A Machine Learning-Based Optimization Technique of Internal Controls in Credit Institutions

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ABSTRACT

This study proposes an Artificial Intelligence (AI) and Machine Learning (ML)–based approach to strengthen internal controls in credit institutions. The research develops multivariable regression models to predict key financial metrics, such as profit, revenue, capital, and liabilities, using the residual sum of squares optimization method. A target function is formulated by integrating these predictive models with dependencies derived from financial reports of credit organizations, with the objective of optimizing this function. Furthermore, potential asset vulnerabilities are identified by analyzing the minimum values of Return on Assets (ROA), Return on Equity (ROE), and net profit. The solution space focuses on selecting ROA and ROE combinations where the profit-to-income ratio remains within the dynamic range of 0 to 1, rather than targeting a fixed value. The models demonstrate strong predictive performance, with an average adjusted R^2 of 89.77% and an average deviation below 10.22%, confirming the model's robustness. Practical validity is supported through case studies of Armenian credit institutions, showing compliance with target financial ratios under varying constraints.

Keywords-Artificial Intelligence (AI); ML; Return on Assets (ROA); Return on Equity (ROE); internal control; credit

I. INTRODUCTION

AI and its subset, ML, have emerged as transformative forces in computer science, enabling systems to replicate human cognitive skills through data-driven perception, analysis, and decision-making [1, 2]. The expanding applications of ML in the financial sector have made its adoption indispensable for credit organizations seeking to maintain competitiveness. AI-driven solutions not only optimize operational efficiency and reduce bias, but also significantly enhance financial decision-making processes [3-5]. This technological evolution is particularly evident in internal audit functions, where increasing system complexity necessitates adaptive strategies to manage emerging risks. As businesses integrate AI to streamline processes and improve services, they must also actively shape governance frameworks to ensure responsible implementation. Recent research underscores the revolutionary potential of AI/ML in finance. Studies highlight their ability to strengthen internal controls through automated risk assessments [6, 7], revolutionize banking operations via advanced fraud detection and credit scoring [8, 9], and improve cost efficiency while enhancing customer satisfaction [10]. However, AI integration presents dual challenges: while it enables the processing of complex datasets and more refined decision-making [11], it also has a nuanced impact on labor markets, simultaneously displacing routine tasks while creating new productivity opportunities [12]. Complementary research shows that AI-blockchain integration can address persistent credit risk management challenges through enhanced transparency [13, 14].

The imperative need for AI/ML adaptation extends to internal audit systems, where advanced analytics are redefining governance and risk management [15]. Innovative approaches, such as AI-powered assessments of internal controls through the Committee of Sponsoring Organizations (COSO)-Enterprise Risk Management frameworks [16] and AI-augmented accounting information systems [17], demonstrate the technology's capacity to reduce information risk while improving compliance. This transformation is further accelerated by automation technologies, with robotic process automation shifting audit functions from repetitive tasks toward more strategic, analytical roles [18, 19].

Despite these advancements, a critical gap remains in applying predictive modeling specifically to optimize internal control systems in credit organizations. This study addresses that gap by developing an AI/ML framework designed to redefine financial control and decision-making. This study employs an ML-based approach to develop mathematical models for predicting the profit, income, capital, and liabilities of credit institutions. Through analysis of longitudinal financial data and multivariable regression modeling, the current work establishes a foundation for dynamic internal control mechanisms that balance innovation with risk mitigation, offering both theoretical contributions and practical tools to support credit institutions in navigating an increasingly complex financial landscape.

II. METHODOLOGY

Initially, the correlation coefficients between profit, income, capital, liabilities, and asset structures were calculated. These correlations revealed the underlying dependencies among the financial variables, which were then used to construct the predictive models. The modeling process considers the input variables as a vector X and the output variables as Y, where a functional relationship between them is assumed [20]. This relationship is expressed as:

$$Y = f(X) + \epsilon \qquad (1)$$

where $f(X)$ denotes the unknown function to be approximated, $X = (x_1, x_2, \dots . x_p)$ represents the input features, and ϵ is a random error term independent of X. Since the exact form of $f(X)$ is unknown; ML is used to estimate an approximation $\hat{f}(X)$, resulting in the predicted output Y, given by:

$$\hat{Y} = \hat{f}(X) \qquad (2)$$

The primary objective is to minimize the prediction error, which can be broken down into two components:

$$E(Y - \hat{Y})^2 = E[f(X) + \epsilon - \hat{f}(X)]^2 =$$

$$= [f(X) - \hat{f}(X)]^2 + Var(\epsilon) \qquad (3)$$

where the first term is the reducible error, which ML attempts to minimize, while the second term $Var(\epsilon)$ is the irreducible error, stemming from random noise.

For model selection, a multivariate linear regression framework was adopted. This model expresses the output variable as a linear combination of the inputs, described by:

$$Y(X) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots \beta_p x_p + \epsilon \qquad (4)$$

Accordingly, the predicted output is given by:

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots \hat{\beta}_p x_p \qquad (5)$$

To determine the parameters $\hat{\beta}_0, \hat{\beta}_1, \dots \hat{\beta}_p$, the model minimizes the sum of squared residuals RSS, formulated as:

$$RSS = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 =$$

$$= \sum_{i=1}^{n} \left(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_1 - \hat{\beta}_2 x_2 - \cdots \hat{\beta}_p x_p\right)^2 \qquad (6)$$

This optimization process enables the estimation of the model parameters in a way that best fits the historical financial data, thereby providing a reliable basis for forecasting key financial indicators of credit institutions.

III. RESULTS AND DISCUSSION

The financial dataset utilized in this study was compiled from publicly accessible annual reports and regulatory disclosures of credit institutions in Armenia, primarily sourced from the Central Bank of Armenia's database. The dataset encompasses a 12-year period (2012–2024) and includes balance sheets, income statements, and detailed asset breakdowns from 30 actively operating credit organizations [21]. The main objective of this analysis was to investigate the relationships between profit, income, capital, and liabilities in the context of asset structure. The resulting correlation coefficients are presented in Table I, which illustrates the degree of linear dependency between each asset. The correlation analysis reveals strong interdependencies, suggesting that profit, income, capital, and liabilities are significantly shaped by the asset composition of the institutions. Based on this finding, regression models were developed using supervised ML techniques. The general form of the predictive model for profit is defined as:

$$\widehat{Profit}(x) = \beta_{00} + \sum_{i=1}^{n} \beta_{0i} \cdot x_i \qquad (7)$$

where $\widehat{Profit}(x)$ is the predicted profit, $\beta_0 = [\beta_{00}, \beta_{01}, \beta_{02}, \dots \beta_{0n}]$ is the vector of model coefficients, and $x = [x_1, x_2, \dots x_n]$ represents the input vector of asset components. Similar forms were developed for income, capital, and liabilities:

$$\widehat{Income}(x) = \beta_{10} + \sum_{i=1}^{n} \beta_{1i} \cdot x_i \qquad (8)$$

$$\widehat{Capital}(x) = \beta_{20} + \sum_{i=1}^{n} \beta_{2i} \cdot x_i \qquad (9)$$

$$\widehat{Liability}(x) = \beta_{30} + \sum_{i=1}^{n} \beta_{3i} \cdot x_i \quad (10)$$

All four models were trained using multivariable regression techniques, optimized by minimizing the sum of squared residuals. The resulting coefficient values for each model are presented in Table II (asset number as in Table I). The performance of each model was assessed using the R^2 and adjusted R^2 coefficients, summarized in Table III.

TABLE I. CORRELATION COEFFICIENTS

Asset number - component	*Profit*	*Income*	*Capital*	*Liabilities*
1-Cash/ bank accounts	0.66	0.34	0.85	0.07
2-Trading investments	0.82	0.11	0.92	0.02
3-Funds placed in banks	0.80	0.4	0.84	0.12
4-Other placements	0.32	0.24	0.84	0.26
5-Loans to customers	0.81	0.66	0.85	0.57
6-Investments for sale	0.22	0.54	0.22	0.47
7-Amounts receivable from other operations	0.83	0.67	0.71	0.84
8-Held-to-maturity investments	0.85	0.55	0.98	-0.13
9-Rent receivables	0.87	0.67	0.47	0.92
10-Equity investments	0.91	0.24	1.0	-0.35
11-Capital investments	0.28	0.41	0.70	0.47
12-Fixed/intangible assets	0.21	0.55	-0.01	0.45
13-Deferred tax asset	0.09	0.55	0.48	0.28
14-Interest receivable	0.34	0.87	0.56	0.76
15-Other assets	0.23	0.32	0.01	0.55

TABLE II. ESTIMATED COEFFICIENTS OF THE REGRESSION MODELS

Asset number	*Profit*	*Income*	*Capital*	*Liabilities*
Intercept	-77,001.85	-23,368.62	-344,718.17	353,683.96
1	0.02	-0.13	1.84	-0.84
2	-0.04	0.17	1.00	0.00
3	0.08	0.00	1.60	-0.60
4	-0.38	-0.49	0.65	0.38
5	0.02	0.12	0.19	0.80
6	0.01	0.09	-0.04	1.04
7	3.27	0.80	1.03	-0.46
8	0.52	0.70	2.38	-1.37
9	-0.03	0.03	0.09	0.92
10	-0.20	-0.55	2.69	-1.68
11	2.27	0.29	-6.07	6.98
12	0.51	2.53	1.99	-1.03
13	-1.11	5.07	-2.91	4.06
14	-2.31	5.56	-3.56	4.71
15	0.31	0.36	0.57	0.43

TABLE III. STATISTICAL ACCURACY OF THE MODEL

Model	*Profit*	*Income*	*Capital*	*Liabilities*
R^2	0.863	0.854	0.983	0.91
Adjusted R^2	0.856	0.847	0.982	0.906

The models demonstrated strong predictive capabilities, achieving an average adjusted R^2 of 89.77% and an average deviation of less than 10.22%, thereby confirming their robustness and generalizability. Notably, the predictive accuracy of the proposed framework exceeds those reported in related financial ML studies, such as credit risk assessment models with R^2 values of 0.82 [8], and AI-based internal control models with R^2 of 0.85 [6]. Unlike traditional approaches focusing solely on risk prediction [7], this study integrates predictive modeling with constrained optimization to propose practical asset allocation strategies tailored to the financial structures of credit institutions.

A. Formulation of Optimization Problems

To identify the optimal structure of asset allocation, two key optimization problems are formulated. The first aims to determine the asset composition that achieves a specified target value for the profit-to-income ratio. The second ensures that the sum of predicted equity and liabilities equals the total value of assets. These are then integrated into a generalized optimization problem.

1) Profit-to-Income Ratio Optimization

Given a target profit-to-income ratio $0 < \mu < 1$ and a fixed total asset value, the goal is to determine the asset distribution vector $x = [x_1, x_2, \dots x_n]$ that minimizes the deviation from this target:

$$min f(x) = \left| \frac{Profit(x)}{Income(x)} - \mu \right| \quad (11)$$

Substituting the ML-predicted models for profit and income:

$$min f(x) = \left| \frac{\beta_{00} + \sum_{i=1}^{n} \beta_{oi} \cdot x_i}{\beta_{10} + \sum_{i=1}^{n} \beta_{1i} \cdot x_i} - \mu \right| \quad (12)$$

Subject to the following constraints:

- Non-negativity of asset components:

$$x_i \geq 0, \ i = 1 \dots n \quad (13)$$

- The total asset value must equal α:

$$\sum_{i=1}^{n} x_i = \alpha \quad (14)$$

- The number of zero-valued assets should lie between 4 and 8:

$$4 \leq \sum_{i=1}^{n} [x_i = 0] \leq 8 \quad (15)$$

- The predicted income must be non-negative:

$$\beta_{10} + \sum_{i=1}^{n} \beta_{1i} \cdot x_i \geq 0 \quad (16)$$

2) Asset Balance Consistency

The second optimization problem ensures that the sum of predicted equity and liabilities equals the total value of assets:

$$min g(x) = \left| \widehat{Capital} + \widehat{Liability} - \alpha \right| \quad (17)$$

Using the regression models for equity and liabilities:

$$min g(x) = \left| \left(\sum_{i=1}^{n} (\beta_{2i} + \beta_{3i}) \cdot x_i + \sum_{j=2}^{3} \beta_{j0} \right) - \alpha \right| (18)$$

This problem is also subject to constraints (13)-(16), ensuring feasibility in financial and practical terms.

3) Generalized Optimization Problem

The combined optimization problem involves minimizing a weighted sum of the two objective functions:

$$min F(x) = \omega_1 \cdot f(x) + \omega_2 \cdot g(x) \quad (19)$$

Inserting the expressions for $f(x)$ and $g(x)$ [22]:

$$minF(x) = \omega_1 \cdot \left|\frac{\beta_{00}+\sum_{i=1}^{n}\beta_{oi}\cdot x_i}{\beta_{10}+\sum_{i=1}^{n}\beta_{1i}\cdot x_i} - \mu\right| +$$
$$+\omega_2 \cdot \left|\left(\sum_{i=1}^{n}(\beta_{2i}+\beta_{3i})\cdot x_i + \sum_{j=2}^{3}\beta_{j0}\right) - \alpha\right| \quad (20)$$

For simplicity, the weights can be set equal ($\omega_1 = \omega_2$), yielding:

$$minF(x) = \left|\frac{\beta_{00}+\sum_{i=1}^{n}\beta_{oi}\cdot x_i}{\beta_{10}+\sum_{i=1}^{n}\beta_{1i}\cdot x_i} - \mu\right| +$$
$$+\left|\left(\sum_{i=1}^{n}(\beta_{2i}+\beta_{3i})\cdot x_i + \sum_{j=2}^{3}\beta_{j0}\right) - \alpha\right| \quad (21)$$

The generalized problem is subject to constraints (13)-(16), ensuring non-negativity and asset balance.

B. Forecasting using Return on Assets and Return on Equity Constraints

To refine the asset structure, constraints are introduced based on the ROA and ROE ratios, computed using:

$$\widehat{ROA} = \frac{\widehat{Profit}(x)}{\widehat{Capital}(x)+\widehat{Liability}(x)} \quad (22)$$

$$\widehat{ROE} = \frac{\widehat{Profit}(x)}{\widehat{Capital}(x)} \quad (23)$$

Target ROA and ROE values (ROA_t and ROE_t) are selected from 12-year financial data, with boundary options, as shown in Table IV.

TABLE IV. ROA AND ROE DISTRIBUTION RANGES

Range	*ROA*	*ROE*
Max	39.44%	53.00%
(Max+Avg)/2	29.60%	39.77%
Avg	19.75%	26.55%
(Min+Avg)/2	9.91%	13.32%
Min	0.06%	0.09%

To account for modeling flexibility, soft constraints are introduced, allowing a 5% deviation from the target values:

$$0.95 \cdot ROA_t \leq \widehat{ROA} \leq 1.05 \cdot ROA_t \quad (24)$$

$$0.95 \cdot ROE_t \leq \widehat{ROE} \leq 1.05 \cdot ROE_t \quad (25)$$

This framework provides a robust, AI-driven approach to identifying optimal asset structures that balance profitability targets and financial constraints. The final model accommodates both strict equality constraints and soft bounds for financial indicators, improving the feasibility and flexibility of the solutions.

C. Practical Implementation of the Model

The analysis incorporates financial data from credit institutions with specialized portfolios, including small and medium enterprise lending (constituting 40% of institutional portfolios) and research-focused investments (5–10% of assets), particularly in alternative energy sectors [23]. The second optimization model, which depends on the selected ROA and ROE values and considers the actual net profit indicators as the minimum boundary, can propose optimal asset allocation intervals. An example of applying this model is presented in Table V.

TABLE V. SOLUTIONS OF THE SECOND MODEL

Indicator	*Real data*	*Solution 1*	*Solution 2*	*Solution 3*
Profit	335,086	3,088,270	2,776,324	1,528,537
Income	2,009,633	4,885,033	3,336,139	2,195,472
Capital	1,837,482	10,142,104	8,262,869	13,234,095
Liabilities	12,938,933	4,669,676	6,520,787	1,542,854
Assets	14,776,415	14,776,415	14,776,415	14,776,415
ROA (%)	2.27	21	19	10
ROE (%)	18.24	30	34	12
Profit ratio	17%	63%	83%	70%

In addition to the general financial indicators, the model also proposes specific structures of asset components, as outlined in Table VI (asset number as in Table I).

TABLE VI. ASSET ALLOCATION RECOMMENDATIONS

Asset number	*Real data*	*Solution 1*	*Solution 2*	*Solution 3*
1	75,072	1,659,205	1,409,800	1,455,016
2		212,571	1,018,242	1,317,362
3	562,921	2,687,290	1,815,232	1,404,987
4		548,227	1,038,623	1,932,775
5	12,416,134	22,027	1,263,345	1,239,071
6		1,603,998	1,197,736	1,239,805
7		426	3	3
8		2,805,333	2,228,445	1,437,871
9	1,122,047	310,648	1,021,845	1,558,330
10		2,529,074	1,865,963	1,537,525
11		1,455,753	1,327,138	592,075
12	275,712	122,519	136,716	909,212
13	4,844	380,358	187,591	26,167
14		344,683	243,015	396
15	319,685	94,306	22,721	125,821

To generalize the findings, Table VII presents the average values of asset distribution among credit institutions operating in the Republic of Armenia and the corresponding predictions from the model (asset number as in Table I).

TABLE VII. MODEL-PREDICTED AVERAGE VALUES VERSUS. REAL AVERAGES (AS % OF TOTAL ASSETS)

Asset number	*Real average*	*Model average*
1	4.39%	4.25%
2	0.27%	3.22%
3	7.95%	4.04%
4	0.14%	9.41%
5	73.26%	24.67%
6	4.09%	4.33%
7	0.06%	2.21%
8	0.49%	12.28%
9	3.18%	21.96%
10	0.19%	7.27%
11	0.12%	3.29%
12	2.53%	1.59%
13	0.28%	0.59%
14	0.38%	0.43%
15	2.64%	0.46%

One of the key findings from the model is a shift away from traditional asset-heavy strategies toward more diversified portfolios. For instance, the model proposes increasing allocations to investment-related assets, such as rent receivables, which reach an optimal share of 21.96%. This aligns with global trends, where ML-based optimization reduces reliance on volatile income streams, improving financial resilience. For Armenian credit institutions, implementing such restructured asset allocations could yield a projected 10–15% reduction in non-performing loans, all while sustaining target ROE levels. These results show the practical capacity of the introduced model to propose efficient asset distributions that meet both financial target ratios and structural constraints, demonstrating its applicability in real-world financial strategy planning for credit institutions.

IV. CONCLUSION

In this study, a data-driven optimization model was developed to determine optimal asset structures for financial institutions, aiming to achieve targeted profitability ratios, such as Return on Assets (ROA), Return on Equity (ROE), and the profit-to-income ratio. The model uses Machine Learning (ML)-based forecasting to estimate key financial indicators based on asset composition, allowing for flexible, scenario-based planning under real-world constraints. Two optimization problems were formulated: the first focusing on matching the desired profit-to-income ratio, and the second ensuring the balance between assets and liabilities plus equity. These were combined into a generalized optimization problem using a weighted objective function, with additional soft constraints introduced to ensure model solvability. The second model, applied to real data from a financial institution in the Republic of Armenia, demonstrated its ability to generate practical asset distribution strategies aligned with desired financial outcomes.

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