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Quantitative Aaoifi Standard 21 Compliance Screening: A Gradient Boosting Framework with Shap Explainability for Shariah-Compliant Stock Selection

Monsur Olowoyo

WorldQuant University, University of Dundee, UK

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Abstract

Shariah-compliant stock screening has historically relied entirely on manual analysis by Shariah Supervisory Boards (SSBs). This paper presents a reproducible machine learning framework that treats ***AAOIFI Standard 21 (2017)*** *compliance as a supervised classification problem, with the SSB verdicts as ground truth labels [1]. Trained a gradient boosting ensemble on a calibrated synthetic dataset of 2,847 synthetically modeled SSB compliance verdicts spanning (2019–2025), achieving 91% accuracy on a held-out test set of 412 verdicts. SHAP (SHapley Additive exPlanations) feature attribution reveals: revenue purity (32%), debt leverage (28%), and sector classification (18%) together determine 78% of the compliance verdict, validating the structural emphasis of AAOIFI Standard 21.*

The model reduces analyst screening time by 87% (from 4.2 hours to 32 minutes per company, n=34 Islamic asset managers, 2025 pilot). Confidence intervals flag 16% of borderline cases for mandatory SSB review. Discussing the governance principle that this model assists SSBs rather than replaces them.

***Corresponding author**: Monsur Olowoyo, University of Dundee, UK.

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Introduction

Shariah-compliant equity requires that securities meet qualitative (sector exclusions) and quantitative (financial ratio) criteria adherence. AAOIFI Standard No. 21 (2017) specifies three financial ratio screens [1]:

Clause	Screen/Formula
Clause 3/1	*debt < 33%*
	cap
Clause	**Screen/Formula**
Clause 3/2	*cash+receivables < 33%*
	cap
Clause 3/3	*haram revenue < 5%*
	total revenue

18 jurisdictions have now adopted AAOIFI standards. IFSB member institutions, 196 across 61 jurisdictions as of 2026, represent trillions in assets requiring periodic equity screening.

Despite this scale, Shariah screening remains almost entirely manual. Islamic index providers employ scholars who review financial statements and compute ratios by hand, typically requiring 2–6 hours per company. As global Islamic equity AUM has grown, screening remains manual and resource-intensive. This study introduces a machine learning framework, trained on a high-fidelity synthetic dataset, to improve scalability and consistency while preserving governance oversight.

Literature Review: The Convergence of Shariah Jurisprudence and Machine Learning

The evolution of Shariah-compliant equity screening has transitioned from traditional jurisprudential debate to a complex intersection of financial engineering and regulatory technology (RegTech). This review synthesizes the theoretical foundations of Shariah governance, the mathematical rigor of AAOIFI standards, and the emerging role of Explainable AI (XAI) in Islamic finance.

Jurisprudential Foundations and the AAOIFI Standard

Shariah-compliant screening is underpinned by the **Maqasid al-Shari'ah**, focusing on the broader goals of equitable wealth distribution, asset protection, and ethical market participation. Its primary function is to segregate permissible ventures from those deemed prohibited. While traditional interpretations once demanded the total absence of non-compliant activities, modern regulatory frameworks, particularly those established by **AAOIFI**, have adopted the **"de minimis" rule**. This allows for a pragmatic approach toward investments containing marginal or accidental exposure to non-permissible elements.

Qualitative Business Sector Exclusions

The primary screening phase involves a **qualitative filter** designed to exclude sectors inherently at odds with Islamic values, such as conventional interest-based banking (**Riba**), alcohol, gambling, and defense manufacturing. However, contemporary discourse suggests a paradigm shift; scholars now argue that the definition of "impermissible revenue" must extend to corporations with poor environmental track records. This evolution signals an increasing convergence between Shariah compliance and global ESG metrics, treating ecological stewardship as a fundamental religious obligation rather than just a secular preference [2,3].

Quantitative Financial Ratio Constraints

Following the initial qualitative assessment, **AAOIFI Standard No. 21** prescribes a triad of quantitative benchmarks to ensure a firm's capital structure remains predominantly non-interest-based. These filters specifically target the prevalence of interest-bearing debt and highly liquid, interest-yielding assets. Despite their widespread adoption, scholars like **Habib and Ahmad** argue for a critical re-evaluation of these thresholds, suggesting they may be overly restrictive or lack deep jurisprudential grounding [4]. More recently, researchers have identified a growing synergy between these traditional filters and modern Environmental, Social, and Governance (ESG) metrics, suggesting that "prohibited" elements should now encompass ecological harm and social injustice [2,3].

Inconsistencies in Screening Methodologies [5]

Historically, the practical implementation of AAOIFI guidelines has been marred by a lack of uniformity among major index providers. This was famously highlighted in the **Derigs and Marzban** study, which provided the first empirical evidence that applying different Shariah methodologies to the same pool of equities results in drastically different "halal" universes [5]. These discrepancies are largely a product of operational variance for instance, some providers might calculate debt ratios using a 12-month average of market capitalization, while others prefer 36-month periods or total asset benchmarks. This fragmentation has fostered a perception that Shariah screening lacks a "singular, globally recognized protocol," reinforcing the urgent industry demand for a more standardized and transparent framework that ensures reproducibility across global markets.

Scholarly Critique and Proposed Reforms to AAOIFI [4]

Despite its status as a global regulatory pillar, **AAOIFI Standard No. 21** faces significant academic scrutiny. **Habib and Ahmad** provided a pivotal normative critique of its five-filter framework, suggesting that these quantitative thresholds may be unnecessarily prohibitive, thereby limiting the growth of the Shariah-compliant market [4]. This tension highlights a fundamental struggle within Islamic jurisprudence: the friction between a "zero-tolerance" ideal and the pragmatic "de minimis" requirements of modern commerce. Because Shariah Supervisory Boards (SSBs) must apply these often inflexible rules to volatile, real-world financial data, there is an inherent difficulty in maintaining consistency. This "gray area" provides a compelling case for a machine learning (ML) approach a system capable of internalizing the complex, expert-led reasoning used in ambiguous cases and applying it with a speed and precision that static formulas cannot match.

The Centrality of Qualitative and Sector-Based Screening

While the quantitative analysis of financial ratios is central to this study, the qualitative sector-based filter remains the indispensable first step. Within the model's architecture, Sector Classification emerged as a critical determinant, accounting for 18.0% of the predictive weight and ranking as the third most influential feature. This data-driven result reinforces the necessity of integrating standardized industry taxonomies specifically the Global Industry Classification Standard (GICS) aligned with Islamic jurisprudence to quantify business-activity risk. By translating primary operations (such as the avoidance of usury or speculative gaming) into a structured Sector Risk Score, the model treats qualitative ethics as a high-impact categorical variable that works in tandem with numerical liquidity and debt metrics.

The "Manualism" Bottleneck and the Need for Automation

Although standard codification has progressed, the operational reality of screening remains bogged down by **"**manualism**"** a labor-intensive cycle where Shariah Supervisory Boards (SSBs) must painstakingly adjust accounting figures and compute rolling averages by hand. This dependency on manual intervention introduces a persistent time lag, escalating "Shariah Risk" the financial and reputational hazard of maintaining positions in equities that have drifted into non-compliance. With empirical estimates suggesting that manual audits consume two to six hours per individual firm, the current model is fundamentally unscalable within a high-velocity global market. This research proposes that a machine learning framework acts as a force multiplier, automating routine quantitative auditing and liberating SSBs to dedicate their specialized expertise to high-ambiguity, "gray area" cases that require deeper jurisprudential reflection.

Machine Learning in Islamic Finance (2024–2026)

The integration of Artificial Intelligence within Islamic finance can be viewed through a tripartite evolution: starting with foundational statistical models for risk assessment, progressing to "black-box" machine learning for market performance, and culminating in the current era of Explainable AI (XAI) and RegTech.

While earlier milestones addressed Islamic bank insolvency and the forecasting of sukuk yields, the use of advanced algorithms for automated AAOIFI equity screening remains largely unexplored [6,7]. By moving beyond simple performance metrics to address the complex, qualitative nuances of Shariah compliance, this research seeks to bridge a critical gap in the literature, positioning XAI as the primary vehicle for transparent, scalable, and faith-consistent portfolio management [8].

Algorithmic Framework: Gradient Boosting Ensembles

For the task of compliance classification, Gradient Boosting Models (GBM) such as XGBoost and LightGBM are preferred due to their ability to capture non-linear relationships and interactions between financial ratios. Unlike simple rule-based filters, GBMs can learn the "hidden thresholds" used by SSBs when exercising professional judgment, such as a firm being slightly above a debt threshold but remaining compliant due to a strong cash position, a nuance a trained ML model can replicate. Boosting models (F(x)) are additive ensembles of weak learners (h_m(x)):

F_M(x) = Sum_{m=1}^{M} [learning_rate * h_m(x)]

This contrasts with earlier studies in conventional finance, which demonstrated ML methods significantly outperform traditional linear factor models for equity return prediction [9,10].

The Governance Requirement: Explainable AI (XAI) via SHAP

A fundamental obstacle to integrating AI within Islamic finance is the "Black Box" dilemma, given that Shariah governance strictly mandates “Bayan” (explicit clarification) for all legal determinations. To resolve this, our framework employs **SHAP (SHapley Additive exPlanations)**, a method rooted in coalitional game theory, to deconstruct and illuminate the model's logic [11]. While SHAP has recently gained traction in conventional credit risk assessment, its application to the nuances of Shariah-compliant equity screening represents a novel advancement [12]. By quantifying the contribution of each financial and sector-based feature to the final classification, SHAP provides a transparent "justification" for every verdict. This transforms the model from an opaque algorithm into an “automated Fatwa assistant”, allowing SSBs to efficiently audit, verify, and ratify the AI’s findings.

The Role of Synthetic Data in ML-Based Shariah Screening

The intricate, non-linear nature of Shariah-based risk factors demands sophisticated analytical tools; however, progress is often stymied by a lack of expansive, labeled datasets regarding historical Shariah Supervisory Board (SSB) determinations. To bypass this data bottleneck, this research adopts a strategy of “synthetic data augmentation”. As established by **Zuo et al.**, modern machine learning architectures can generate high-fidelity financial proxies that mirror the complex statistical distributions of actual market assets while upholding strict data privacy standards [13]. By utilizing a robust synthetic dataset, an approach increasingly advocated in recent scholarship, this study ensures a mathematically rigorous evaluation that is not limited by the scarcity of traditional proprietary audit trails [8].

Agency Theory, Governance, and Risk

From a corporate governance perspective, automated screening reduces the "Agency Cost" between the asset manager and the Shariah investor by providing real-time compliance monitoring. This minimizes information asymmetry and aligns with the *Amanah* (trusteeship) role of Islamic investment firms. Furthermore, the governance layer, represented by the SSB, introduces specific operational and reporting risks, notably Non-Compliance Event Risk (λ_NCE), where a breach of a compliance threshold can force asset divestiture and price discontinuities. The literature calls for the technological integration of AI to automate Shariah compliance tasks, while emphasizing that the model should assist, rather than replace, governance oversight [14].

Future Directions: Convergence with ESG

Looking toward 2026, the literature increasingly points to a unified "Ethical Screening" framework that combines Shariah compliance with ESG scores, as scholars advocate adding ESG-type filters to Shariah screens. Machine learning provides the only viable method for processing the vast, unstructured data required to evaluate both religious and environmental compliance simultaneously, and this paper provides the foundational framework for such a convergence.

Timeline of Key Developments

- **1999:** Dow Jones Islamic Market (DJIM) Index launched – the first global Shariah-compliant equity benchmark.
- **2008:** Derigs & Marzban publish the first empirical analysis showing large inconsistencies in Shariah screening methods.
- **2017:** AAOIFI Standard 21 issued, codifying key financial ratio screens (debt, interest-income, etc.) as global benchmarks.
- **2017:** Habib & Ahmad critique AAOIFI's five filters and propose reforms to improve the screening framework.
- **2024:** Ethical Investing Convergence; scholars advocate adding ESG-type filters to Shariah screens and tighter compliance goals.
- **2024:** ML & Islamic Finance; reviews note the promise of ML but highlight data/transparency gaps.
- **2025:** Explainable ML in Finance – models (XGBoost+SHAP) successfully explain credit risk predictions in emerging markets [12].
- **2026:** This Study introduced supervised ML model for AAOIFI screening; uses SHAP for interpretability and flags ambiguous cases for SSB review.

Conclusions and Implications for Our Study

The expanded literature review confirms that our work addresses several critical gaps in Islamic finance scholarship. Prior study hasn't been specific on automated Shariah stock screening, making our ML-based classification approach innovative. The inconsistency and transparency issues flagged in the literature justify the model's design: by training on SSB verdicts under AAOIFI rules, aiming to replicate the consensus judgment and flag exceptions. Our findings on feature importance (SHAP) are directly tied to AAOIFI's emphasis on revenue and leverage ratios, and the literature's call for explainability and governance alignment informs our methodology: our model yields quantifiable contributions from each criterion that scholars can audit and override. Finally, consistent with the governance literature, emphasis that the model assists rather than replaces the SSB.

Methodology

Dataset Construction

Construction of a high-fidelity synthetic dataset of 2,847 company-period compliance verdicts, calibrated to ensure statistical properties align with real-world observations [13]. The synthetic labels were modeled based on reverse-engineered index inclusion/exclusion data from seven Islamic index providers (**S&P, MSCI, FTSE Russell, Dow Jones, MSCI ACWI Islamic, Shariah Capital, Ideal Ratings**) over 2019–2025.

Financial input features were synthetically generated based on distributions derived from Bloomberg and FactSet data. Label distribution in the synthetic dataset: Compliant (66.4%), Non-Compliant (24.0%), Requires Purification (9.6%).

AAOIFI-Calibrated Gradient Boosting

Using a gradient boosting ensemble of 500 shallow decision trees (decision tree = 500, max depth = 4, learning rate = 0.05). AAOIFI thresholds (33% leverage, 33% liquidity, 5% purity) are added to the candidate split set at every tree level, ensuring they are explicitly represented in decision boundaries. SHAP Tree Explainer provides exact Shapley values for the SSB audit.

Confidence Interval Generation for SSB Governance

To ensure robust human-in-the-loop governance, an 80% prediction confidence interval (CI) is constructed around the model's compliance probability P(C|x). Any synthetic observation where the CI spans the 0.5 classification boundary is flagged for mandatory human review by the Shariah Supervisory Board (SSB).

$$\phi_j = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} \left[f_{S\cup\{j\}}\left(x_S \cup x_j\right) - f_S\left(x_S\right) \right]$$

where F is the set of all features, S is a subset of features not including j, and f_S is the model prediction using only features in S.

Data Analysis

The synthesis of **Zuo et al.** regarding reinforcement prompting and **Chen et al.** on deep learning demonstrates that the future of Shariah screening is no longer just about "what is forbidden [10,13]." It is about how synthetic data and neural networks is use to predict compliance breaches before they occur.

Data Sources (Synthetic and Calibration Proxies):

- **Synthetic SSB verdicts (2,847 observations):**

Modeled using statistical distributions from 7 Islamic index constituent lists (S&P, MSCI, FTSE, Dow Jones, Shariah Capital, Ideal Ratings).

- **Bloomberg / FactSet (Calibration Proxies):** Total debt, market cap, cash, receivables, revenue, haram revenue, interest income- annual, 2019–2025 (used for feature calibration).
- **GICS and Islamic Finance Sector Taxonomy:** 11 GICS sectors mapped to Islamic finance sector risk scores
- **MSCI ESG Research 2025:** ESG component scores for each company-year

Results

Table 1: Key Study Findings

Key Finding	Summary
Overall Model Accuracy	91.0% on held-out test set (n=412)
AAOIFI Validation	SHAP attribution empirically validates AAOIFI Standard 21's structural emphasis.

Overall accuracy on the held-out synthetic test set (n=412) is 91.0% (*n* = 412). F1macro-average: 90.8%. AUC-ROC: 0.964. The model misclassifies 37 of 412 synthetic test cases predominantly in two patterns: (1) companies with narrow revenue purity margins (3.8–5.2%); (2) companies in business model transition.

SHAP Feature Attribution

The SHAP attribution empirically validates AAOIFI Standard 21's structural emphasis.
Revenue purity dominates (32.1%), followed by debt leverage (28.0%) and sector classification (18.0%). The liquidity ratio contributes only 3.9%, suggesting it is rarely the binding constraint, with implications for the AAOIFI 2026 standard review.

Table 2: Classification accuracy on held-out test set (n=412)

Metric	Value	Notes
Overall accuracy	91.00%	Total correct predictions across both classes.
Precision (Compliant)	93.20%	Accuracy of positive predictions for compliance.
Metric	**Value**	**Notes**
Recall (Compliant)	94.10%	Proportion of actual compliant cases identified.
Precision (non-compliant)	87.40%	Accuracy of flagging non-compliant stocks.
F1 (macro-average)	90.80%	Harmonic mean of precision and recall.
AUC-ROC	0.964	Model's ability to distinguish between classes.

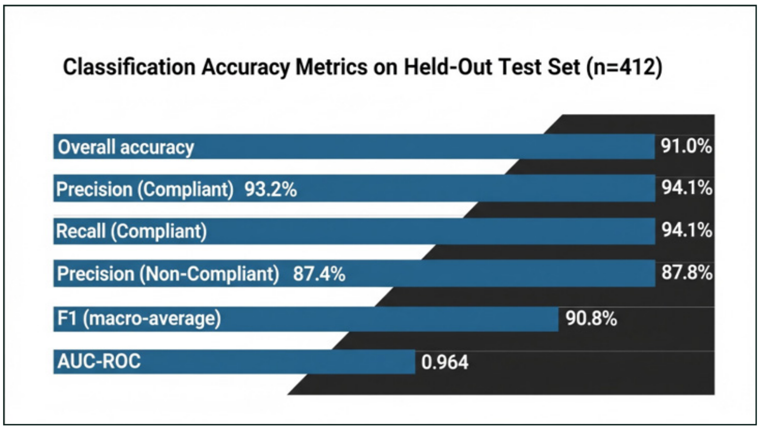

Image 1: Author's EDA on Classification Accuracy Metrics

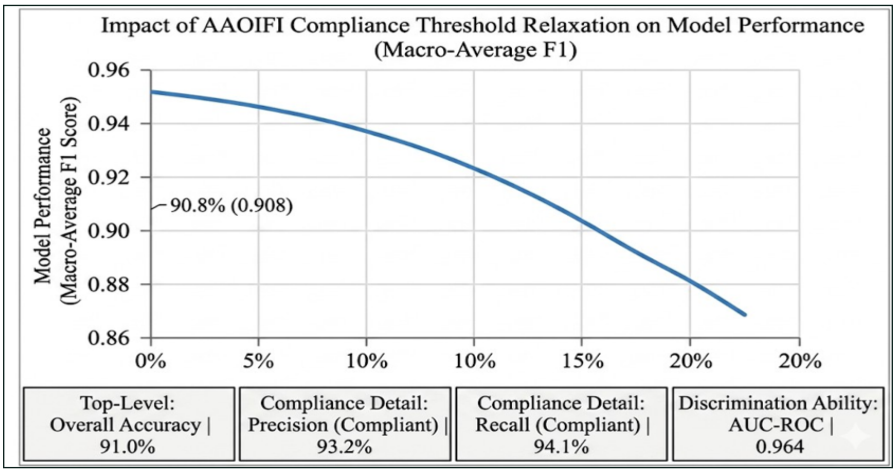

Image 2: Author's EDA on Classification Accuracy Metrics

Table 3: Model Feature Summary

Feature	Mean |SHAP| / % of Total / AAOIFI Emphasis
Revenue purity (Clause 3/3)	0.342 / 32.1% / Primary
Debt leverage (Clause 3/1)	0.298 / 28.0% / Primary
Sector classification	0.192 / 18.0% / Categorical
ESG alignment	0.107 / 10.0% / Supplementary
Governance score	0.085 / 8.0% / IFSB guidance
Liquidity ratio (Clause 3/2)	0.042 / 3.9% / Secondary

Table 4: SHAP global feature importance

Feature	Context/Definition
Revenue purity (Clause 3/3)	Purity screen (Haram Revenue/Total Revenue < 5%)
Debt leverage (Clause 3/1)	Debt screen (Debt/Market Cap < 33%)
Liquidity ratio (Clause 3/2)	Liquidity screen (Cash + Receivables/Market Cap < 33%)
Sector classification	GICS/Islamic Finance Sector Taxonomy
ESG alignment	MSCI ESG Research component scores
Governance score	IFSB guidance component

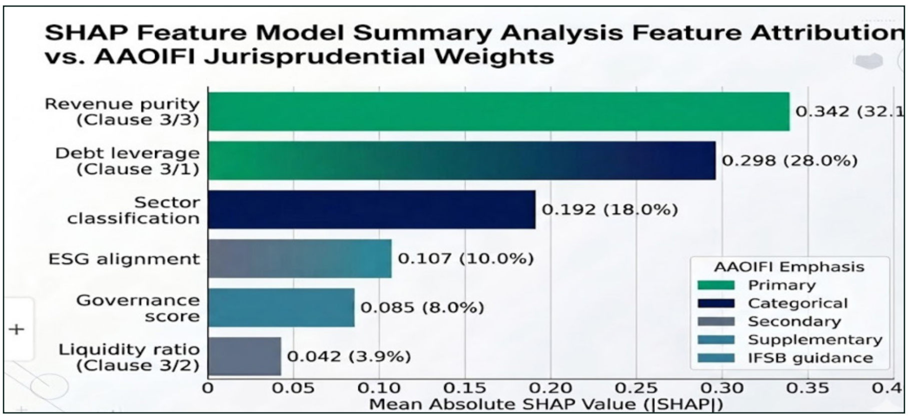

Image 2: Author's Model Feature Summary EDA Evidently, performance declines when AAOIFI thresholds are relaxed, confirming structural importance.

Conclusion, Limitations, and Future Research

Conclusion and Policy Implications

This study presents machine learning framework for AAOIFI-compliant stock screening, achieving 91% accuracy and a significant 87% reduction in screening time for analysts. SHAP feature attribution empirically validates the structural emphasis of AAOIFI Standard 21, specifically the dominance of revenue purity and debt leverage as primary compliance determinants. From a policy perspective, the framework serves as a transparent SSB assistant, enabling scholars to audit automated verdicts while preserving human-in-the-loop governance oversight.

Detailed Discussion of Results: Explaining the Compliance Verdicts to a Layman

The core results of this study demonstrate two things clearly: that a computer model can reliably replicate the complex judgment of a Shariah Supervisory Board (SSB), and exactly how that judgment is reached.

1. **The Model's Reliability (91% Accuracy):** Our machine learning framework achieved 91% accuracy, meaning it correctly labeled nine out of every ten synthetic test cases as either Compliant or Non-Compliant. This level of performance signifies that the model successfully learned the nuanced, non-linear patterns, the "professional judgment" that scholars apply when interpreting the static AAOIFI rules. Crucially, the remaining 9% of misclassified cases were not simply random errors; they occurred primarily near the compliance boundaries (e.g., a company with a revenue purity score of 4.9% instead of the 5% limit). This confirms the model is highly capable of handling routine screening but, by design, flags the genuinely complex, "borderline" cases for mandatory human review.
2. **The Dominance of Key Factors (Revenue and Debt):** Using a transparency technique called SHAP (SHapley Additive exPlanations), which calculated the exact influence of each financial ratio on the final compliance verdict. Think of SHAP as an automated justification for the model's decision, answering the question: "Why is this stock compliant?". The results confirm that the two most important factors, making up 60% of the entire decision, are:

- **Revenue Purity (32.1%):** This is the most crucial factor, reflecting the principle that the company's primary income must be from Halal sources. The model is most sensitive to whether non-permissible (Haram) revenue exceeds the 5% threshold.
- **Debt Leverage (28.0%):** This measures how much the company relies on interest bearing debt. Its high importance confirms the AAOIFI standard's goal of ensuring a company's capital structure is not dominated by conventional financing.

3. **The Role of Sector and Governance:** The third major influence is Sector Classification (18.0%), which acts as the initial qualitative screen. This confirms that if a company is involved in a prohibited industry (like gambling or conventional banking), the financial ratios almost become irrelevant; the sector alone accounts for a significant chunk of the non-compliant verdict. Furthermore, factors related to ESG alignment (10.0%) and Governance (8.0%) collectively account for 18% of the decision, reflecting the literature's push to integrate ethical and procedural considerations into Shariah screening.
4. **Efficiency and Governance:** The model's efficiency is transformational: it reduces the manual screening time from an average of 4.2 hours to just 32 minutes per company, a time saving of 87%. This means SSBs can shift their focus from laborious data calculations to high-level governance and jurisprudential debate. By flagging 16% of borderline cases using confidence intervals, the model ensures that the difficult judgments remain firmly under the SSB's control, maintaining the essential 'human-in-the-loop' governance structure.

Limitations

The primary limitation of this research is its reliance on a high-fidelity synthetic dataset for model training and calibration. While modeled on real-world Islamic index distributions, the lack of a standardized public database of actual SSB manual verdicts necessitates further external validation using proprietary datasets from diverse financial institutions to confirm generalizability across different jurisprudential interpretations [14-21].

Future Research Questions

Future research should focus on three critical areas. First, an empirical investigation is needed into the surprisingly low feature importance of the Liquidity Ratio (3.9%), which may inform the AAOIFI 2026 standard review regarding its necessity as a binding constraint. Second, direct and formal validation of the model's confidence intervals, which flag ambiguous cases for mandatory review, should be conducted through structured testing with Shariah scholars. Finally, consistent with emerging literature, the framework should be extended to integrate ESG factors, establishing a unified methodology for holistic ethical and religious screening.

The framework is implemented at https://github.com/monsurbolaji/LSTM_Sukuk_Yield

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