range, have a higher debt burden and lower credit ratings. According to the graph, those who do not have a history of defaulting on loans tend to have higher credit scores than those who do, regardless of their debt-to-income ratio. However, when the debt-to-income ratio approaches 20, the number of people with great credit ratings decreases considerably, regardless of whether or not they have a history of defaulting. This scatter plot clearly shows the negative association between the debt-to-income ratio and credit score, while also underlining the impact of default history on creditworthiness.

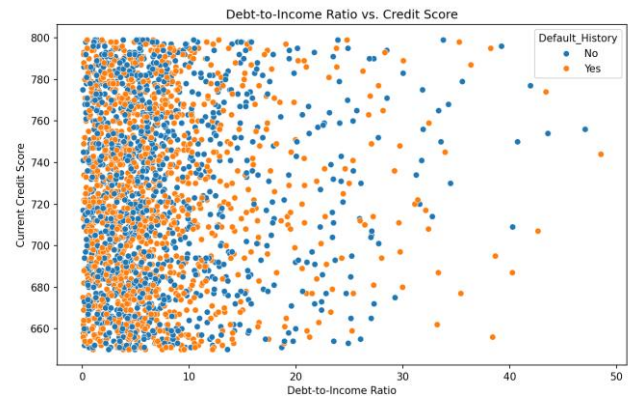


Fig 3. Debt-to-income ratio and the current credit score

iii. Real and predicted credit score

Figure 4 depicts the juxtaposition of real and forecasted credit scores. The x-axis denotes real credit scores, spanning from 660 to 800, whilst the y-axis indicates the corresponding anticipated credit scores within the identical range. Each blue dot signifies a distinct data point, juxtaposing the anticipated credit score produced by the model with the actual observed credit score. The red line denotes the optimal scenario in which the projected credit score aligns precisely with the actual credit score, functioning as a benchmark for assessing the model's accuracy. The arrangement of the blue dots indicates that the majority of forecasts are concentrated along the red line, signifying that the model effectively approximates the real credit scores. Nonetheless, there are discernible discrepancies where predicted scores marginally overestimate or underestimate the actual values, especially for people at the extremities of the credit score spectrum. Notwithstanding these discrepancies, the majority of forecasts remain closely aligned with the optimal trajectory, illustrating the model's dependability and limited inaccuracy in forecasting credit ratings. The congruence of the data points with the red line indicates a robust link between actual and anticipated credit scores, demonstrating the model's proficiency in generalizing across various credit scores. This visualization underscores the accuracy and potential biases of the predictive model, providing insights into areas for additional modification to improve performance.

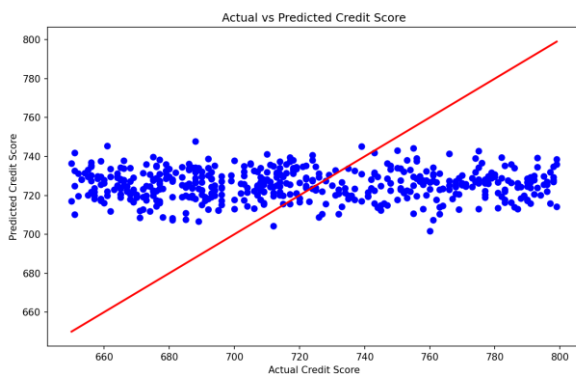


Fig 4. Real and predicted credit score

IV. CONCLUSION AND FUTURE WORK

This section concludes the article and provides future work.

A. Conclusion

This study examined how machine learning may improve creditworthiness and financial risk scoring. Predictive analytics and advanced models like Random Forest, XGBoost, and Neural Networks better classify people into credit risk groups than traditional statistical methods. LIME and SHAP improve credit evaluation trust and decision-making transparency with explainable AI. Research shows machine learning-driven credit score models predict loan payback and eliminate credit risk assessment biases better than traditional methods. These models leverage more financial data to make loan decisions fairer and more

inclusive, especially in dynamic economies like Kazakhstan. Real-time credit score updates, adaptive learning, and alternate data sources improve credit rating systems, according to studies.

The research notes model implementation limitations, processing expense, and fairness issues across financial conditions despite encouraging results. Future research should combine financial information, improve algorithmic fairness, and improve interpretability using sophisticated AI-driven credit analysis to improve these models for real-world deployment. Credit risk models benefit from regional and global financial data.

B. Future Work

Future research should enhance credit rating systems by advanced feature engineering, fairness-aware AI, and real-time financial data integration. Mitigating biases and adhering to regulations will enhance algorithmic fairness, model transparency, and trustworthiness. The integration of deep learning with ensemble models enhances predictive accuracy. Moreover, international financial records and other data sources would enhance credit accessibility and promote financial inclusion. Ultimately, resilient and scalable credit risk assessment systems require adaptive models capable of withstanding economic volatility.

Funding: This research was funded by the Committee of Science of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant No. AP19675226).

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