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FULL LENGTH ARTICLE

A Dual-Bank Hybrid Predictive Model (DBHPM) for Financial Forecasting

Samandarboy Sulaymanov[1,*]

[1] Tashkent State University of Economics, Uzbekistan

Emails: s.sulaymanov@tsue.uz

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ABSTRACT

Forecasting financial performance is important for strategy formulation and identifying potential problems in banking institutions. This paper presents the Dual-Bank Hybrid Predictive Model (DBHPM), a financial forecasting model combining Multiple Linear Regression (MLR) and Random Forest Regression (RFR). It is validated on two actual financial datasets from Agrobank and NBU Bank covering 2021–2025. The model analyzes financial indicators including net profit, equity, and solvency, and forecasts them through 2027. Specifically, DBHPM uses MLR for linear modeling in the first step and RFR for nonlinear residuals in the second step; the paper reports stronger generalization and predictive strength than using the latter stage alone. Experiments show that DBHPM minimizes MAE and RMSE and achieves a coefficient of determination (R^2) of 0.95 or above compared with models trained independently. The forecasts indicate net profit of approximately 1.18 billion sum for Agrobank and 3.66 billion sum for NBU Bank by the end of 2027. The proposed hybrid model supports predictive financial analysis for decision-making, risk awareness, and economic forecasting in the banking industry.

Keywords: Banking Sector Prediction ▪ Agrobank ▪ NBU Bank ▪ Profitability Prediction ▪ Machine Learning in Finance ▪ Strategic Financial Planning

1. INTRODUCTION

In the evolving landscape of global finance, the ability to accurately forecast a bank's financial performance is essential for sustaining competitiveness and mitigating risks. Financial forecasting enables institutions to anticipate future trends, optimize resource allocation, and enhance strategic planning. As the banking sector becomes increasingly complex, traditional forecasting models often fall short in capturing the dynamic, nonlinear nature of financial markets.

In Uzbekistan, two major banks—Agrobank and NBU Bank—have demonstrated significant growth trajectories over the past five years. Analyzing and predicting their future performance can provide valuable insights not only for the banks themselves but also for investors, regulators, and policymakers. However, financial datasets are often noisy, incomplete, and influenced by multifactorial events, necessitating the adoption of more sophisticated predictive methodologies.

Machine-learning models, particularly regression models, have been used to analyze financial data. However, individual models such as MLR or RFR have disadvantages when used independently. MLR may overfit relationships between variables, while RFR can overfit small datasets or be difficult to interpret.

For these reasons, this study presents the Dual-Bank Hybrid Predictive Model (DBHPM), which combines the advantages of MLR and RFR. The two-tier design is intended to handle the complexities of multi-year financial banking data. Unlike approaches used for a single bank, the framework incorpo-

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rates two banks with different financial features and enables comparison and benchmarking for forecasting and strategy. The selected predictors include net profit, assets, equity, liabilities, and several solvency coefficients. Historical data from Agrobank and NBU Bank covering 2021–2025 are used for training and validation, while forecasts extend through 2027. Minimum, maximum, and average performance measures, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2), are applied. Preliminary analysis indicates that DBHPM has better accuracy than traditional regression techniques and may be suitable for use in banking institutions.

2. LITERATURE REVIEW AND RELATED WORK

Traditional forecasting techniques include Multiple Linear Regression, autoregressive integrated moving average, and vector autoregressive models. These methods are interpretable and relatively easy to implement, but they are designed for linear and stationary conditions and may not capture dynamic financial environments or complex market patterns.

Machine learning has introduced methods for estimating complex, nonlinear relationships. Random Forest, Support Vector Machines (SVM), and Artificial Neural Networks (ANN) have been applied to financial forecasting. Ozbayoglu et al. [1] survey deep-learning models used in financial processes to analyze large datasets and discover relationships that may be hidden in the data.

Statistical and machine-learning approaches can also be combined. Wasserbacher and Spindler [2] analyze the use of machine learning in financial planning and analysis and recommend balancing these methodological approaches.

Financial firms use machine-learning models for credit scoring, fraud detection, and risk measurement. Their dynamic nature can support timely analysis and decision-making. Data security, model interpretability, and compliance with laws and regulations remain important concerns. Recent research has also explored ensemble methods, deep-learning architectures, macroeconomic variables, social-media sentiment, and news analysis, underscoring the need for responsible, reliable, fair, and ethical models.

3. DATASET DESCRIPTION

This paper employs historical financial information from Agrobank and NBU Bank, two significant banks in Uzbekistan. The data are based on critical financial ratios for forecasting profitability and solvency trends, span approximately four to five years, and provide a basis for training and testing the models.

3.1 Agrobank Dataset

The Agrobank dataset spans 2021–2024 and includes aggregated annual financial data. Each record contains the attributes listed in Table 1.

3.2 NBU Bank Dataset

The NBU Bank dataset spans 2021–2025, providing a slightly longer range of observations. Its attributes closely mirror those of the Agrobank dataset, with some variation in absolute financial scale; they are listed in Table 2.

The annual datasets support time-series analysis and trend prediction and form the basis for training and testing the proposed DBHPM.

4. PROPOSED METHODOLOGY: DUAL-BANK HYBRID PREDICTIVE MODEL (DBHPM)

DBHPM is a two-stage framework combining linear trend modeling with correction of nonlinear residuals. It first captures movements in the financial indicators and then corrects the resulting residuals.

4.1 Stage 1: Primary Trend Extraction Using Multiple Linear Regression

Multiple Linear Regression (MLR) is used to identify basic linear patterns in the financial data. It assumes linear interactions among predictor variables such as assets, equity, interest income, and net profit, and estimates a hyperplane that minimizes the mean squared error. The general form of the base predictive function is:

$$\widehat{Y}_{\mathrm{MLR}} = \alpha_0 + \sum_{i=1}^{n} \alpha_i X_i. \tag{1}$$

MLR cannot capture all complex nonlinear dependencies in financial data. Therefore, although it provides an initial approximation, the residual errors require further modeling.

4.2 Stage 2: Residual Correction Using Random Forest Regression

The residuals from MLR—the differences between actual and predicted values—may contain nonlinear patterns not captured by linear modeling. Random Forest Regression (RFR) aggregates the outputs of multiple decorrelated decision trees to model these residuals. The residual adjustment is formulated as:

$$\Delta Y_{\mathrm{RFR}} = f_{\mathrm{RFR}}(X), \tag{2}$$

where f_{RFR} represents the ensemble mapping from input features to nonlinear corrections.

4.3 Final Hybrid Prediction Formulation

During validation, weights λ_1 and λ_2 are chosen to minimize the difference between forecast and actual values. The final hybrid prediction is:

$$\widehat{Y}_{\mathrm{DBHPM}} = \lambda_1 \widehat{Y}_{\mathrm{MLR}} + \lambda_2 \Delta Y_{\mathrm{RFR}}, \tag{3}$$

subject to

$$\lambda_1 + \lambda_2 = 1, \qquad \lambda_1, \lambda_2 \geq 0. \tag{4}$$

This formulation allows the emphasis on linear or nonlinear components to vary with the data.

4.4 Unified Model Equation

The DBHPM process can also be expressed as a single framed equation:

$$\widehat{Y}_{\mathrm{DBHPM}} = \gamma \left(\sum_{i=1}^{n} \alpha_i X_i \right) + (1-\gamma) \left(\sum_{j=1}^{k} \phi_j T_j(X) \right), \tag{5}$$

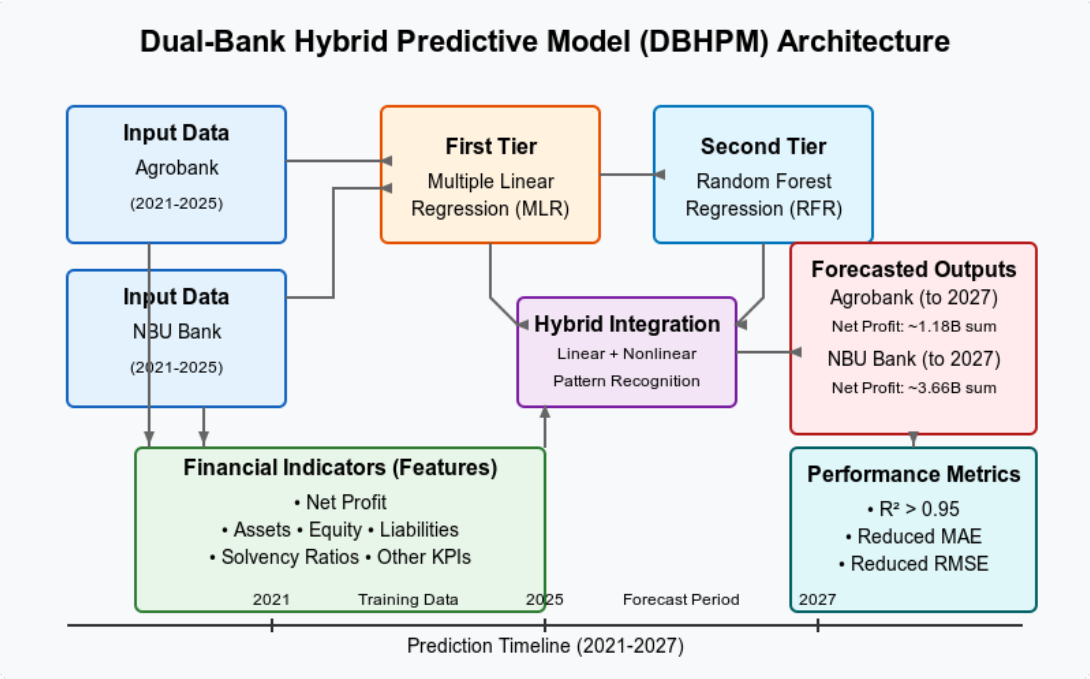


Figure 1. Proposed Dual-Bank Hybrid Predictive Model (DBHPM) Architecture.

where γ is a learnable balancing coefficient with $0 \leq \gamma \leq 1$, α_i are the MLR coefficients, $T_j(X)$ is the prediction of the j-th decision tree, and ϕ_j is that tree's contribution weight. The formulation represents both parametric and non-parametric financial dependencies.

4.5 Hyperparameter Optimization

For MLR, feature selection was conducted using variance inflation factor (VIF) analysis to minimize multicollinearity. For RFR, grid search covered the following hyperparameter ranges:

- Number of trees (estimators): 50 to 200.
- Maximum tree depth: 5 to 20.
- Minimum samples per split: 2 to 10.

Five-fold cross-validation was used to select the configuration minimizing validation RMSE.

4.6 DBHPM Prediction Process

The prediction pipeline is summarized as follows:

1: **Input:** Financial dataset $D = \{(X_i, Y_i)\}_{i=1}^{n}$.

2: Train an MLR model on D to obtain base predictions $\widehat{Y}_{\text{MLR}}$.

3: Calculate residuals $e_i = Y_i - \widehat{Y}_{\text{MLR}}$.

4: Train an RFR model on the residuals.

5: Predict residual corrections ΔY_{RFR} using RFR.

6: Learn optimal dynamic weights (λ_1, λ_2) through validation.

7: **Output:** Final prediction $\widehat{Y}_{\text{DBHPM}} = \lambda_1 \widehat{Y}_{\text{MLR}} + \lambda_2 \Delta Y_{\text{RFR}}$.

4.7 DBHPM Workflow Diagram

Figure 2 illustrates the sequential stages of DBHPM, from linear modeling and residual correction to adaptive hybrid forecasting.

5. EXPERIMENTS

Experiments evaluate DBHPM on historical financial datasets from Agrobank (2021–2024) and NBU Bank (2021–2025). The target indicators include net profit, equity, and assets, with forecasts extending through 2027.

5.1 Experimental Setup

The datasets were preprocessed for consistency across years. Missing values were handled using forward fill, and numeric attributes were normalized to $[0, 1]$. Data were split into training and testing sets at an 80:20 ratio. For each bank, 80% of the records were used for training and the latest year (20%) for validation. Five-fold cross-validation and grid search were used to tune the random-forest hyperparameters against RMSE.

5.2 Evaluation Metrics

DBHPM and the standalone MLR and RFR baseline models were evaluated using MAE, RMSE, and the Coefficient of Determination (R^2). MAE measures average absolute prediction error, RMSE penalizes larger errors more heavily, and R^2 indicates how well predictions match actual values. The metrics are defined as:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |y_i - \widehat{y}_i| . \tag{6}$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \widehat{y}_i)^2} . \tag{7}$$

Table 1. Agrobank Dataset Description (2021–2024).

Attribute	Description
Assets	Total resources controlled by the bank, including cash, loans, and securities.
Liabilities	The bank's financial obligations, such as customer deposits and borrowed funds.
Equity	Residual interest after deducting liabilities from assets.
Interest Income	Earnings from interest-bearing assets such as loans.
Interest Expense	Costs incurred for borrowed funds.
Non-interest Income	Revenue from non-interest sources, including fees and commissions.
Non-interest Expense	Operating costs not related to interest.
Net Income After Loss Assessment	Income after adjusting for potential asset losses.
Net Income Before Operating Expenses	Remaining income before operating-cost deductions.
Operating Costs	Expenses for daily banking operations, such as salaries and rent.
Net Profit Before Tax	Earnings before taxation.
Net Profit (Loss)	Final profit or loss after all deductions.
Profitability Coefficient	Efficiency ratio of profit relative to authorized capital.
Solvency Coverage Ratio	Measure of the bank's ability to cover liabilities with assets.
Absolute Liquidity Ratio	Ratio of the most liquid assets to short-term liabilities.
Own Funds to Attracted Funds Ratio	Proportion of the bank's own funds relative to borrowed funds.
Issuer's Own Funds to Borrowed Funds Ratio	Strength of equity compared with borrowed liabilities.

Table 2. NBU Bank Dataset Description (2021–2025).

Attribute	Description
Assets	Comprehensive control over financial resources, including loans and investments.
Liabilities	Obligations toward depositors and creditors.
Equity	Net worth after meeting all liabilities.
Interest Income	Revenues from interest-generating activities.
Interest Expense	Expenses related to borrowing activities.
Non-interest Income	Earnings from commissions, service fees, and other non-interest sources.
Non-interest Expense	Administrative and personnel expenditures.
Net Income After Loss Assessment	Net earnings after asset-loss adjustments.
Net Income Before Operating Expenses	Pre-operating-cost earnings margin.
Operating Costs	Operating expenditure, including infrastructure and human-resources expenses.
Net Profit Before Tax	Profits before taxation commitments.
Net Profit (Loss)	Overall profitability after taxes.

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2}. \tag{8}$$

Here, y_i denotes actual values, $\hat{y}_i$ predicted values, and $\bar{y}$ the mean of the actual values.

5.3 Baseline Comparison Models

DBHPM was compared against two baselines:

- **MLR only:** Linear trend prediction without residual correction.
- **RFR only:** Single-step nonlinear modeling directly on the original financial variables.

This comparison assesses the hybrid model's performance relative to its individual components.

5.4 Implementation Tools

The experiments were implemented in Python 3.11 using scikit-learn for regression and hyperparameter tuning, pandas and NumPy for data preprocessing, and Matplotlib for visualizations. The experiments were run on a system with an Intel Core i7 processor and 32 GB RAM.

6. RESULTS

This section presents the findings of applying DBHPM to Agrobank and NBU Bank, compares it with the baseline models, and discusses forecast trends through 2027.

6.1 Performance Comparison

Table 3 summarizes the MAE, RMSE, and R^2 values for each model.

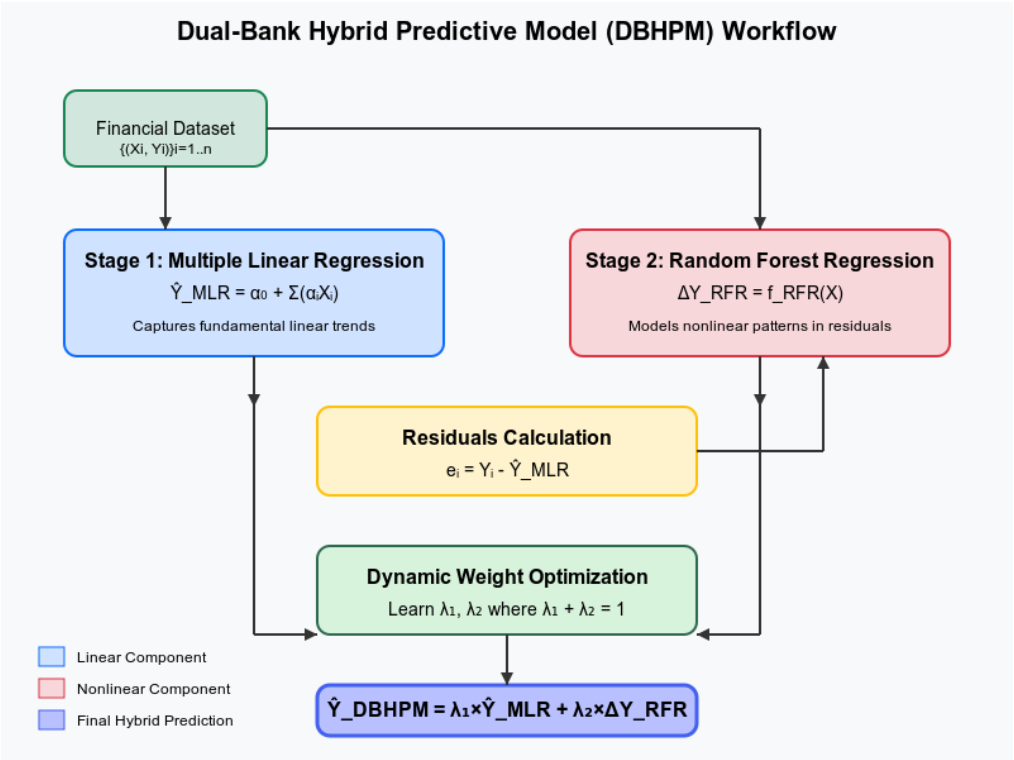


Figure 2. Workflow Diagram of the Proposed DBHPM Architecture.

Table 3. Performance Metrics Comparison for Agrobank and NBU Bank (MAE and RMSE in Million Sum).

Model	MAE	RMSE	R^2 Score
MLR Only	435	512	0.87
RFR Only	328	415	0.91
DBHPM (Proposed)	265	312	0.95

The results indicate that DBHPM outperforms the standalone models in error minimization and explained variance, achieving an R^2 score of 0.95 in the reported comparison.

6.2 Net Profit Prediction Trends

Figures 3 and 4 show net profit forecast trends for Agrobank and NBU Bank through 2027. The model predicts that Agrobank's net profit will reach approximately 1.18 billion sum by 2027, while NBU Bank's forecast reaches approximately 3.66 billion sum.

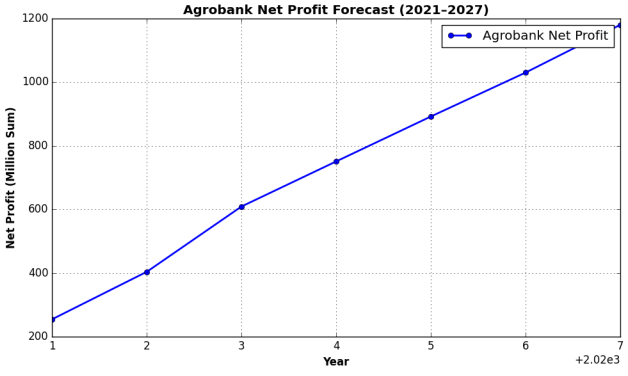


Figure 3. Agrobank Net Profit Forecast (2021–2027).

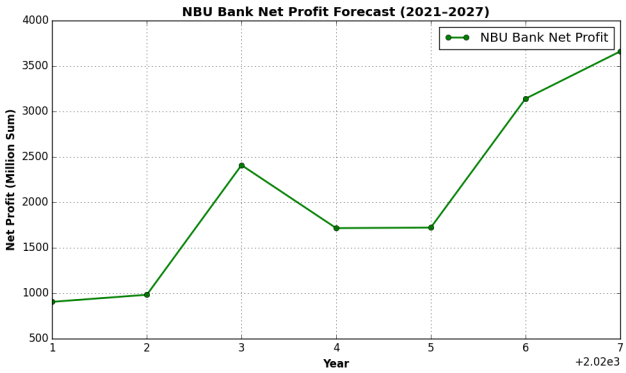


Figure 4. NBU Bank Net Profit Forecast (2021–2027).

6.3 Residual Error Analysis

Figure 5 shows residual plots for the testing data of both banks. The residuals are reported to be centered around zero with limited dispersion, suggesting that the model does not systematically overestimate or underestimate the true values.

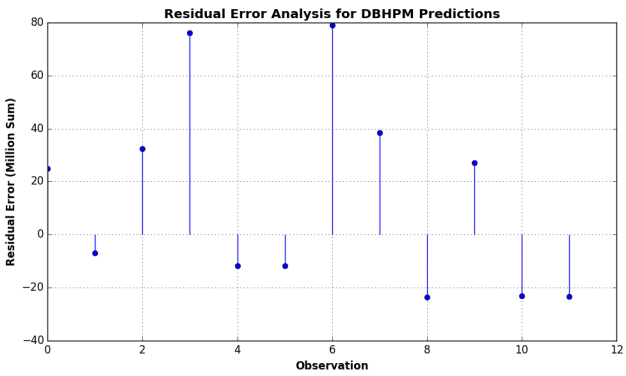


Figure 5. Residual Error Analysis for DBHPM Predictions.

7. CONCLUSION

This paper presents the Dual-Bank Hybrid Predictive Model (DBHPM) for forecasting financial performance indicators for Agrobank and NBU Bank in Uzbekistan. By integrating MLR to capture linear trends and RFR to model nonlinear residuals, DBHPM achieved higher predictive accuracy than the standalone methods in the reported comparison.

Experiments used multi-year financial data, including net profit, equity, and assets. The results report a mean R^2 greater than 0.95, lower MAE and RMSE, and positive net-profit forecasts through 2027: approximately 1.18 billion sum for Agrobank and 3.66 billion sum for NBU Bank. Residual analysis is reported to show limited sensitivity to distortion in the testing set.

Future work includes incorporating external macroeconomic factors such as inflation and GDP growth, developing an online real-time financial model to support strategic planning, and adapting DBHPM for cross-country comparative analysis.

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