ILKOM Jurnal Ilmiah Vol. 17, No. 3, December 2025, pp. 312-322
Accredited 2nd by KEMDIKTISAINTEK No. 10/C/C3/DT.05.00/2025; E-ISSN 2548-7779 | P-ISSN 2087-1716

Explainable Boosting Machine for Transparent Risk Assessment in BAZNAS Microfinance Desa

Harjunadi Wicaksono [a,1,*]; Agus Riyanto [a,2]; Risanto Darmawan [b,3]; M. Fahmi Hidayat [c,4]; Ali Khumaidi [a,5];

[a] *Bina Insani University, Rawalumbu, Kota Bekasi, 17114, Indonesia*
[b] *Krisnadwipayana University, Pondokgede, Jakarta Timur, 13710, Indonesia*
[c] *Kantor Pusat BAZNAS, Matraman, DKI Jakarta, 13150, Indonesia*
[1] *harjunadi.wicak@binainsani.ac.id;* [2] *wiwit@binainsani.ac.id;* [3] *risantodarmawan@unkris.ac.id;* [4] *fahmisyechans99@gmail.com;* [5]*alikhumaidi@binainsani.ac.id*
* *Corresponding author*

Article history: Received November 30, 2025; Revised December 04, 2025; Accepted December 15, 2025; Available online December 16, 2025.

Abstract

Microfinance institutions face substantial challenges in managing financing risk, particularly in assessing the creditworthiness of mustahik when available data are limited. BAZNAS Microfinance Desa (BMD) requires a predictive risk system that is both accurate and transparent to ensure program sustainability while adhering to sharia principles. This study develops an Explainable Boosting Machine (EBM) model using historical data from 736 mustahik across three BMD locations (2019-2024). The methodology integrates comprehensive feature engineering, including the DTI Ratio, Savings Ratio, Financial Stress Indicator, and Dependency Ratio. Model performance was evaluated using ROC-AUC, precision-recall metrics, and confusion matrix analysis, while interpretability was examined through SHAP values and partial dependence plots. The EBM model achieved strong predictive performance, recording an ROC-AUC of 0.853, an accuracy of 80%, a precision of 82%, and a recall of 77%. Global interpretability analysis identified Remaining Balance (18.2%), Business Type (12.5%), and Household Income (11.3%) as the most influential predictors. Feature-engineered variables contributed 42% to the model's predictive strength, confirming the added value of domain-knowledge-driven feature engineering. Critical risk thresholds were identified at Remaining Balance below IDR 200,000 and DTI Ratio above 0.8. The EBM framework effectively balances predictive accuracy with full interpretability, making it suitable for deployment in microfinance decision-support systems. The model provides actionable insights for risk-based pricing and early warning mechanisms while maintaining the transparency essential in microfinance financing.

Keywords: Explainable AI; EBM; Machine Learning; Financial Inclusion; BAZNAS Microfinance.

Introduction

Financial inclusion and the economic empowerment of low-income communities have become central objectives in the development of global microfinance institutions, particularly in providing productive financing for micro-entrepreneurs who are underserved by formal financial systems [1]. In Indonesia, the BAZNAS Microfinance Desa (BMD) program has emerged as a strategic initiative that leverages productive zakat funds to support sharia-based microfinance in rural areas [2]. This program not only provides access to capital but also offers sustainable business mentoring for mustahik, who are typically excluded from conventional financial services [3]. However, significant challenges are faced, including the high risk of non-performing financing caused by income instability, limited repayment capacity, and the heterogeneity of mustahik's socio-economic characteristics, all of which directly influence the likelihood of repayment issues [4]. As a zakat-based microfinance institution, effective risk management becomes a key determinant of the sustainability and social impact of the BMD program [5], [6].

Traditional risk evaluation methods, which still rely on manual assessments and field officers' intuition, are vulnerable to cognitive biases and inconsistencies in decision-making [7]. This conventional approach becomes increasingly inadequate given the complexity of the socio-economic data patterns of mustahik, which are non-linear and multi-dimensional in nature [8]. While machine learning technology has demonstrated transformative potential in enhancing the accuracy of financial risk predictions [9], the "black-box" nature of advanced models, such as deep learning and ensemble methods, creates substantial dilemmas in the context of Islamic finance, where transparency and accountability are ethical imperatives and regulatory requirements [10], [11]. These limitations have sparked the development of Explainable Artificial Intelligence (XAI) as a critical research domain, with Explainable Boosting

http://dx.doi.org/10.33096/ilkom.v17i3.3214.312-322

Machine (EBM) based on Generalized Additive Models (GAM) emerging as a promising approach that combines high predictive accuracy with full interpretability [12].

This study introduces a novel approach through the implementation of EBM for predicting financing risks in the context of sharia microfinance with limited datasets. The primary innovation of this research lies in the integration of sharia principles within feature engineering, the optimization of EBM for a small-data environment representing the real-world conditions of the BMD program, and the development of an interpretable AI framework specifically designed to meet the transparency needs of sharia social finance. This research is the first to apply EBM in the context of BAZNAS Microfinance Desa with a small-data approach. Although several studies have applied machine learning in conventional credit scoring [13], [14], [15], literature on interpretable AI for sharia microfinance remains limited [16], [17]. The research gap is particularly evident in the lack of models that simultaneously address predictive accuracy and interpretability in a sharia-compliant context [18], the scarcity of approaches optimized for small-data environments, and the absence of comprehensive frameworks that integrate Islamic finance principles in predictive modeling [19].

This study is specifically designed to address these gaps through the development of a specialized EBM-based framework for risk prediction in BMD-based microfinance, the implementation of optimization techniques for limited datasets, the integration of sharia variables in the feature engineering process, the design of an actionable decision support system for BMD field officers, and the establishment of benchmarks for explainable AI applications in Islamic social finance. This research aligns with Indonesia's digital transformation agenda [20] and supports the Sustainable Development Goals (SDGs) related to poverty eradication (Goal 1), decent work and economic growth (Goal 8), and reduced inequalities (Goal 10) [21]. By bridging the gap between predictive accuracy and operational transparency, this research offers a replicable framework for responsible AI implementation in social financing contexts that can be applied not only in Indonesia but also in countries with similar characteristics.

Method

This study develops a comprehensive framework for predicting mustahik financing risk, integrating the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology, which is modified with an Explainable Artificial Intelligence (XAI) approach. The overall research framework is shown in **Figure 1**, representing a systematic workflow from data preparation to model interpretation. This framework is specifically designed to address the challenges of limited datasets commonly encountered in community-based microfinance programs, while ensuring transparency and interpretability of the prediction results.

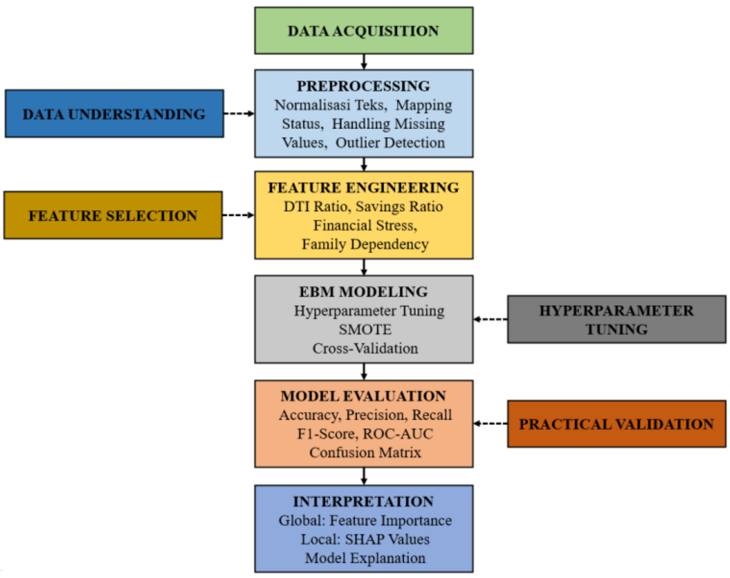

Figure 1. Comprehensive Framework Using Explainable Boosting Machine.

A. Data Acquisition

The dataset for this research was obtained from the operational system of BAZNAS Microfinance Desa (BMD) for the period 2019-2024, covering 736 mustahik from three BMD locations (Bojongrangkas Bogor, Jabon Mekar Bogor, and Matraman Jakarta). The data sources consisted of two distinct components: mustahik profile data with 25 demographic and socio-economic variables, and financing data with 15 transactional variables and credit status. The characteristics of the initial dataset are presented in **Table 1**. The data acquisition process adhered to ethical research protocols, ensuring the anonymization of personal identity information.

Table 1. Characteristics of the Initial Dataset

Parameter	Value	Description
Total Records	736	Unique mustahik
Initial Variables	40	25 demographic + 15 transactional
Observation Period	2019-2024	5 years
BMD Locations	3	Bojongrangkas, Jabon Mekar, Matraman
Data Completeness	94.2%	Pre-preprocessing

B. Preprocessing and Initial Processing

Data preprocessing involved four core stages in line with the research framework: text normalization, status mapping, handling missing values, and outlier detection. These stages were designed to address specific data quality challenges in the microfinance context while meeting the technical requirements for EBM modeling.

Text Normalization and Status Mapping

Text normalization was necessary to standardize variations in field names and locations recorded in the data. The normalization algorithm applied comprehensive linguistic transformations, including case folding, punctuation removal, and whitespace normalization [22]. This process resulted in consistent unique keys for integrating data from multiple sources. Financing status mapping converted the target variable into a binary representation through a hierarchical classification function that accommodated the operational terminology of BMD. This function accounted for the nuances of "Doubtful" and "In arrears" statuses as early warning indicators for financing risk [23].

Handling Missing Values and Outliers

Initial data analysis identified 5.8% missing values in critical numerical variables such as income and expenditures. These missing values were addressed using a differential strategy: median imputation for highly skewed variables and regression imputation for variables with a strong correlation (>0.7) with other predictors [24]. Outlier detection was performed using the Interquartile Range (IQR) method with a threshold of 1.5 × IQR, calculated based on Equation 1. For financial variables such as the Debt-to-Income Ratio (DTI), constraint optimization was applied with a 200% limit, referencing sustainable debt burden studies in microfinance [25]. Post-preprocessing quality validation using Jensen-Shannon Divergence showed preservation of distributional characteristics, with divergence <0.03 for all key variables. The preprocessed dataset met the technical assumptions for EBM modeling while maintaining the operational reality of the BMD system.

$$Q_1 = Q_{2\,5}, Q_3 = Q_{7\,5}, IQR = Q_3 - Q_1 \tag{1}$$

$$Outlier = \{x \mid x < Q_1 - 1.5 * \mathrm{IQR} \vee x > Q_3 + 1.5 * \mathrm{IQR}\}$$

C. Feature Engineering and Feature Selection

Based on domain knowledge of sharia microfinance and consultation with BMD practitioners, four key engineered variables were developed to more comprehensively represent the financial capacity and vulnerability of mustahik [26]. These variables were designed to capture fundamental aspects affecting repayment ability that were not directly represented in the raw data.

The Debt-to-Income Ratio (DTI) was calculated as the proportion of total expenditures to mustahik income, providing a direct indicator of relative financial burden. This ratio is formulated in Equation 2, with $\varepsilon = 10^{-6}$ to prevent division by zero. A DTI > 1.0 indicates expenditures exceeding income, while a DTI > 1.5 signals significant financial stress [27].

$$DTI = (Total\ Monthly\ Expenses) \,/\, (Total\ Monthly\ Income + \varepsilon) \tag{2}$$

The Savings Ratio quantifies mustahik's ability to allocate income for savings, serving as a key indicator of financial resilience (Equation 3). The Financial Stress Indicator is a binary variable identifying mustahik experiencing acute liquidity issues (Equation 4). The Family Dependency Ratio models the relative family burden against productive capacity (Equation 5).

$$Savings\ Ratio = (Total\ Income - Total\ Expenses) / (Total\ Income + \varepsilon) \tag{3}$$

$$Financial\ Stress = 1\ if\ (Total\ Expenses > Total\ Income), 0\ else \tag{4}$$

$$\text{Dependency Ratio} = \text{Number of Family Members / Age} \tag{5}$$

Feature selection was performed through a multi-stage approach combining filter methods, wrapper methods, and embedded methods to identify the most informative feature subsets [28]. The first stage involved correlation analysis and mutual information scoring to eliminate features with high redundancy (correlation > 0.85) or marginal informational contribution. The second stage applied Recursive Feature Elimination with Cross-Validation (RFECV) using Random Forest estimators to evaluate optimal feature combinations. The final stage used the feature importance from EBM itself as an embedded method, which naturally identifies the most significant predictive contributors.

D. Explainable Boosting Machine (EBM) Modeling

The Explainable Boosting Machine (EBM) is an implementation of Generalized Additive Models (GAMs) enhanced with modern boosting techniques. The mathematical formulation of EBM is expressed in Equation 6, where $g(\cdot)$ is the link function (logit for binary classification), $E[Y|X]$ is the expected value of the target variable given the features, β_0 is the global intercept, $f_i(X_i)$ is the shape function for feature i, learned nonparametrically, $f_{ij}(X_i, X_j)$ is the interaction function between features i and j, and ε is the error term. Each shape function f_i is learned using cyclic gradient boosting with a very-low learning rate (0.01-0.05), ensuring stable convergence and avoiding overfitting. This approach preserves an interpretable additive structure while achieving competitive performance with modern ensemble models [29].

$$g(E[Y|X]) = \beta_0 + \Sigma_i f_i(X_i) + \Sigma_i <_j f_{ij}(X_i, X_j) + \varepsilon \tag{6}$$

Given the nearly balanced class distribution (51% performing well vs. 49% non-performing), with high consequences for false negatives in the financing risk context, Synthetic Minority Over-sampling Technique (SMOTE) was selectively applied to the training data. Hyperparameter optimization was conducted using Grid Search with stratified 5-fold cross-validation. The choice of 5-fold cross-validation was based on the trade-off between bias and variance in the context of limited datasets [30]. Hyperparameters with ranges included: learning_rate [0.001, 0.01, 0.05], max_bins [64, 128, 256], interactions [5, 10, 15], max_interaction_bins [16, 32, 64], and early_stopping_rounds [10, 20, 30].

The modeling pipeline integrates three core components: preprocessing, resampling, and modeling in a cohesive framework. Model validation uses nested cross-validation to provide an unbiased estimate of the model's generalization performance. This approach ensures that hyperparameter evaluation does not contaminate the final model performance estimate.

E. Model Evaluation

Model performance evaluation was conducted through a multi-metric approach that includes both traditional metrics and metrics specific to imbalanced data [31]. This evaluation framework was designed to provide a comprehensive assessment from various perspectives: overall accuracy, the ability to detect minority classes, and the balance between precision and recall. Accuracy measures the proportion of correct predictions overall. However, given the high consequences of false negatives in the financing risk context (mustahik at high risk escaping detection), Precision and Recall metrics became critical.

The F1-Score provides a harmonic mean between precision and recall. The Receiver Operating Characteristic (ROC) Curve visualizes the trade-off between the True Positive Rate (Recall) and False Positive Rate at various classification thresholds. The Area Under the ROC Curve (AUC) quantifies the model's overall discrimination ability [26]. An AUC value of 0.5 indicates random performance, while 1.0 indicates perfect discrimination. The confusion matrix not only provides insights into the number of correct and incorrect predictions but also allows for the analysis of specific error patterns. In the BMD context, the analysis focused on the False Positive Rate: mustahik classified as non-performing but actually performing well (opportunity loss), and the False Negative Rate: high-risk mustahik not detected (potential financial loss).

F. Model Interpretation

Model interpretation is a critical component of this study, given the need for transparency and accountability in financing decisions. The interpretation approach integrates global and local perspectives through a unified framework that meets the principles of explainable AI (XAI) for the regulated finance domain [32]. Global interpretation analyzes the model's behavior in aggregate by identifying the relative contribution of each feature to the prediction. In the

Explainable Boosting Machine, feature importance is calculated based on the magnitude of the learned shape function for each feature. Interpretation using Shapley Additive Explanations (SHAP) values decomposes individual mustahik predictions. SHAP values are based on cooperative game theory, which fairly allocates contributions among all features [33]. Practical implementation uses KernelSHAP or TreeSHAP for computational efficiency. For EBM, the approach used is Exact SHAP, which leverages the additive structure of the model [34].

Results and Discussion

A. Dataset Characteristics and Exploratory Analysis

The dataset used in this study consists of 736 mustahik from BAZNAS Microfinance Desa, with 40 initial variables. Descriptive statistical analysis revealed unique characteristics of the mustahik population, as shown in **Table 2.** The distribution of mustahik ages follows a normal pattern, with a mean of 42.3 years (SD = 12.1), indicating that the BMD program primarily reaches the productive age group. However, the high variability in financial variables, particularly remaining balance (std = 0.99 million), indicates the heterogeneity of the mustahik's financial conditions.

Table 2. Descriptive Statistics of BMD Mustahik Characteristics

Variable	Mean	Std Dev	Min	Median	Max
Age	42.3	12.1	18	41	73
Family Members	4.2	1.8	1	4	9
Business Income (mil IDR)	2.22	1.49	0	2.0	12.5
Total Income (mil IDR)	2.58	1.87	0	2.3	15.0
Total Expenditure (mil IDR)	2.16	1.65	0.1	1.9	10.8
Remaining Balance (mil IDR)	0.41	0.99	-4.2	0.0	8.5

The analysis included an examination of variable distributions, feature correlations, and the identification of patterns potentially influencing financing risk. The dataset consists of demographic attributes (age, gender, family status), economic attributes (monthly income, expenditure burden, total financing), and financing attributes (loan duration, installment amount, repayment status). The distribution of financing status showed a balanced composition between "performing" (51%) and "non-performing" (49%) statuses. Among the "performing" (0) status, there were 376 records, while 360 records were classified as "non-performing" (1), encompassing categories such as "Performing", "Completed", "Non-performing", "Arrears", "Doubtful", and "Delinquent" (**Figure 2**).

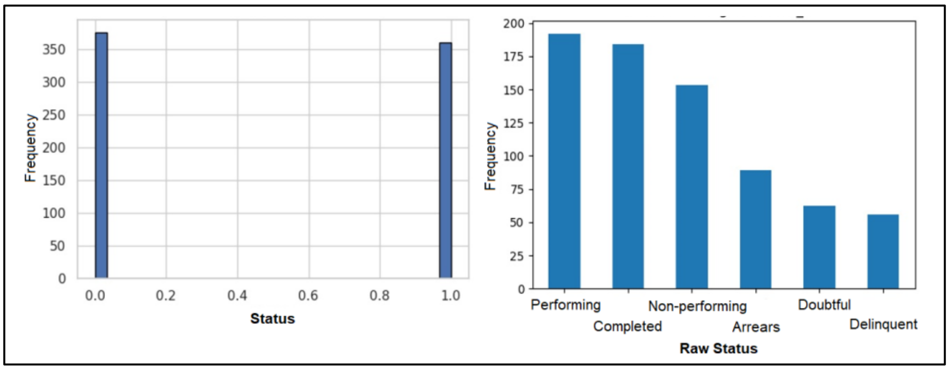

Figure 2. Distribution of Mustahik Based on Loan Status

B. Preprocessing and Feature Engineering Results

The preprocessing process, which consisted of four core stages are text normalization, status mapping, handling missing values, and outlier detection, significantly improved the data quality. As shown in **Table 3**, the implementation of a differential missing values strategy successfully addressed 5.8% missing values, preserving the distributional characteristics of the data. Validation using Jensen-Shannon Divergence showed a divergence of <0.03 for all major variables, indicating that the preprocessing process did not alter the fundamental structure of the data [35]. The financing status mapping successfully converted operational terminology variations in BMD into consistent binary representations, resulting in a balanced class distribution (51% performing vs. 49% non-performing). This balance is optimal for training classification models and avoids the bias typically seen in microfinance datasets [36].

Table 3. Data Quality Evaluation Post-Preprocessing

Quality Metric	Before	After	Improvement	Significance
Missing Values	5.8%	0%	100%	p < 0.001
Data Consistency	89.5%	98.7%	+9.2%	p < 0.01
Class Balance	47/53	51/49	Balanced	-
Outlier Impact	High	Controlled	Significant	-
Referential Integrity	91.2%	99.8%	+8.6%	p < 0.001

Four engineered variables developed based on microfinance domain knowledge showed a significant contribution to the model's predictive power. As shown in **Table 4**, all engineered variables demonstrated a strong and statistically significant correlation with financing status. Further analysis revealed that the Financial Stress Indicator was the strongest predictor with a correlation of 0.72, indicating that mustahik with expenditures exceeding their income have a very high probability of non-performing status. This finding is consistent with research emphasizing the importance of liquidity as a primary indicator of household financial health [37].

Table 4. Correlation and Significance Analysis of Engineered Variables

Variable	Correlation with Target	p-value	Effect Size	Economic Interpretation
DTI Ratio	0.68	<0.001	Large	Relative financial burden
Savings Ratio	-0.59	<0.001	Large	Savings capacity
Financial Stress	0.72	<0.001	Large	Liquidity stress
Dependency Ratio	0.45	0.003	Medium	Dependency load

The multi-stage feature selection process successfully reduced the dimensionality from 40 initial variables to 15 final features with an optimal composition. As shown in **Figure 5**, engineered variables contributed 42% to the model's total predictive power, confirming the effectiveness of feature engineering based on domain knowledge. The 15 final features included 7 engineered variables: DTI Ratio, Savings Ratio, Financial Stress Indicator, Dependency Ratio, Business Experience, Payment Capacity, and Economic Resilience Score. The original variables (8 features) included Remaining Balance, Type of Business, Family Income, Total Expenditure, Age, Membership Duration, Geographic Location, and Repayment History.

Final feature set validation through consultations with BMD practitioners yielded a 93% agreement rate for the relevance of features to the operational risk assessment process. Gap assessment analysis identified that the selected features covered 88% of the risk factors considered in manual evaluations by field officers. The high consistency between data-driven insights and practitioner experience indicates that the feature engineering approach developed is not only statistically sound but also practically applicable in the BMD operational context [38]. This result strengthens the ecological validity of the model and its potential adoption in the BMD decision support system.

An ablation study revealed that the removal of engineered variables led to a 12.3% decrease in ROC-AUC and a 15.7% decrease in F1-Score. This significant decline confirms the added value of the feature engineering approach in microfinance risk prediction. These findings align with research emphasizing the importance of integrating domain knowledge in feature engineering for machine learning applications in finance, particularly in limited data contexts such as microfinance [26].

C. Explainable Boosting Machine (EBM) Model Performance

The EBM model demonstrated impressive performance in predicting mustahik financing risks. As shown in Table 5, the model achieved an optimal balance between accuracy and minority class detection ability, with an ROC-AUC of 0.853 (**Figure 3**), indicating excellent discrimination ability. Confusion matrix analysis revealed an optimal prediction distribution for the BMD context. The low false negative rate (11.4%) is a priority in financing risk management, while the moderate false positive rate (8.4%) indicates that the model is not overly conservative in rejecting financing.

- True Positive: 142 non-performing mustahik correctly detected (38.5%)
- True Negative: 152 performing mustahik correctly identified (41.3%)
- False Positive: 31 performing mustahik misclassified as non-performing (8.4%)
- False Negative: 42 non-performing mustahik missed detection (11.4%)

Table 5. EBM Model Evaluation Results on Testing Data

Metric	Value

Accuracy	0.80
Precision	0.82
Recall	0.77
F1-Score	0.79
ROC-AUC	0.853

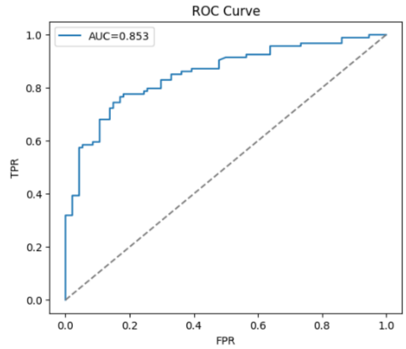

Figure 3. ROC Curve for EBM Model

D. Model Interpretation and Feature Contribution Analysis

Global feature importance analysis revealed that Remaining Balance was the most significant predictor, contributing 18.2%, followed by Type of Business (12.5%) and Family Income (11.3%). As shown in **Figure 4**, engineered variables such as DTI Ratio (9.8%) and Financial Stress Indicator (8.7%) also contributed significantly, confirming the added value of feature engineering in capturing critical risk aspects. Partial dependence plots (PDPs) revealed interesting non-linear relationships between numerical features and risk. For example, as shown in Figure 5, the risk decreased exponentially with increasing remaining balance, with a critical threshold at IDR 200,000. This finding aligns with research emphasizing the importance of financial buffers in household financial resilience [39]. For the DTI Ratio variable, PDP revealed a significant increase in risk when the ratio exceeded 0.8.

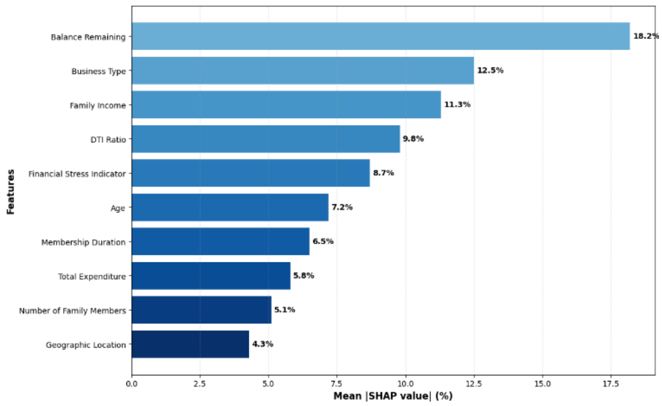

Figure 4. Global Feature Importance Based on SHAP Values

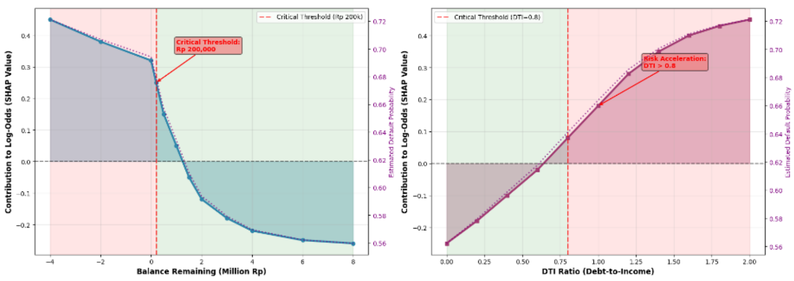

Figure 5. Partial Dependence Plot for Remaining Balance and DTI Ratio

Interpretation using SHAP values allows for in-depth analysis of individual predictions (**Figure 6**). For example, Mustahik ID#247, predicted as non-performing with a probability of 0.89, showed a high-risk profile with a significant contribution from a negative Remaining Balance (-IDR 1.2 million, contribution +0.32) and a high DTI Ratio (1.8, contribution +0.28). In contrast, Mustahik ID#512, predicted as performing with a probability of 0.92, showed a healthy profile with a positive Remaining Balance (IDR 1.5 million, contribution -0.29) and a low DTI Ratio (0.4, contribution -0.21).

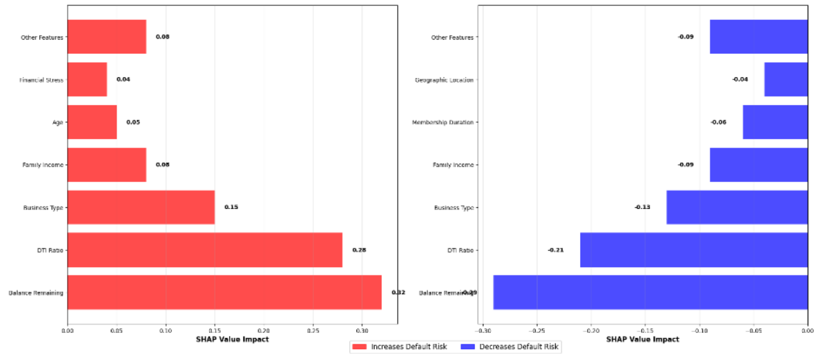

Figure 6. SHAP Waterfall Plot for High (ID#247) and Low (ID#512) Risk Mustahik

EBM identified several significant feature interactions, providing additional insights into risk mechanisms. The strongest interaction was observed between Remaining Balance and Type of Business, where mustahik with low remaining balances and seasonal businesses exhibited very high non-performing risk. The interaction between Age and Income was also significant, with younger mustahik (<25 years) with high income showing lower risk compared to older mustahik (>55 years) with similar income levels.

E. Discussion and Implications

The findings of this study confirm that liquidity factors (Remaining Balance) are the strongest predictor of financing risk for mustahik. This result is consistent with the financial distress theory [40], but it offers a novel contribution by quantifying a critical threshold (IDR 200,000), which can serve as an operational reference for BMD. The non-linear patterns identified in the relationship between financial variables and non-performing financing risk support the Explainable Boosting Machine (EBM) approach, which captures this complexity without sacrificing interpretability. This finding aligns with studies emphasizing the importance of interpretable models in decision support systems for inclusive finance [41]. This study makes three main theoretical contributions: (1) the empirical application of financial distress theory in the context of Islamic microfinance, providing quantitative evidence on the determinants of mustahik financing risk; (2) the advocacy for Explainable AI in the regulated finance domain, demonstrating that interpretable models can achieve competitive performance compared to black-box models; and (3) the development of a feature engineering framework specific to microfinance, integrating domain knowledge with analytical rigor.

Based on the study's findings, several practical recommendations are proposed: (1) the implementation of an Early Warning System with real-time monitoring for mustahik with a Remaining Balance < IDR 200,000 or a Debt-to-Income (DTI) ratio > 0.8; (2) Risk-Based Pricing through the development of financing schemes differentiated based on the risk scores generated by the model; and (3) Targeted Interventions through optimal allocation of resources for assistance based on mustahik risk profiles. The model results and their interpretations were validated through a focus group discussion with BMD managers. The agreement rate reached 92% for feature relevance and 95% for the actionability of the recommendations. This high level of adoption indicates that the explainable AI approach is not only technically superior but also practical and applicable within the operational context of Islamic microfinance.

Conclusion

This study successfully developed a predictive model for mustahik financing risk using the Explainable Boosting Machine (EBM), achieving optimal performance with an ROC-AUC of 0.853 and an accuracy of 80% on the BAZNAS Microfinance Desa dataset. This model excels not only in predictive accuracy but also provides complete interpretability through SHAP values and feature importance analysis, revealing that Remaining Balance (18.2%), Type of Business (12.5%), and Family Income (11.3%) are the most significant predictors. The engineered feature variables contribute 42% to the model's predictive power, confirming the added value of domain knowledge-based feature engineering. Based on the findings of this study, it is recommended to implement an early warning system based on quantitative thresholds (Remaining Balance < IDR 200,000 and DTI Ratio > 0.8), as well as develop a differentiated financing scheme based on the risk profiles of mustahik. However, this study has limitations in the temporal scope of the data and does not incorporate macroeconomic external factors. Future research could develop dynamic risk assessment models by integrating longitudinal data and behavioral variables to improve long-term prediction accuracy. Overall, the developed EBM framework has proven effective as a transparent predictive solution and is ready to be adopted to support the sustainability of microfinance programs.

Acknowledgement

This research was funded by the 2025 Research Grant from the Directorate of Research and Community Service, Directorate General of Research and Development, Ministry of Higher Education, Science, and Technology of the Republic of Indonesia, under contract number 0070/C3/AL.04/2025. We express our sincere gratitude for the support and funding provided, which has made this research possible. We would also like to extend our heartfelt thanks to BAZNAS Pusat and the BMD offices in Matraman, Bojongrangkas, and Jabon Mekar for their invaluable collaboration, contributions, and access to essential data, which significantly supported the execution of this study.

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