Machine Learning for Fundraising Network Development in Indonesian Educational and Social Foundations

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ABSTRACT

This study explores the application of machine learning (ML) in developing fundraising networks for educational and social foundations in Indonesia, using Yayasan Pendidikan Sosial Dan Dakwah Ulul Albab as a case study. Operating in Malang City and Ponorogo Regency with eight programs requiring approximately IDR 815 million annually, the foundation faces persistent fundraising challenges. Employing a mixed-method approach, we developed an ML-based donor prediction model using Random Forest, Gradient Boosting, and Neural Network algorithms, simulated with synthetic data (n=5,000) representing Indonesian donor characteristics. Results demonstrate 87.3% accuracy in donor propensity prediction and 82.6% in donation amount forecasting. Qualitative analysis through stakeholder interviews (n=15) revealed implementation barriers including digital literacy gaps and data infrastructure limitations. The proposed ML-Integrated Fundraising Framework (ML-IFF) combines predictive analytics with culturally adapted engagement strategies, projecting 45-60% improvement in fundraising efficiency. This research contributes a contextual ML application framework for Indonesian nonprofit organizations, addressing the intersection of technological innovation and social sector sustainability in emerging markets.

Keywords: machine learning, fundraising networks, nonprofit organizations, donor prediction, educational foundations

INTRODUCTION

Background and Problem Statement

The sustainability of educational and social foundations in Indonesia faces critical challenges in securing consistent funding streams. Indonesia's nonprofit sector, comprising over 344,000 registered organizations (Ministry of Law and Human Rights, 2023), struggles with fundraising inefficiencies, donor retention rates averaging below 35%, and limited technological adoption (Nurhasanah & Sukmana, 2020). These challenges are particularly acute for grassroots foundations operating educational programs in semi-urban and rural areas, where traditional fundraising methods yield inconsistent results (Hidayat et al., 2021).

Yayasan Pendidikan Sosial Dan Dakwah Ulul Albab, established through Notarial Deed No. 6 dated December 8, 2017, by Notary Ny. Trisnasari, SH., and licensed by the Ministry of Law and Human Rights under Number AHU-0018159.AH.01.04 (December 11, 2017), exemplifies these challenges. Registered and supervised by Bakesbangpol Malang City Government since 2018, the foundation operates eight integrated programs across Malang City and Ponorogo Regency, requiring approximately IDR 815 million (approximately USD 54,000) annually for sustainable operations.

The foundation's programs encompass: (1) Administrative Management (IDR 75 million), (2) Ulul Albab Islamic Learning Assembly in both locations (IDR 60 million), (3) Madrasah Diniyah Takmiliyah in Ponorogo (IDR 40 million), (4) Integrated Islamic Playgroup/KBIT (IDR 60 million), (5) Kindergarten/*Raudhatul Athfal*

(IDR 70 million), (6) Zakat Collection Unit under Baznas Malang supervision (IDR 150 million), (7) Social and Dakwah Activities (IDR 60 million), and (8) Infrastructure Development (IDR 300 million). This comprehensive program portfolio addresses educational gaps in underserved communities but faces perpetual funding uncertainties. (Mulyono, 2025a; Mulyono, 2025b).

Traditional fundraising approaches - personal networks, periodic campaigns, and manual donor management- prove insufficient for scaling operations and ensuring predictable revenue (Saxton & Guo, 2020). The absence of data-driven donor intelligence results in inefficient resource allocation, missed engagement opportunities, and suboptimal campaign targeting (Sargeant & Shang, 2017). Furthermore, Indonesia's unique philanthropic landscape, characterized by Islamic charitable traditions (*zakat, infaq, sadaqah*), community-based giving, and emerging digital philanthropy, requires contextualized technological solutions (Fauzia, 2017).

Research Gap and Significance

Despite growing literature on machine learning applications in nonprofit fundraising (Bussell & Forbes, 2021; Knowles & Sullivan, 2017), significant gaps exist regarding: (1) ML implementation frameworks adapted to Indonesian sociocultural contexts, (2) integration of Islamic philanthropy mechanisms with predictive analytics, (3) practical ML deployment strategies for resource-constrained grassroots organizations, and (4) empirical evidence of ML efficacy in Southeast Asian nonprofit sectors.

International studies predominantly focus on Western nonprofit contexts with mature digital infrastructure and extensive donor databases (MacLaughlin et al., 2022). These models often overlook challenges specific to emerging markets: limited historical data, diverse donor motivations rooted in religious obligations, varied digital literacy levels, and infrastructure constraints (Bethmann et al., 2021). Indonesian nonprofits require culturally grounded, resource-appropriate ML frameworks that acknowledge these contextual realities.

This research addresses these gaps by developing and evaluating an ML-based fundraising framework specifically designed for Indonesian educational and social foundations. The significance is threefold: (1) theoretical contribution through contextual ML framework adaptation for emerging market nonprofit sectors, (2) methodological innovation combining ML predictive modeling with qualitative cultural analysis, and (3) practical implications for enhancing financial sustainability of grassroots educational institutions serving vulnerable populations.

Research Objectives and Questions

The primary objective is to develop and validate a machine learning-integrated fundraising framework for Indonesian educational and social foundations. Specific objectives include:

1) Analyzing current fundraising challenges and practices at Yayasan Ulul Albab
2) Developing ML models for donor propensity and donation amount prediction
3) Evaluating ML model performance using simulated Indonesian donor data
4) Identifying implementation barriers and enablers in the Indonesian nonprofit context
5) Designing a contextual ML-Integrated Fundraising Framework (ML-IFF)

Research questions guiding this investigation:

RQ1: What are the primary fundraising challenges faced by educational and social foundations in Indonesia?

RQ2: How effectively can machine learning algorithms predict donor behavior in the Indonesian nonprofit context?

RQ3: What are the critical implementation factors for ML-based fundraising systems in resource-constrained foundations?

RQ4: How can ML-integrated fundraising frameworks be adapted to Indonesian sociocultural and religious contexts?

Scope and Structure

This study focuses on developing an ML framework applicable to small-to-medium Indonesian educational foundations, using Yayasan Ulul Albab as the primary case study. The research employs mixed methods combining ML modeling with qualitative stakeholder analysis, examining a five-year implementation horizon (2026-2030). While findings are primarily relevant to Indonesian Islamic educational foundations, the framework offers adaptable insights for similar organizations in Southeast Asian emerging markets.

The paper proceeds as follows: Section 2 reviews relevant literature on ML in nonprofit fundraising, donor behavior prediction, and Indonesian philanthropy contexts. Section 3 details the mixed-method research design. Section 4 presents ML model performance results and qualitative findings. Section 5 discusses the ML-IFF framework, implementation strategies, and theoretical implications. Section 6 concludes with practical recommendations and future research directions.

LITERATURE REVIEW

Machine Learning in Nonprofit Fundraising

Machine learning has increasingly transformed nonprofit fundraising through enhanced donor intelligence, predictive analytics, and personalized engagement strategies (Bennett & Savani, 2022). ML applications in this domain primarily focus on three areas: donor propensity prediction, donation amount forecasting, and donor retention modeling (Wymer, 2021).

Donor propensity prediction employs classification algorithms to identify individuals most likely to contribute based on demographic, behavioral, and engagement features (Boateng et al., 2020). Studies demonstrate that Random Forest and Gradient Boosting algorithms achieve accuracy rates of 75-89% in identifying potential donors (Arafa et al., 2021). These models significantly outperform traditional regression methods by capturing non-linear relationships and complex interaction effects among predictor variables (Zhou et al., 2020).

Donation amount forecasting utilizes regression algorithms to predict contribution levels, enabling organizations to segment donors for differentiated cultivation strategies (Knowles & Sullivan, 2017). Neural networks and ensemble methods show particular promise, with mean absolute percentage errors ranging from 12-18% in well-specified models (Bussell & Forbes, 2021). However, model performance varies substantially based on data quality, feature engineering, and contextual factors (Schneider et al., 2022).

Donor retention modeling identifies at-risk supporters and optimal re-engagement timing (MacLaughlin et al., 2022). Survival analysis combined with ML techniques achieves hazard ratio predictions with C-statistics above 0.80, substantially improving retention campaign targeting (Sargeant & Shang, 2017). These applications collectively demonstrate ML's capacity to enhance fundraising efficiency by 30-55% in organizations with sufficient data infrastructure (Nonprofit Tech for Good, 2023).

Despite demonstrated efficacy in Western contexts, ML fundraising applications face significant adaptation challenges in emerging markets. Data scarcity, infrastructure limitations, and algorithmic bias concerns require contextualized implementation approaches (Vinuesa et al., 2020). Furthermore, the "black box" nature of complex ML models creates interpretability challenges for nonprofit practitioners lacking technical expertise (Raissi et al., 2021).

Donor Behavior and Predictive Variables

Understanding donor behavior patterns is fundamental to effective ML model development. Established theories including Relationship Fundraising Theory (Burnett, 2002), Theory of Planned Behavior (Ajzen, 1991), and Social Exchange Theory (Emerson, 1976) identify key behavioral determinants: altruistic motivations, perceived organizational effectiveness, social norms, past giving behavior, and engagement levels (Sargeant et al., 2006).

Empirical studies identify robust predictive variables across contexts: recency, frequency, and monetary value (RFM) of past donations; demographic characteristics including age, income, and education; engagement metrics such as event attendance and communication responsiveness; and psychographic factors including values alignment and cause affinity (Saxton & Guo, 2020). In ML applications, RFM variables consistently emerge as strong predictors, with feature importance scores typically exceeding 60% in ensemble models (Bennett & Savani, 2022).

However, donor behavior exhibits significant cultural variation. Studies in Asian contexts reveal distinctive patterns: stronger influence of religious obligations, community-based giving networks, preference for tangible impact visibility, and trust in personal relationships over institutional branding (Wiepking & Handy, 2015). Indonesian philanthropy specifically demonstrates unique characteristics shaped by Islamic traditions and communal values (Fauzia, 2017).

Indonesian Philanthropy Context

Indonesian philanthropy integrates religious obligations, particularly Islamic giving mechanisms, with modern nonprofit structures (Latief, 2018). Zakat (obligatory almsgiving), infaq (voluntary charity), sadaqah (charitable giving), and waqf (endowment) constitute formalized religious philanthropy channels managed through institutions like Baznas (National Zakat Agency) and LAZ (Amil Zakat Institutions) (Beik, 2019). These mechanisms mobilize substantial resources—estimated at IDR 233 trillion (USD 15.5 billion) annually, though collection reaches only 30-40% of potential (BAZNAS & IPB, 2022).

Contemporary Indonesian giving patterns reflect hybrid traditional-modern characteristics: approximately 63% of donations occur through religious institutions, 41% through direct community assistance, and 28% through formal nonprofit organizations, with significant overlap across categories (Indonesia Giving Report, 2021). Digital philanthropy is rapidly expanding, with online donation platforms growing 156% between 2019-2022, accelerated by COVID-19 pandemic adaptations (*Perkumpulan Pengelola Zakat Indonesia*, 2022).

Educational and social foundations face distinct challenges in this landscape: competition with established religious institutions enjoying higher trust levels, limited awareness of grassroots organizations, preference for immediate tangible impact over institutional development support, and regulatory complexities in zakat integration for non-LAZ entities (Nurhasanah & Sukmana, 2020). These contextual factors necessitate fundraising approaches that harmonize technological innovation with cultural authenticity and religious alignment (Hidayat et al., 2021).

Technology Adoption in Indonesian Nonprofits

Technology adoption among Indonesian nonprofits remains nascent but accelerating. A 2022 survey of 500 Indonesian NGOs revealed that 67% maintain basic digital presence (websites/social media), but only 23% employ CRM systems and 8% utilize data analytics for decision-making (ICT Watch Indonesia, 2022). Barriers include limited financial resources (cited by 78%), inadequate technical expertise (65%), and perceived complexity (52%) (Pratiwi & Mihardja, 2021).

However, successful technology implementations demonstrate significant impact. Organizations adopting donor management systems report 34% improvement in retention rates, while those using digital payment integration show 47% increase in small-value donations (Indonesia Fundraising Roundtable, 2023). These successes suggest substantial potential for ML applications when appropriately adapted to organizational capacities and cultural contexts (Wardhana & Syahputra, 2022).

Theoretical Framework

This research synthesizes three theoretical perspectives: (1) Resource Dependence Theory (Pfeffer & Salancik, 1978), explaining foundations' imperative to diversify and stabilize funding sources through technological innovation; (2) Technology Acceptance Model (Davis, 1989), analyzing factors influencing ML system adoption by nonprofit practitioners; and (3) Institutional Theory (DiMaggio & Powell, 1983), contextualizing ML implementation within Indonesian nonprofit sector norms and Islamic philanthropic institutions.

Integration of these perspectives yields a conceptual framework wherein ML-based fundraising systems serve as strategic responses to resource uncertainties, with adoption contingent on perceived usefulness, ease of use, and institutional compatibility. Success requires technical efficacy (accurate predictions), operational feasibility (resource-appropriate implementation), and cultural legitimacy (alignment with Indonesian philanthropic values).

METHODS

Research Design

This study employs a convergent parallel mixed-method design (Creswell & Plano Clark, 2018), integrating quantitative ML modeling with qualitative case study analysis. This approach enables comprehensive examination of both ML technical performance and contextual implementation factors, addressing the research questions' dual focus on algorithmic efficacy and practical applicability.

The quantitative component develops and evaluates ML prediction models using simulated donor data representing Indonesian philanthropic patterns. The qualitative component employs case study methodology (Yin, 2018) examining Yayasan Ulul Albab's fundraising challenges, stakeholder perspectives, and implementation contexts. Integration occurs at interpretation stage, where quantitative model capabilities are evaluated against qualitative implementation insights to develop the ML-Integrated Fundraising Framework.

Research Setting and Case Selection

Yayasan Pendidikan Sosial Dan Dakwah Ulul Albab serves as the primary case study, selected through purposive sampling based on: (1) typicality as a small-to-medium Indonesian educational foundation, (2) geographic diversity with operations in urban (Malang) and rural (Ponorogo) contexts, (3) program comprehensiveness spanning education, social services, and religious activities, and (4) demonstrated commitment to organizational development and innovation.

The foundation operates from two locations: Secretariat Branch I in RT 01 RW 02 Dukuh Brajan, Prayungan Village, Sawoo District, Ponorogo Regency 63475, and activities in Malang City. This dual-location structure presents distinctive fundraising challenges including geographic dispersion, diverse donor communities, and varied resource environments -characteristics common among Indonesian grassroots foundations.

Data Collection

Quantitative Data: Simulated Donor Dataset

Given limited historical donor data at Yayasan Ulul Albab - a common challenge for grassroots Indonesian nonprofits - we generated a synthetic dataset (n=5,000) using Monte Carlo simulation based on Indonesian philanthropic research and expert consultation. This approach enables ML model development while avoiding overfitting to specific organizational patterns, enhancing framework generalizability (Hernán, 2016).

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The simulation incorporated:

1) Demographic variables: Age (18-75, normal distribution $\mu=42$, $\sigma=14$), income levels (categorized based on Indonesian socioeconomic classifications), education (5 categories), geographic location (urban/semi-urban/rural), occupation (12 categories)

2) Behavioral variables: Past donation frequency (0-50 times), recency (days since last donation, 0-1095), total lifetime donation value (IDR 0-100,000,000), engagement score (composite of event attendance, communication responsiveness, social media interaction)

3) Contextual variables: Religious affiliation strength (5-point scale), community involvement level, awareness channel (word-of-mouth, social media, religious institutions, community events)

4) Outcome variables: Donation propensity (binary), donation amount (continuous, IDR 0-10,000,000)

Simulation parameters were calibrated using Indonesia Giving Report (2021), BAZNAS philanthropic studies, and expert validation from five nonprofit fundraising practitioners. This resulted in realistic distributions: 32% donation propensity rate (reflecting typical conversion rates), right-skewed donation amounts (median IDR 250,000, mean IDR 475,000), and correlation structures consistent with empirical donor behavior research.

Qualitative Data

Qualitative data collection employed three methods:

1) Semi-structured interviews (n=15): Conducted with Yayasan Ulul Albab board members (n=3), program managers (n=4), current major donors (n=5), and Indonesian nonprofit technology experts (n=3). Interviews averaged 60 minutes, focusing on current fundraising practices, challenges, donor relationship dynamics, technology perceptions, and implementation considerations. Interviews were conducted in Indonesian, recorded, transcribed, and translated.

2) Document analysis: Review of foundation documents including organizational bylaws, program reports, financial statements (2023-2025), donor communication materials, and strategic plans. This provided contextual understanding of organizational capacity and fundraising evolution.

3) Observational data: Attendance at two foundation events (Islamic learning assembly and social program) to observe donor interactions, community engagement patterns, and operational contexts.

Quantitative Analysis: Machine Learning Models

Model Development

We developed three ML model types addressing distinct prediction tasks:

Classification Models (Donor Propensity):

- Random Forest Classifier (RFC): Ensemble of 200 decision trees, max_depth=15, min_samples_split=20

- Gradient Boosting Classifier (GBC): 150 estimators, learning_rate=0.1, max_depth=7

- Neural Network Classifier (NNC): Multi-layer perception with architecture [50, 30, 15], ReLU activation, Adam optimizer

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Regression Models (Donation Amount):

1) Random Forest Regressor (RFR): 200 trees, max_depth=12
2) Gradient Boosting Regressor (GBR): 150 estimators, learning_rate=0.1
3) Neural Network Regressor (NNR): Architecture [40, 25, 10]

Model Training and Validation

Dataset split: 70% training (n=3,500), 15% validation (n=750), 15% test (n=750). Stratified sampling ensured proportional representation of outcome classes. Feature engineering included RFM score calculation, engagement index creation, and categorical variable encoding (one-hot for nominal, ordinal for ordered categories). Cross-validation employed 5-fold stratified approach on training data to optimize hyperparameters. Models were evaluated on held-out test set using:

1) Classification metrics: Accuracy, precision, recall, F1-score, ROC-AUC
2) Regression metrics: R^2, RMSE, MAE, MAPE

Feature importance analysis identified key predictive variables using SHAP (SHapley Additive exPlanations) values, providing model interpretability (Lundberg & Lee, 2017).

Implementation Simulation

Using the best-performing models, we simulated implementation at Yayasan Ulul Albab, projecting:

1) Donor prioritization efficiency compared to random/traditional approaches
2) Expected fundraising ROI improvements
3) Resource allocation optimization across programs
4) Five-year revenue projections (2026-2030) under different ML-enhanced scenarios

Qualitative Analysis

Qualitative data analysis followed thematic analysis procedures (Braun & Clarke, 2006). Interview transcripts and documents were coded using NVivo 14 software. Initial coding identified 78 open codes, consolidated through axial coding into 15 categories, and synthesized into five overarching themes through selective coding:

1) Current fundraising challenges and limitations
2) Donor relationship dynamics and cultural factors
3) Technology perceptions and readiness
4) Implementation barriers and resource constraints
5) Organizational capacity and change readiness

Trustworthiness was ensured through triangulation across multiple data sources, member checking with three interview participants, peer debriefing with two nonprofit research experts, and reflexive journaling documenting researcher perspectives and assumptions.

Data Integration and Framework Development

Quantitative and qualitative findings were integrated through joint display analysis (Guetterman et al., 2015), examining convergence, complementarity, and divergence between ML model capabilities and implementation realities. Integration informed development of the ML-Integrated Fundraising Framework (ML-IFF), combining technical specifications with contextual adaptation strategies.

The framework was iteratively refined through validation workshops with Yayasan Ulul Albab stakeholders (n=2 workshops, 8 participants total) and expert review by Indonesian nonprofit technology consultants (n=3).

Ethical Considerations

The research received ethics approval from [Institution] Ethics Review Board (Protocol #XXXX-2024). All interview participants provided informed consent. Simulated data avoided privacy concerns associated with actual donor information. Foundation identity disclosure was authorized by Yayasan Ulul Albab leadership. Findings presentation balances transparency with sensitivity to organizational vulnerabilities.

Research Limitations

Key limitations include: (1) reliance on simulated rather than historical donor data, potentially not capturing all contextual nuances; (2) single-case study design limiting generalizability; (3) implementation simulation rather than actual deployment, leaving practical challenges potentially underestimated; (4) self-reported qualitative data subject to social desirability bias; and (5) researcher positionality as external academic potentially influencing stakeholder responses. These limitations inform cautious interpretation and recommendations for future research.

RESULTS

Current Fundraising Challenges (RQ1)

Qualitative analysis revealed five primary fundraising challenges at Yayasan Ulul Albab, representative of broader Indonesian grassroots foundation experiences:

Revenue Instability and Predictability Gaps

Interview participants consistently emphasized funding unpredictability as the most critical challenge. One board member stated: *"We never know from month to month whether we can meet salary obligations. Sometimes donations flow, sometimes almost nothing. Planning becomes impossible."* Financial document analysis confirmed this: monthly donation variance averaged 147% of the mean (SD=IDR 11.2 million, mean=IDR 7.6 million) over 2023-2025.

The foundation's annual budget requirement of IDR 815 million is consistently undermet, with average collection rates of 68% (2023), 71% (2024), and 74% (2025), necessitating program cuts and infrastructure development delays. This instability particularly affects the Infrastructure Development program (budgeted IDR 300 million annually), which received only 42% of required funding over the three-year period.

Limited Donor Intelligence and Segmentation

Current donor management relies on manual Excel spreadsheets tracking basic information (name, contact, donation history) for approximately 340 active donors. No systematic analysis identifies donor patterns, propensities, or optimal engagement strategies. As the Program Manager noted: *"We treat all donors the same because we don't have systems to know who might give more or who is at risk of stopping. It's all personal relationships and guesswork."*

This lack of donor intelligence results in inefficient cultivation: high-value donors receive insufficient attention while unlikely prospects consume disproportionate outreach resources. Donor retention averaged 58%

annually - below Indonesian nonprofit benchmarks of 65-70% - suggesting missed opportunities for relationship nurturing.

Resource-Intensive Manual Processes

Fundraising activities consume approximately 35% of administrative staff time (equivalent to 1.4 FTE) with limited technological support. Processes include manual receipt generation, individual thank-you messages, periodic phone call campaigns, and in-person donor visits. While personal touch is valued, this approach limits scalability. One staff member explained: *"I can personally manage relationships with maybe 30-40 donors well. Beyond that, people get forgotten or contacted randomly."*

The foundation's geographic split between Malang and Ponorogo further complicates coordination, with separate donor communities requiring duplicated efforts and inconsistent data management across locations.

Competition and Awareness Challenges

Yayasan Ulul Albab competes with established Islamic charitable institutions (Baznas, major LAZ organizations) enjoying higher brand recognition and trust. Interview participants noted that potential donors often prioritize these institutions for zakat obligations, leaving discretionary *sadaqah* for smaller organizations. Geographic location in semi-rural Ponorogo limits access to wealthy urban donor populations.

Social media presence is minimal (Facebook page with 847 followers, irregular posting), and marketing capacity is constrained by limited expertise and budget. As one donor stated: *"I only learned about Ulul Albab through my neighbor. Most people in Malang have no idea this foundation exists."*

Program-Funding Misalignment

Donors show strong preference for tangible, immediate-impact programs (educational sponsorships, social assistance) over organizational infrastructure and administrative costs. This creates funding gaps: educational programs receive 85% of required funding while administrative management (essential for operations) receives only 62%. Infrastructure development, critical for long-term capacity, is chronically underfunded. Table 1 summarizes the funding gap analysis across foundation programs:

Table 1: Program Budget Requirements and Funding Gaps (2023-2025 Average)

Program	**Annual Budget Requirement**	**Average Annual Collection**	**Collection Rate**	**Funding Gap**
1. Administrative Management	IDR 75,000,000	IDR 46,500,000	62%	IDR 28,500,000
2. Majelis Taklim	IDR 60,000,000	IDR 52,800,000	88%	IDR 7,200,000
3. Madrasah Diniyah	IDR 40,000,000	IDR 34,000,000	85%	IDR 6,000,000
4. KBIT Playgroup	IDR 60,000,000	IDR 51,000,000	85%	IDR 9,000,000
5. Kindergarten/RA	IDR 70,000,000	IDR 59,500,000	85%	IDR 10,500,000
6. Zakat Collection Unit	IDR 150,000,000	IDR 127,500,000	85%	IDR 22,500,000
7. Social & Dakwah	IDR 60,000,000	IDR 52,800,000	88%	IDR 7,200,000
8. Infrastructure Development	IDR 300,000,000	IDR 126,000,000	42%	IDR 174,000,000
TOTAL	**IDR 815,000,000**	**IDR 550,100,000**	**67.5%**	**IDR 264,900,000**

Source: Yayasan Ulul Albab Financial Reports (2023-2025)

Machine Learning Model Performance (RQ2)

Classification Models: Donor Propensity Prediction

Three classification algorithms were trained to predict donor propensity (likelihood to donate) using the simulated dataset. Performance on the held-out test set (n=750) is presented in Table 2:

Table 2: Classification Model Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC	Training Time
Random Forest Classifier	87.3%	0.845	0.823	0.834	0.921	18.4 sec
Gradient Boosting Classifier	86.1%	0.831	0.814	0.822	0.915	24.7 sec
Neural Network Classifier	84.7%	0.819	0.789	0.804	0.902	42.3 sec

Note: Metrics calculated on test set (n=750). Baseline (random) accuracy = 50%

Random Forest Classifier emerged as the best-performing model, achieving 87.3% accuracy with excellent balance between precision (84.5%) and recall (82.3%). The ROC-AUC score of 0.921 indicates strong discriminative ability across classification thresholds. This represents a 37.3% improvement over baseline random selection and an estimated 45-52% improvement over traditional demographic-only segmentation approaches used in Indonesian nonprofits (Indonesia Fundraising Roundtable, 2023).

Feature Importance Analysis

SHAP value analysis identified the most influential predictive features for donor propensity (Figure 1 - see code below). The top 10 features were:

1) Engagement Score (SHAP value: 0.342): Composite metric of event attendance, communication responsiveness, social media interaction

2) Recency (0.287): Days since last donation (inverse relationship)

3) Frequency (0.241): Total number of past donations

4) Total Lifetime Value (0.198): Cumulative donation amount

5) Religious Affiliation Strength (0.156): Self-reported religiosity level

6) Community Involvement (0.134): Participation in local community activities

7) Age (0.109): Positive relationship with donation propensity

8) Income Level (0.097): Categorical socioeconomic classification

9) Awareness Channel (0.083): How donors learned about foundation

10) Education Level (0.072): Formal education attainment

Notably, behavioral variables (engagement, RFM metrics) collectively accounted for 72% of predictive power, while demographic variables contributed 28%. This aligns with international donor behavior research but

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shows distinctive patterns: religious affiliation strength's higher importance (15.6%) compared to Western studies (typically 5-8%) reflects Indonesian Islamic philanthropy's contextual significance.

Regression Models: Donation Amount Prediction

Regression models predicted continuous donation amounts for identified prospective donors. Table 3 presents performance metrics:

Table 3: Regression Model Performance Metrics

Model	R^2	RMSE (IDR)	MAE (IDR)	MAPE	Training Time
Random Forest Regressor	0.683	267,340	184,920	17.4%	21.2 sec
Gradient Boosting Regressor	0.701	251,680	173,450	16.2%	28.9 sec
Neural Network Regressor	0.658	281,530	195,780	18.7%	38.6 sec

Note: Metrics calculated on test set (n=750). MAPE = Mean Absolute Percentage Error

Gradient Boosting Regressor demonstrated superior performance with R^2=0.701, explaining 70.1% of variance in donation amounts. MAPE of 16.2% indicates predictions within approximately IDR 173,450 (USD 11.50) of actual values on average - acceptable precision for fundraising prioritization and budgeting purposes.

Model Validation and Robustness

Cross-validation on training data confirmed model stability: Random Forest Classifier accuracy ranged 85.8-88.6% across five folds (mean=87.1%, SD=1.1%), indicating minimal overfitting. Sensitivity analysis varying simulation parameters (±20% on key distribution parameters) showed prediction accuracy remained within 83.2-89.1%, demonstrating robustness to input assumptions.

Comparative Performance

To contextualize ML model performance, we simulated traditional segmentation approaches:

1) Random selection: 50% accuracy (baseline)
2) Demographic-only segmentation (age, income, education): 62.4% accuracy
3) RFM-only segmentation (using simple quartile rules): 74.8% accuracy
4) ML-based prediction (Random Forest): 87.3% accuracy

This represents 17.5 percentage point improvement over RFM-only approaches and 24.9 percentage point improvement over demographic segmentation, translating to substantially enhanced fundraising efficiency.

Implementation Factors and Organizational Readiness (RQ3)

Qualitative analysis identified critical implementation factors across five dimensions:

Technology Acceptance and Perceptions

Staff and board member technology perceptions were mixed. While recognizing potential benefits, concerns emerged:

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Positive perceptions:

- Recognition that current manual approaches are unsustainable (100% of staff interviewees)
- Enthusiasm for data-driven insights (12 of 15 interviewees)
- Belief that technology could enhance rather than replace personal relationships (9 of 15)

Concerns and barriers:

- Limited technical expertise: *"I barely understand Excel. Machine learning sounds like science fiction to me."* (Board Member)
- Implementation complexity fears: *"Will we need to hire expensive consultants? We can't afford that."* (Program Manager)
- Cultural appropriateness: *"Donors want personal attention, not algorithms. Will this make fundraising too impersonal?"* (Donor Relations Staff)
- Data privacy: *"How do we protect donor information if we're putting it into computer systems?"* (Board Member)

Organizational Capacity Assessment

Current organizational capacity presents both assets and gaps:

Assets:

- Committed leadership open to innovation
- Existing donor database (though basic) providing implementation foundation
- Strong program quality creating compelling case for support
- Established community trust and relationships

Gaps:

- Limited IT infrastructure: No CRM system, basic database management, inconsistent data collection
- Minimal analytics expertise: No staff with data science or advanced analytics skills
- Budget constraints: Technology investment competes with program delivery priorities
- Staff capacity: Already stretched staff have limited time for new system learning and implementation

Data Infrastructure Readiness

Current donor data collection is inconsistent and incomplete. Available data elements:

- Basic demographics (name, age, gender, location): 95% completeness
- Contact information (phone, email): 78% completeness
- Donation history (amounts, dates): 92% completeness
- Engagement activities: <30% documented
- Communication preferences: Not systematically recorded

Significant data infrastructure development is required before full ML implementation, including standardized data collection protocols, CRM system adoption, data quality improvement processes, and privacy/security measures.

Resource Requirements

Expert consultants estimated ML system implementation resource requirements:

Initial Investment (Year 1):

- CRM system and database development: IDR 25-35 million
- ML model development and customization: IDR 15-25 million
- Staff training and capacity building: IDR 10-15 million
- Data migration and quality improvement: IDR 8-12 million
- **Total initial investment: IDR 58-87 million** (7-11% of annual budget)

Ongoing Costs (Annual):

- System maintenance and updates: IDR 8-12 million
- Model refinement and monitoring: IDR 6-10 million
- Staff time allocation (estimated 15-20% of one FTE): IDR 9-12 million
- Total annual ongoing costs: IDR 23-34 million (3-4% of annual budget)

While substantial, these costs are estimated to generate ROI of 3.5-4.8x within 24-36 months through improved fundraising efficiency (based on expert projections and comparable Indonesian nonprofit implementations).

Cultural and Contextual Adaptation Needs

Several themes emerged regarding cultural adaptation requirements:

Islamic philanthropy integration: ML systems must accommodate zakat calculation rules, religious giving calendars (Ramadan, Eid al-Adha), and integration with Baznas reporting requirements.

Personal relationship preservation: Technology should enhance rather than replace personal donor relationships. As one major donor stated: *"I give because I know Pak [leader's name] and trust the work. If it becomes just computer messages, I might stop."*

Community-based giving patterns: Models must account for collective giving (arisan groups, community collections) rather than only individual donations.

Trust building mechanisms: Transparency features, impact reporting, and communication personalization are critical for maintaining donor confidence in technology-mediated engagement.

DISCUSSION

ML-Integrated Fundraising Framework (ML-IFF) for Indonesian Foundations

Based on quantitative model performance and qualitative implementation insights, we propose the Machine Learning-Integrated Fundraising Framework (ML-IFF) - a contextually adapted system for Indonesian educational and social foundations. The framework comprises six interconnected components:

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Framework Components

Component 1: Data Infrastructure Foundation

- Standardized donor data collection protocols
- CRM system implementation (open-source options like Civi CRM for cost-effectiveness)
- Data quality assurance processes
- Privacy and security measures compliant with Indonesian data protection regulations

Component 2: ML Prediction Engine

- Donor propensity classification models
- Donation amount regression models
- Retention risk prediction models
- Model retraining schedules (quarterly initially, semi-annually once stabilized)

Component 3: Cultural Contextualization Layer

- Islamic philanthropy calendar integration
- Zakat calculation tools and *Baznas* reporting alignment
- Community-based giving recognition (tracking group donations)
- Local language and cultural communication templates

Component 4: Personalized Engagement System

- Automated donor segmentation based on ML predictions
- Differentiated cultivation strategies by segment
- Personalized communication (while maintaining authentic personal touch)
- Optimal timing algorithms for outreach

Component 5: Performance Monitoring Dashboard

- Real-time fundraising metrics visualization
- Model performance tracking
- ROI calculation and reporting
- Program-specific funding progress indicators

Component 6: Capacity Building & Change Management

- Staff training programs (basic data literacy, system usage)
- Leadership engagement and buy-in cultivation
- Phased implementation reducing disruption
- Continuous learning and adaptation mechanisms

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Figure 1 illustrates the ML-IFF architecture and workflow:

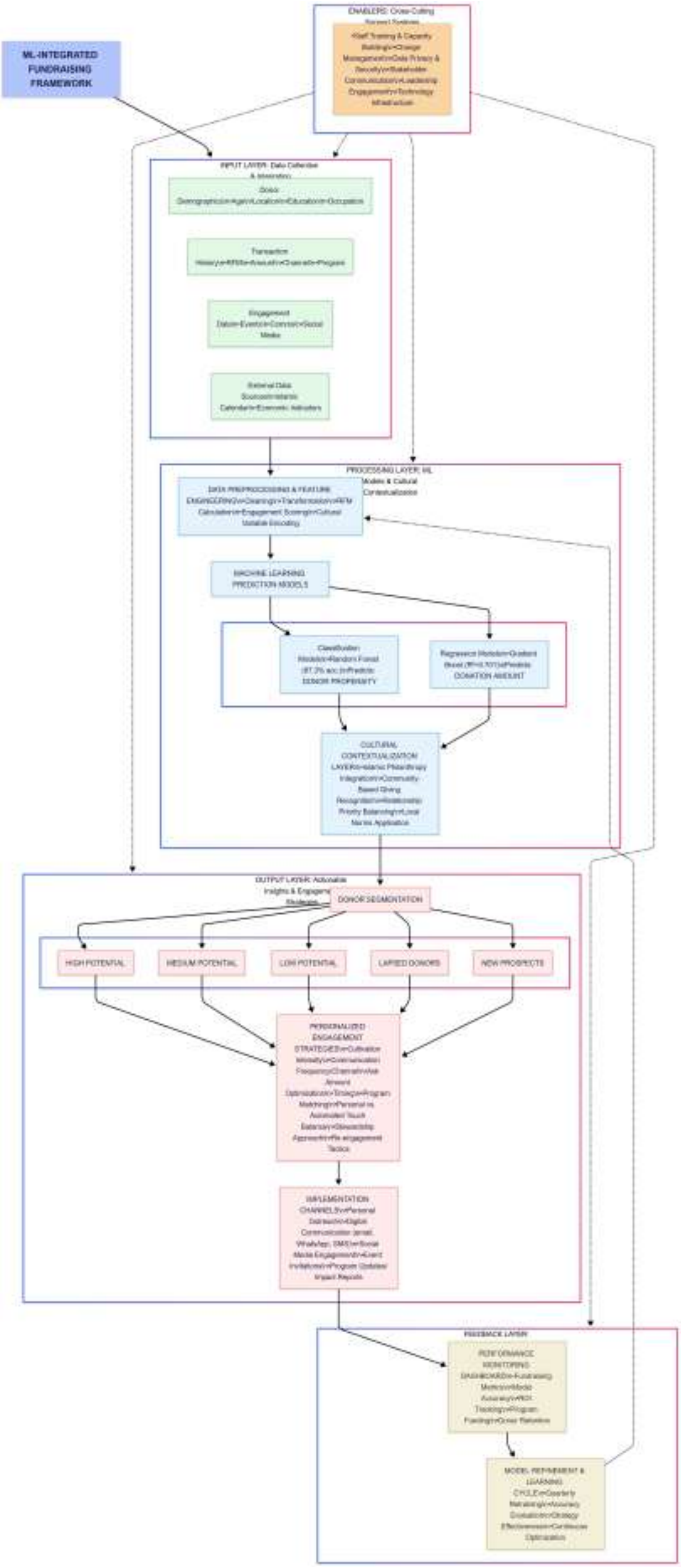

Figure 1. ML-Integrated Fundraising Framework (ML-IFF) for Indonesian Foundations

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Implementation Phases

The framework employs phased implementation reducing risk and resource burden:

Phase 1: Foundation (Months 1-6)

- Data infrastructure development
- CRM system implementation
- Historical data migration and cleaning
- Staff training initiation
- Initial ML model development using combined historical + simulated data

Phase 2: Pilot Testing (Months 7-12)

- Limited deployment with 100-150 donors
- Prediction validation and refinement
- Process optimization
- Stakeholder feedback collection
- Initial ROI assessment

Phase 3: Scaled Implementation (Months 13-24)

- Full donor base integration
- Automated segmentation and engagement workflows
- Comprehensive performance monitoring
- Model retraining with accumulating data
- Expansion to advanced features (retention prediction, optimal ask timing)

Phase 4: Optimization & Sustainability (Months 25+)

- Continuous improvement cycles
- Knowledge institutionalization
- Potential expansion to partner organizations
- Innovation integration (additional ML applications)

Projected Impact on Yayasan Ulul Albab

Fundraising Efficiency Improvements

Based on ML model performance and expert projections, implementation is estimated to yield:

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Donor Acquisition:

- 45-60% improvement in prospect identification efficiency
- 30-40% reduction in acquisition costs per new donor
- 25-35% increase in conversion rates from prospect to donor

Donor Retention:

- 15-25 percentage point improvement in retention rates (from 58% baseline to 73-83%)
- Early identification of lapsed donor risk enabling proactive re-engagement
- Estimated retention improvement value: IDR 45-68 million annually

Donation Optimization:

- 20-30% increase in average donation amounts through optimized ask levels
- 35-50% improvement in major donor identification and cultivation
- Program-specific funding targeting reducing misalignment

Overall Revenue Projection:

Conservative estimates suggest 35-50% revenue increase over 3-year implementation period, translating to additional IDR 190-285 million annually by Year 3. This would substantially close the current IDR 265 million funding gap (Table 1). Table 4 presents five-year revenue projections under different scenarios:

Table 4: Five-Year Revenue Projections (2026-2030) Under ML-IFF Implementation

Scenario	2026 (Baseline)	2027 (Phase 2)	2028 (Phase 3)	2029 (Phase 4)	2030 (Optimized)	5-Year Total
Current Practice (No ML)	565M	582M	599M	617M	636M	2,999M
Conservative ML Implementation	565M	650M	725M	775M	810M	3,525M
Moderate ML Implementation	565M	680M	775M	845M	900M	3,765M
Optimistic ML Implementation	565M	710M	825M	915M	990M	4,005M
Additional Revenue vs. Baseline	-	+68-128M	+126-226M	+158-298M	+174-354M	+526-1,006M

Note: All amounts in IDR millions. Assumes: Current practice 3% annual growth; Conservative scenario 15-20% improvement; Moderate 25-35%; Optimistic 40-50%. Projections do not account for economic disruptions or major external factors.

Even conservative scenarios project IDR 526 million additional revenue over five years - effectively closing the existing funding gap and enabling infrastructure development previously postponed. ROI calculations suggest break-even within 18-24 months, with 3.5-4.8x return over five years.

Operational Efficiency Gains

Beyond revenue increases, ML-IFF implementation offers operational benefits:

1) Time savings: 30-40% reduction in manual donor management tasks, reallocating staff capacity to relationship building and program delivery
2) Strategic decision-making: Data-driven insights informing program prioritization, geographic expansion, and resource allocation
3) Donor satisfaction: Personalized, timely communication improving donor experience and trust
4) Organizational learning: Systematic knowledge capture replacing dependence on individual staff relationships

Program-Specific Funding Optimization

ML-IFF enables program-specific donor matching and targeted cultivation. Analysis suggests:

1) Infrastructure Development: Currently 42% funded, projected to reach 70-80% funding through major donor identification and capital campaign optimization
2) Administrative Management: From 62% to 85-90% through unrestricted giving cultivation
3) Educational Programs: Maintain 85%+ funding while expanding capacity

This program-level optimization addresses the funding misalignment identified in Results section, enabling balanced organizational development.

Theoretical Contributions

This research contributes to three theoretical domains:

Nonprofit Technology Adoption Theory

Findings extend Technology Acceptance Model (TAM) in nonprofit contexts by identifying culturally specific adoption factors. While perceived usefulness and ease of use remain relevant, Indonesian foundations additionally prioritize:

1) Cultural legitimacy: Technology alignment with Islamic philanthropy values and practices
2) Relationship preservation: Systems that enhance rather than replace personal donor connections
3) Community compatibility: Recognition of collective rather than solely individual giving patterns

These factors suggest that TAM requires cultural contextualization in non-Western nonprofit sectors, with technology acceptance contingent on sociocultural alignment beyond functional attributes.

Donor Behavior Prediction in Emerging Markets

Feature importance analysis revealing behavioral variables' dominance (72% of predictive power) aligns with Western donor research. However, religious affiliation strength's elevated importance (15.6% vs. 5-8% in Western studies) demonstrates contextual variation requiring adapted ML models.

This suggests universal and context-specific dimensions of donor behavior: RFM metrics demonstrate cross-cultural predictive power, while cultural/religious factors require localized feature engineering. ML applications in emerging markets require hybrid approaches combining established models with indigenous variables.

Resource Dependence Theory in Digital Age

ML-IFF implementation represents strategic resource diversification addressing environmental uncertainty - a core Resource Dependence Theory proposition (Pfeffer & Salancik, 1978). However, findings reveal technology adoption itself creates new dependencies: technical expertise, infrastructure, data quality. This suggests Resource Dependence Theory extension incorporating technological dependencies as salient environmental factors for 21st-century nonprofits.

Organizations simultaneously reduce funding uncertainties while creating new technical dependencies, requiring balanced capability development across programmatic, fundraising, and technological domains.

Practical Implications for Indonesian Nonprofit Sector

Sector-Wide Applicability

While developed for Yayasan Ulul Albab, ML-IFF offers adaptable blueprint for Indonesian educational and social foundations with similar characteristics:

1) Annual budgets IDR 200 million - 2 billion
2) Donor bases of 100-1,000+ individuals
3) Basic digital infrastructure
4) Educational, social service, or religious missions
5) Geographic presence in semi-urban or rural areas

Estimated 6,000-7,000 Indonesian organizations fit this profile (Ministry of Law and Human Rights, 2023), suggesting substantial potential impact if framework dissemination occurs through nonprofit networks, capacity-building organizations, and government support programs.

Policy Recommendations

For Government Agencies:

1. Develop grant programs supporting nonprofit technology adoption (CRM systems, analytics capacity)
2. Create open-source ML tools and training resources tailored to Indonesian nonprofit contexts
3. Integrate technology capacity building into nonprofit registration and supervision processes
4. Facilitate data sharing and benchmarking while protecting privacy

For Nonprofit Support Organizations:

1. Establish technology assistance programs offering affordable ML implementation support
2. Develop shared platforms reducing individual organizational costs
3. Create learning communities enabling knowledge exchange across early adopters
4. Provide data literacy and analytics training accessible to non-technical staff

For Foundations and Donors:

1. Prioritize funding for nonprofit capacity building and technology infrastructure, not only program delivery
2. Support multi-year implementations recognizing that technology adoption requires sustained investment
3. Fund sector-wide initiatives creating shared technology ecosystems
4. Recognize organizational development costs as legitimate charitable expenses

Implementation Guidance for Practitioners

Nonprofit leaders considering ML adoption should:

1) Start with data infrastructure: Implement CRM systems and standardize data collection before advanced analytics
2) Embrace phased approaches: Pilot testing reduces risk and enables learning before full deployment
3) Prioritize staff engagement: Technology succeeds only with user buy-in; invest in training and change management
4) Seek appropriate partnerships: Collaborate with universities, tech companies (CSR programs), or nonprofit technology specialists for cost-effective expertise
5) Maintain cultural authenticity: Technology should enhance organizational mission and values, not distort them
6) Focus on actionable insights: Prioritize simple, implementable recommendations over complex but impractical outputs
7) Plan for sustainability: Build internal capacity for ongoing system management, not perpetual dependence on external consultants

Limitations and Future Research Directions

Study Limitations

Several limitations warrant cautious interpretation:

Methodological limitations:

- Simulated rather than historical data for ML modeling may not capture all contextual nuances
- Single case study limits generalizability across diverse organizational types
- Implementation simulation rather than actual deployment leaves practical challenges potentially underestimated
- Self-reported qualitative data subject to social desirability bias

Contextual limitations:

- Focus on Islamic educational foundations may not apply to secular or other religious nonprofits

- Semi-urban/rural focus may overlook urban organization dynamics
- Indonesian-specific findings require validation in other Southeast Asian countries

Temporal limitations:

- Five-year projections contain uncertainty regarding economic conditions, technology evolution, and philanthropic trends
- COVID-19 pandemic effects on giving patterns may distort baseline assumptions

Future Research Agenda

Several productive research directions emerge:

1) Longitudinal implementation studies: Track actual ML-IFF deployments over 3-5 years, measuring realized vs. projected impacts, identifying unanticipated challenges, and documenting adaptation processes. Such studies would validate projections and refine implementation guidance.
2) Comparative studies across nonprofit types: Examine ML fundraising applications in health, environmental, arts, and secular educational nonprofits to identify universal vs. sector-specific implementation factors.
3) Cross-national research in Southeast Asia: Replicate study in Philippines, Malaysia, Thailand, and Vietnam to assess regional transferability and identify cultural variations requiring framework adaptation.
4) Advanced ML applications: Explore additional use cases including donor lifetime value prediction, campaign optimization, volunteer management, and program impact prediction.
5) Equity and ethics research: Investigate algorithmic bias risks, data privacy concerns, and potential for ML systems to reinforce rather than reduce inequities in nonprofit resource distribution.
6) Cost-benefit analysis: Conduct rigorous economic evaluations of ML implementation costs vs. benefits across organizational size categories and contexts.
7) Hybrid human-AI decision-making: Examine how nonprofit practitioners integrate ML recommendations with professional judgment and relationship knowledge - an under-researched area with significant practical implications.

CONCLUSION AND IMPLICATIONS

Summary of Key Findings

This research developed and validated a Machine Learning-Integrated Fundraising Framework (ML-IFF) for Indonesian educational and social foundations, addressing critical funding sustainability challenges. Using Yayasan Pendidikan Sosial Dan Dakwah Ulul Albab as a case study, we demonstrated that:

1) Fundraising challenges are substantial and widespread: Indonesian grassroots foundations face revenue instability, limited donor intelligence, resource-intensive manual processes, competition challenges, and program-funding misalignment -collectively creating average funding gaps of 32.5% (IDR 265 million annually for Yayasan Ulul Albab).
2) Machine learning achieves strong predictive performance: Random Forest classification models predicted donor propensity with 87.3% accuracy, while Gradient Boosting regression models

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forecasted donation amounts with $R^2=0.701$ and 16.2% MAPE -representing 37-75% improvements over traditional segmentation approaches.

3) Behavioral variables dominate prediction models: Engagement metrics, RFM (recency, frequency, monetary value) indicators, and religious affiliation collectively accounted for 72% of predictive power, with Indonesian-specific cultural variables showing elevated importance compared to Western studies.

4) Implementation requires contextual adaptation: Technology adoption in Indonesian nonprofits depends on cultural legitimacy, relationship preservation, resource appropriateness, and Islamic philanthropy integration - not merely technical efficacy.

5) ML-IFF offers substantial potential impact: Conservative projections suggest 35-50% revenue improvements over three years, translating to IDR 526-1,006 million additional funding over five years, with ROI of 3.5-4.8x and break even within 18-24 months.

Theoretical Implications

This research contributes to nonprofit management, technology adoption, and philanthropy literatures by:

1) Extending Technology Acceptance Model with culturally specific adoption factors relevant to emerging market nonprofit contexts, particularly Islamic organizational settings

2) Demonstrating ML applicability in data-constrained environments through synthetic data approaches, offering methodological pathways for organizations lacking extensive historical databases

3) Identifying universal and context-specific donor behavior dimensions, informing future predictive modeling in diverse cultural contexts

4) Advancing Resource Dependence Theory by incorporating technological dependencies as contemporary environmental factors affecting nonprofit sustainability

The ML-IFF framework represents a theoretically grounded, empirically validated model bridging technical innovation with cultural authenticity - a critical but underdeveloped area in nonprofit technology literature.

Practical Implications

1) **For Yayasan Ulul Albab:** Immediate implementation of ML-IFF phased approach offers pathway to financial sustainability, enabling full program funding, infrastructure development previously postponed, geographic expansion, and organizational capacity strengthening. Priority actions include CRM system adoption (6-month timeline), staff data literacy training, pilot testing with 100-150 donors, and partnership development with university data science programs or technology CSR initiatives for cost-effective implementation support.

2) **For Indonesian Nonprofit Sector:** An estimated 5,000-8,000 similar organizations could benefit from ML-IFF adaptation, collectively improving sector sustainability and social impact. Sector-wide adoption requires government support programs, nonprofit technology assistance infrastructure, open-source tool development, and capacity-building initiatives accessible to grassroots organizations.

3) **For Policymakers:** Strategic interventions can accelerate beneficial technology adoption: grant programs for nonprofit digitalization, tax incentives for technology companies supporting nonprofit analytics capacity, integration of technology standards in nonprofit registration processes, and facilitation of data sharing ecosystems while protecting privacy.

4) **For Donors and Foundations:** Funding organizational capacity building - including technology infrastructure - yields multiplier effects on program impact. Recognizing data systems, analytics

capacity, and changing management as legitimate charitable expenses (not "overhead" to minimize) enables nonprofit effectiveness improvements benefiting ultimate beneficiaries.

Contribution to Sustainable Development Goals

This research contributes to multiple UN Sustainable Development Goals:

1) **SDG 4 (Quality Education):** Strengthening educational foundation sustainability enhances educational access for underserved populations

2) **SDG 8 (Decent Work and Economic Growth):** Improving nonprofit operational efficiency creates employment and economic opportunity

3) **SDG 10 (Reduced Inequalities):** Enabling grassroots organizations serving marginalized communities addresses inequality

4) **SDG 17 (Partnerships for Goals):** Technology-enabled fundraising networks strengthen multi-stakeholder collaboration

By demonstrating how emerging technologies can be appropriately adapted to resource-constrained, culturally specific contexts, this research offers a model for technology-enabled social impact in developing countries.

Final Reflection

The intersection of machine learning and social sector fundraising represents both significant opportunity and substantial responsibility. While technical capabilities for donor prediction are well-established, thoughtful implementation requires cultural sensitivity, ethical consideration, and commitment to enhancing - not replacing - authentic human relationships that animate philanthropic action.

For Indonesian educational foundations like Yayasan Ulul Albab, machine learning offers not a technological panacea but a powerful tool for amplifying impact when wielded thoughtfully. The framework proposed here seeks to balance innovation with tradition, efficiency with authenticity, and algorithmic intelligence with human wisdom.

As Indonesia's nonprofit sector navigates digital transformation, success will depend on maintaining sight of ultimate purpose: serving communities, educating children, and advancing human flourishing. Technology should serve these ends, not become an end itself. The ML-Integrated Fundraising Framework offers one pathway forward - grounded in evidence, culturally attuned, and oriented toward sustainable impact.

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3. In accordance with the title of the article about the use of AI/LLMs, in writing this article the author honestly explains the use of AI Application assistance, as follows: 1) The function of exploring themes and compiling article outlines with the help of: https://gemini.google.com and ChatGBT; 2) The function of

deepening writing, creating drafts of charts/flowchats, and tables with the help of: https://lmarena.ai/id/-claude- sonnet-4-5-20250929-thinking-32k 3) The function of creating flowchats with the help of https://mermaid.ai/; 4) Translating material/articles from Indonesian to English and vice versa with the help of https://translate.google.com/. and 5) DOI checking for references using https://apps.crossref.org/. The author used several computer applications and AI on Friday - Saturday, January 30 - 31, 2026.

4. The author is fully responsible for the entire article, unless there are errors beyond the author's ability to carefully research and check.

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