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Predictive Power of Random Forests in Analyzing Risk Management in Islamic Banking

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Abstract: This study utilizes the random forest technique to investigate risk management practices and concerns in Islamic banks using survey data from 2016 to 2021. Findings reveal that larger banks provide more consistent survey responses, driven by their confidence and larger survey budgets. Moreover, a positive link is established between a country's development, characterized by high GDPs and low inflation and interest rates, and the precision of Islamic banks' survey responses. Analyzing risk-related concerns, the study notes a significant reduction in credit portfolio risk attributed to improved risk management practices, global economic growth, stricter regulations, and diversified asset portfolios. Concerns related to terrorism financing and cybersecurity risks have also decreased due to the better enforcement of anti-money laundering regulations and investments in cybersecurity infrastructure and education. This research enhances our understanding of risk management in Islamic banks, highlighting the impact of bank size and country development. Additionally, it emphasizes the need for ongoing analysis beyond 2021 to account for potential COVID-19 effects and evolving risk management and regulatory practices in Islamic banking.

Keywords: risk management; Islamic banks; survey analysis; random forest; machine learning

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1. Introduction

The banking sector has experienced multiple instances of digital change, commencing with the extensive integration of automated teller machines (ATMs) and credit cards. Technology has become integral to the banking industry in the past decade. The emergence of the Bank 4.0 idea is characterized by converting a wide range of financial services into an online format (King 2018). The rapid adoption of digital transformation has become imperative for banks to maintain competitiveness within an industry encompassing financial institutions, technology giants, start-ups, and media-telecommunication corporations.

The utilization of financial technology, commonly known as fintech, can aid banks in maintaining their competitiveness within a progressively digitized global landscape. Banks that exhibit limited success in adopting technology face the potential consequence of client attrition to micro-scale fintech businesses, which effectively cater to the demands of digitally proficient customers, particularly the younger demographic. According to Aysan and Unal (2021), banks can maintain relevance in a highly competitive market by embracing fintech solutions.

On the other side, financial institutions have faced the complex challenge of managing risk for many years, a fundamental aspect of their operations. The advent of financial technology, commonly referred to as fintech, has brought about significant and revolutionary developments in the financial industry. This essay aims to understand these risk

management strategies via an alternative method of random forest, which is desired to bring an alternative to the existing Islamic financial risk management literature.

Risk assessment automation has been identified as a significant contribution of fintech to risk management (Sibanda et al. 2020). Fintech advancements enable financial organizations to automate diverse aspects of risk assessment. By utilizing machine learning algorithms, these technologies can evaluate large datasets in real-time, enabling financial institutions to gain a more comprehensive and timely understanding of market conditions, creditworthiness, and operational risks. Implementing automation mitigates reliance on manual procedures, thereby reducing the probability of human fallibility and enhancing the accuracy of risk assessments (Yunita 2021). Moreover, it has been observed that fintech systems can provide automated notifications if they surpass predetermined risk thresholds. This functionality enables prompt intervention and mitigates potential financial losses (Diener and Špaček 2021).

In order to ensure effective risk management, it is necessary to assess the capacity of an organization to withstand and recover from unfavorable circumstances. Fintech solutions enable this by employing stress testing and scenario analysis techniques. According to Giatsidis et al. (2019), financial institutions can utilize these tools to assess vulnerabilities and adopt risk mitigation methods by simulating different scenarios, such as economic downturns and market volatility.

Given the ongoing evolution of the financial landscape, it is anticipated that the incorporation of fintech advancements will assume greater significance for financial institutions in their efforts to proficiently handle and alleviate risks, thereby safeguarding the stability and resilience of the financial sector (Khanboubi and Boulmakoul 2019; Abuhasan and Moreb 2021). The nature of this relationship is marked by a fragile equilibrium, wherein the judicious management of risks can augment a bank's performance. In contrast, insufficient risk management can result in financial instability and potential collapse (Firmansyah and Anwar 2019). Banks can mitigate potential losses and maximize investment returns by implementing efficient risk management measures. For example, the effective management of credit risk portfolios ensures that loans are granted to individuals with strong creditworthiness, hence decreasing the probability of loan defaults and enhancing the overall profitability of the institution (Khanboubi and Boulmakoul 2019; Tsindeliani et al. 2022).

Moreover, according to Diener and Špaček (2021), the ability of banks to accurately identify and efficiently manage risks plays a crucial role in preserving a favorable reputation, attracting a larger client base, and obtaining finance under advantageous conditions. These factors all contribute to enhancing the banks' financial performance.

The strong relationship between regulatory compliance and risk management is a fundamental aspect, as the continuing functioning of a bank relies heavily on strict adherence to regulatory regulations. Financial institutions that fail to adhere to regulatory requirements expose themselves to potential monetary penalties and risk detrimental effects on their public image and standing. Therefore, it is imperative to implement effective risk management strategies that guarantee adherence to regulatory requirements in order to maintain long-term performance.

In summary, a mutually beneficial association exists between a bank's performance and risk management strategies. Using efficient risk management strategies can enhance a bank's financial performance, reputation, and adherence to regulatory requirements, facilitating its sustained prosperity. On the contrary, inadequate risk management practices can lead to financial instability and a deterioration in overall performance. Hence, banks must give precedence to establishing resilient risk management frameworks to navigate the intricacies of the financial sector effectively.

The goal of the study consists of two parts. Firstly, to derive findings from a comprehensive financial performance analysis of Islamic banks on a global scale, focusing on assessing their risk management practices based on the results obtained from surveys. Secondly, to prove that damaged or heavily missing datasets can still bring significant results for a survey study via utilizing the random forest machine learning method. The

paper focuses on examining the risk management scenario of Islamic banks through an evaluation of their financial performance, as obtained from survey findings. It encompasses a comprehensive methodology for evaluating the soundness and resilience of these financial establishments. Through analyzing significant financial indicators, including capital adequacy ratios, asset quality, liquidity, and profitability, stakeholders and regulators can acquire useful insights into the effective management of diverse risks within Islamic banks. These insights are derived from survey responses and serve to assess the banks' risk management practices. This research facilitates the identification of possible vulnerabilities and areas of strength within the risk management frameworks of these organizations. Through the correlation of financial performance data and survey results about risk management practices, it becomes possible to establish a holistic comprehension of the risk environment prevalent in Islamic banks. This understanding facilitates well-informed decisions, regulatory supervision, and the adoption of strategies to bolster their ability to withstand economic and financial uncertainties.

The subsequent sections of the paper are presented in the following manner. Section 2 provides a comprehensive overview of the existing scholarly works on the subject issue. Section 3 presents a thorough exposition of the data and technique employed. Section 4 delves into the outcomes derived from the data by applying the recommended methodology. The final section encompasses the concluding remarks.

2. Literature Review

Risk management in Islamic finance and banking is a heavily studied area. Besides the main risk challenges in the financial sector, Islamic banks also have sector-specific risks, such as Shariah non-compliance risk. While Islamic banks cover these risks by applying standards, mainly Basel III, some exposures are covered by international Islamic financial institutions' standards, such as AAOIFI or Bank Negara Malaysia (Malim 2015).

With the advanced risk mitigation techniques, Islamic banks have significantly improved their risk exposures and overall risk management capabilities. Moreover, the global standardization of Shariah-related risk management has improved the overall compatibility of Islamic banks in the last decade. The overall picture of Islamic banking from a risk governance perspective is shifting to a positive window at this time (Al Rahahleh et al. 2019).

Overall, Islamic banks have significantly improved their risk management methodology and techniques. A portion of the literature focuses on the effect of Fintech on these risk management capabilities. Hasan (2019) comprehensively analyzed how fintech improves the risk management techniques of Islamic financial institutions. The author mentions that each department of Islamic banks benefits from the fintech-focused risk management improvement in their own way. Although fintech brings some new types of risks, it covers those too, with increasing efficiency.

Several survey studies in the current literature have been conducted to measure and understand the risk management strategies used in Islamic banks. Abu Hussain and Al-Ajmi (2012) surveyed a group of Islamic bankers in Bahrain to understand the efficiency of their risk management strategies. The authors mentioned that, while the risks faced by Islamic banks are significantly higher than those faced by conventional banks, the management strategies are competent enough to drive Islamic banks, even in this decade's harsh financial environment.

While survey studies remain an important part of the Islamic finance risk management literature, the robustness and reliability of the survey studies are questioned from time to time. Surveys are mainly based on personal opinions, and significant biases exist. Miller and Mitamura (2003) questioned the trustworthiness of survey studies with a deep analysis of their biases. This type of methodological weakness requires an extra robustness test to ensure the results are correct. Machine learning techniques in the latest technology may help in this purpose. Buskirk and Kolenikov (2015) conducted a study using the random forest machine learning method to improve survey analysis studies. Their methodology and results are in line with this study.

While the random forest is a heavily utilized technique in financial analysis and survey studies, the literature lacks an analysis of this technique for improving Islamic financial institutions' survey data. This research is motivated to bring a new focus area in Islamic finance risk literature by using advanced machine learning techniques to improve survey quality, thus opening new horizons with global data that have not been used before. It is desired that the famous Global Islamic Banking Survey that is used in this study (more of which is in the upcoming sections) will yield significant results because of its size and value in the Islamic financial world.

3. Data and Methodology

The data of this research consist of variables shown in the below table. Among these variables, the first group represents data for bank performance in CAMEL format, the second group represents bank-level data, the third group variable is the GIBS survey data, and the last group is country-level data for reducing error. Table 1 below illustrates the types of data used in this research. CAMEL data are used to understand the financial situation of the banks (Ping and Kusairi 2020; Aebi et al. 2012). Thus, their risk exposure of different points, such as credit risk, interest rate risk, and so on, will be cleared out. Table 1 is a summary of the variables used in the study. The fintech survey questions are categorized as one in this table, while there are many questions in the survey for ease of reading. There are 72 variables in this study, including survey questions.

Table 1. Types of data. Source: Author's own.

Variable Names	Code	Variable
Total Equity/Total Assets (%)	C	Capitalization
Imp. Loans (NPLs)/Gross Loans	A1	Asset Quality
Non-Performing Loans/Gross Loans (%)	A2	Asset Quality 2
Cost to Income Ratio (%)	M	Management Efficiency
Net Interest Margin	E1	Earnings
ROAA (%)	E2	Earnings
ROAE (%)	E3	Earnings
Liquid Assets/Deposits and ST Funding (%)	L	Liquidity
Total Assets—Banks	TA_USD	
Log of Total Assets	Z	Size
Total Operating Expense	TOE	
Operating Income (GS)	OIGS	
Net Fees and Commissions	NFC	
Total Cap. Ratio	TCR	
Equity/Total Assets	E/TA	
Total Cap.	TCAP	
Fintech Survey Questions	SURVEY	
GDP (USD) LOG	LOGGDP	
Annual Inflation (Percentage)	INF	
Real Interest Rates (Percentage)	IR	

a. GIBS Survey 2016–2021

The present study utilizes a distinctive dataset and implements a quantitative research methodology. The data utilized in this study are derived from the Global Islamic Bankers' Survey undertaken by the General Council for Islamic Banks and Financial Institutions (CIBAFI) from 2016 to 2021.

The acronym CIBAFI stands for the General Council for Islamic Banks and Financial Institutions, a globally recognized entity serving as a representative body for the Islamic finance sector. The organization was established in 1993 and is headquartered in Manama, Bahrain. The organization's primary objective is to foster and enhance the global Islamic finance industry. The goals above are achieved by establishing a platform wherein member

institutions can exchange knowledge and expertise. Additionally, the organization conducts research endeavors and disseminates publications about the Islamic finance industry. Furthermore, active engagement with regulators and policymakers is undertaken to foster the growth and advancement of the Islamic finance sector. According to CIBAFI (2022), the number of member institutions affiliated with CIBAFI exceeds 130, spanning more than 30 countries globally.

The Global Islamic Banking Survey (GIBS) is an annual survey conducted by CIBAFI among senior executives of Islamic banks worldwide. Its purpose is to obtain insights into the present state of the sector and its prospective trajectory. The survey plays a pivotal role in the direct observation of management goals and motivations of decision-makers, enabling the utilization of this knowledge in quantitative testing. The survey was initiated in 2016 and is still ongoing. The dataset included in this paper encompasses survey data spanning from the year 2016 to 2021.

The dataset included in this study comprises around 37 countries and a total of 175 Islamic banks. Nevertheless, it should be noted that not all 175 banks participate in this poll regularly each year. On average, approximately 100–105 banks join the survey annually. These countries are classified into seven groups to analyze and extrapolate geographical patterns. CIBAFI annually releases survey reports and executive summaries that provide comprehensive overviews of the important highlights within the worldwide Islamic banking business. From a scholarly standpoint, the Global Islamic Bankers Survey (GIBS) is a great resource for gathering a wide range of data pertaining to Islamic financial institutions worldwide.

b. Bank-level and Country-level data from Fitch Connect and World Bank Databases

Bank-level data in this article were collected from Fitch Connect. Fitch Connect is a platform provided by Fitch Ratings, global credit ratings, and research firms. It is a comprehensive resource for financial market participants, providing access to various credit ratings, research, and analytics tools (Aysan and Bergigui 2021). Collected data include "Total Equity/Total Assets (%), Imp. Loans (NPLs)/Gross Loans, Non-Performing Loans/Gross Loans (%), Cost to Income Ratio (%), Net Interest Margin, ROAA (%), ROAE (%), Liquid Assets/Deposits and ST Funding (%), Total Assets—Banks, Log of Total Assets, Total Operating Expense, Operating Income (GS), Net Fees and Commissions, Total Cap. Ratio, Equity/Total Assets, and Total Cap" (Ameur and Mhiri 2013).

More data on a country level are collected from the World Bank Database to be used to reduce errors. Country-level data include GDP, inflation, and interest rates. All collected data are from 2016 to 2021.

Table 2 below shows the number of columns for each variable. In the upcoming parts, these numbers are used to represent each variable for a clear look at the figures.

Table 2. Variable numbers. Source: Author's Own.

#	Variable Name	#	Variable Name
1	IDB (Bank ID)	37	Competition from conventional financial institutions
2	IDC (Country ID)	38	Margin pressure
3	Region	39	Service quality
4	Country Code	40	Back office operations
5	Fitch ID	41	Risk management
6	Year	42	Investment capability
7	A1	43	Product offering and innovation
8	A2	44	Corporate governance
9	C	45	Shariah Standards, compliance, and governance framework
10	E/TA	46	Information technology

Table 2. *Cont.*

#	Variable Name	#	Variable Name
11	E1	47	Compliance (anti-money laundering, counter terrorist financing, etc.)
12	E2	48	Human resources and talent development
13	E3	49	Business growth and expansion
14	Inflation	50	Financial inclusion, micro- and SME financing
15	Interest rates	51	Consumer attraction, relation, and retention
16	Liquid Assets	52	Consumer protection
17	Log(GDP)	53	Shareholder value and expectations
18	M	54	Q 2.1 Score the level of riskiness faced by your institution from the following types of risks in the next 1–3 years (where 5 = extreme risk and 1 = no risk at all)—Credit risk
19	NFC	55	Collateral risk
20	OIGS	56	Credit portfolio risk
21	TA_USD	57	Rate of return risk
22	TCAP	58	Commodity price risk
23	TCR	59	Currency risk
24	TOE	60	Equity investment risk
25	Z	61	Liquidity risk
26	SURVEY—Financial Performance	62	Competencies of people risk
27	Bank Size	63	Misconduct and fraud risk
28	Q1.1 What is your level of optimism about the state of the banking market in your jurisdiction this year?	64	Technology risk and IT security
29	Q 1.2 Score your optimism level in the future of the Islamic banking industry in your jurisdiction today compared to your confidence level in 2015	65	Transactions, process, and delivery risk
30	Q 1.3 What is your expectation for the revenue growth of your institution relative to conventional banks in the year 2016 within your jurisdiction?	66	Legal risk
31	Q 1.4 Score your institution's main concerns regarding various issues and challenges facing your institution over the next 1–3 years (where 5 = extremely important and 1 = not important at all)—Macro-economic environment	67	Shariah non-compliance risk
32	Political uncertainty	68	Strategic risk
33	Regulations concerning Islamic finance	69	Enterprise/Managerial risk
34	Islamic financial market infrastructure	70	Reputational risk
35	Capital adequacy, callable capital, and reserve requirements	71	Tax risk
36	Competition from other Islamic financial institutions	72	Money laundering and financing of terrorism risk

c. Methodology

The global Islamic banking data exhibits many shortcomings, particularly its continuity. Certain regions exhibit a deficiency in maintaining meticulous records, posing challenges in obtaining a comprehensive set of bank-level data.

The presence of missing data compromises the integrity of the regression findings. To address this difficulty, it is necessary to employ a suitable approach for populating the vacant sections of the dataset. This research will employ the random forest strategy, which is well-recognized as a highly practical and accurate method for compiling machine learning data.

The random forest classifier methodology is widely utilized in machine learning for various applications, encompassing classification, regression, and feature selection. The

technique described in the study conducted by Speiser et al. (2019) involves the integration of numerous decision trees in order to generate predictions or assess the relative significance of various parameters.

The random forest technique is characterized by its excellent accuracy and robustness. The integration of numerous decision trees enables the detection and representation of diverse patterns and relationships within the dataset, hence mitigating the risk of overfitting and enhancing the model's overall performance (Schonlau and Zou 2020). The random forest technique is widely favored among data scientists and analysts due to its ease of use and implementation.

The methodology can effectively process extensive and intricate datasets. In contrast to most machine learning approaches, the random forest algorithm exhibits a notable resilience towards expanding dataset size and dimensions. This characteristic enables the algorithm to effectively adjust and accommodate these particular attributes of the dataset (Ahmad et al. 2018). This feature renders it advantageous for picture or text categorization applications, particularly in scenarios where the dataset is voluminous and characterized by many dimensions.

Although the random forest technique is widely used and well-regarded, it is not without its limits. One of this approach's primary limitations is its substantial computational expenses, particularly in instances where the dataset is of considerable size. The interpretability of this technique is comparatively lower than that of other machine learning methods, which poses challenges in comprehending the rationale behind the model's predictions or the assessment of feature significance (Brieuc et al. 2018).

The random forest technique does not directly impute or replace missing or empty data. In contrast, the employed methodology involves using the bootstrapping technique to generate several decision trees, each trained on a distinct subset of the dataset (Egbert and Plonsky 2021). The random forest technique utilizes all decision trees to make predictions, hence mitigating the influence of missing data on the model's overall performance.

It is important to acknowledge that the random forest technique does not fully address the issue of missing data. The model's performance may be adversely impacted if there is a substantial quantity of missing data or if the data are missing randomly. In instances of missing data, it may be imperative to employ alternative techniques, such as imputation, to address the gaps before training the random forest model. This approach has the potential to enhance both the performance and dependability of the model. Before applying the random forest algorithm, the necessary adoptions and manual fills were carried out on the data to obtain the most accurate prediction results.

The bank performance measurement design is predicated on maximizing the proportion of non-blank data within the dataset. In order to achieve this objective, a conventional yet resilient method known as CAMEL is employed. The CAMEL methodology is employed as a means of evaluating the comprehensive financial soundness of a banking institution. CAMEL stands for capital adequacy, asset quality, management quality, earnings, and liquidity (Karma and Sukasih 2019; Aysan et al. 2022). Bank regulators employ the CAMEL grading system to assess a bank's performance and detect potential dangers. The process entails comprehensively examining a bank's financial statements and operational aspects, encompassing factors such as capital adequacy, asset quality, managerial strategies, profitability, and liquidity (Vadrale 2019). According to Naushad (2021), the CAMEL analysis outcomes are employed to assign a rating to the bank, whereby higher ratings indicate a more robust financial position, while lower ratings suggest a comparatively weaker financial situation.

The use of the methodology commences with the enhancement of the data. The Google Colab application is utilized for this particular section of the program. Implementing a machine learning application involved importing the requisite libraries, namely, Pandas, Numpy, Seaborn, and MatPlot. Following the application of formatting parameters to the dataset, it was observed that the data had 948 rows and 72 columns. Following this procedure, the SkLearn libraries provide several tools, such as the random forest classifier,

random forest regressor, train test split model, and normalization tools. In addition to the random forest models, the K-Nearest regressor and K-Nearest classifiers were also obtained to conduct a robustness assessment. Figure A1 displays the number of non-null rows for each variable out of 948.

Figure A1 shows the empty cells of the data, especially in the survey answers. The main reason is that many banks did not regularly partake in the survey. Instead, most of them joined the survey for a few years on average. Some regions' undisciplined bookkeeping caused other missing data in the banking part. One important point is that the Python programming language starts listing variables with zero. Therefore, although there are 72 variables, the last variable is 71, not 72. This is to prevent possible confusion for the readers. Figure 1 below shows the heatmap of the correlation for 72 variables before random forest application.

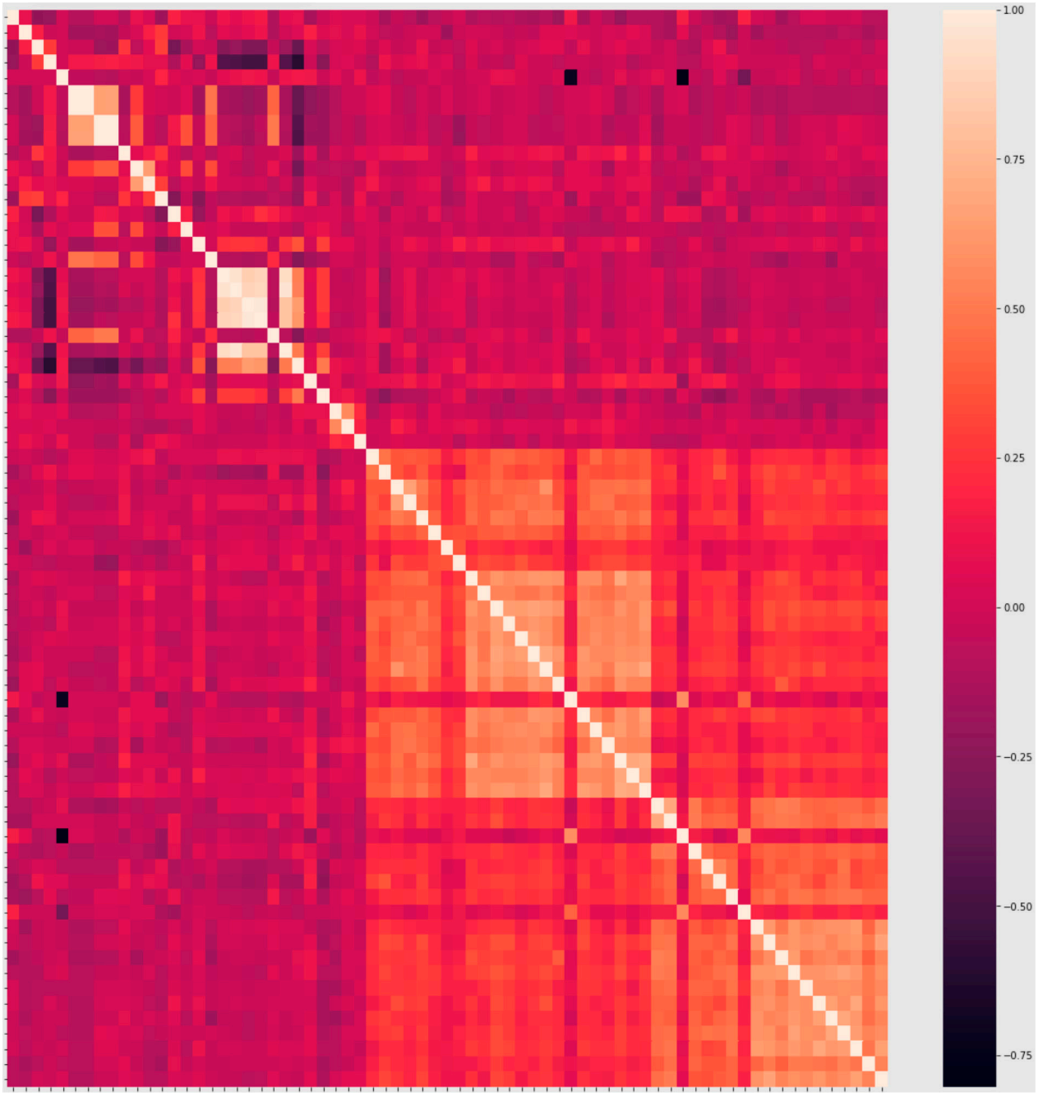

Figure 1. Correlation heatmap. Source: Author's Own, Google Colab.

The heatmap shows higher correlations with a lighter color. From this point, variables 5 and 6, meaning A1 and A2 (Asset qualities), show 100% correlation, representing the same value. Similarly, variables 17 to 20 are highly correlated. These variables will be reduced into one value for representative purposes, as more than one variable for the exact measurements worsens the test quality of the random forest. This is explained as follows: While the random forest builds the decision trees, it uses the closest variables to the empty target cell. A 100% correlation with this cell directly leads the random forest classifier to

fill the cell with the same data, which may not be desired. The expected outcome is to determine the empty cell value from the other cells' correlation. Therefore, some of the values will be eliminated in this step.

The correlations in Figure 1 already give some clear results. However, the interpretation of the results requires the improvement of the data. In this part, the random forest application is explained.

The test train split for this dataset is kept at 30–70%. An extensive test size is used to maintain high accuracy in the results. With this application, a random forest classifier resulted in 99% accuracy in training and 76% in testing. Here, a supposition is applied by considering if a bank has two or three close values for the same variable; other variables are also accepted as close. The random forest regressor also gives a similar accuracy result for both parts in Figure 2.

```
[ ]  RFR = RandomForestRegressor(10)
     RFR.fit(predictors_train,target_train)
     print("Training: "+str(RFR.score(predictors_train,target_train)))
     print("Testing : "+str(RFR.score(predictors_test,target_test)))

     Training: 0.9220159806358662
     Testing : 0.5588196411709159
```

Figure 2. Random forest regressor accuracy.

With this classification, the random forest has filled the dataset with the Figure 3 summary. K-Nearest methods resulted in much lower accuracy, possibly because the number of years is only six, which is not enough for this method to predict the cells accurately. Therefore, a random forest was used to interpret the results.

```
[77] RFC = RandomForestClassifier(10)
     RFC.fit(predictors_train,target_train)
     print("Training: "+str(RFC.score(predictors_train,target_train)))
     print("Testing : "+str(RFC.score(predictors_test,target_test)))

     Training: 0.996042216358839
     Testing : 0.7631578947368421
```

Figure 3. Random forest classifier accuracy.

Additionally, for a specific cell, if the specific bank has value for other years, the random forest keeps a relationship between all years while considering a relationship web between all bank performances, survey answers, and its country's economic situation. Suppose there are no data for the specific variable for all years. In that case, the random forest engine predicts the relative value by considering other banks with similar performances, the bank's overall variables for all years, and the country's economic data. These decision trees help maintain highly accurate results without losing consistency. With this version of the data, we performed the random forest regression tests, and the results are given in the next chapter.

4. Results and Discussion

After data improvement, a dataset of 948 × 72 is repaired completely, with the results being around 85% accurate. Table 3 below shows the summary statistics before and after the random forest application. Improvements are visible in non-null data and the protection of the values in general.

Table 3. Summary of the data before and after the random forest application. Source: Author's Own.

Before Random Forest Classifier									After Random Forest Classifier								
#	Count	Mean	Std	Min	25%	50%	75%	Max	#	Count	Mean	Std	Min	25%	50%	75%	Max
1	948	86.47	51.55	1.00	41.00	85.50	127.00	182.00	1	948	86.47	51.55	1.00	41.00	85.50	127.00	182.00
2	948	19.78	10.41	1.00	11.00	21.00	29.00	37.00	2	948	19.78	10.41	1.00	11.00	21.00	29.00	37.00
3	948	3.18	1.92	1.00	1.00	3.00	5.00	7.00	3	948	3.18	1.92	1.00	1.00	3.00	5.00	7.00
4	948	999,292	422,835	107,486	1,004,008	1,068,892	1,238,970	1,502,960	4	948	999,292	422,835	107,486	1,004,008	1,068,892	1,238,970	1,502,960
5	948	2018.50	1.71	2016.00	2017.00	2018.50	2020.00	2021.00	5	948	2018.50	1.71	2016.00	2017.00	2018.50	2020.00	2021.00
6	596	7.56	12.49	-	2.02	3.88	7.75	100.00	6	596	7.56	12.49	-	2.02	3.88	7.75	100.00
7	596	7.56	12.49	-	2.02	3.88	7.75	100.00	7	596	7.56	12.49	-	2.02	3.88	7.75	100.00
8	772	18.40	19.46	0.14	8.69	12.52	16.63	153.87	8	772	18.40	19.46	0.14	8.69	12.52	16.63	153.87
9	772	18.08	19.55	0.14	8.48	11.55	16.50	153.87	9	772	18.08	19.55	0.14	8.48	11.55	16.50	153.87
10	747	3.89	3.45	-	2.33	3.15	4.55	40.07	10	747	3.89	3.45	-	2.33	3.15	4.55	40.07
11	757	2.15	4.19	-	0.68	1.17	1.90	49.62	11	757	2.15	4.19	-	0.68	1.17	1.90	49.62
12	751	13.33	14.88	-	5.75	10.03	15.74	168.74	12	751	13.33	14.88	-	5.75	10.03	15.74	168.74
13	754	10.14	24.18	0.13	1.49	2.79	5.69	150.32	13	754	10.14	24.18	0.13	1.49	2.79	5.69	150.32
14	421	7.14	5.31	0.32	3.84	5.93	8.51	26.79	14	421	7.14	5.31	0.32	3.84	5.93	8.51	26.79
15	757	88.99	516.39	0,98	11.01	20.39	37.06	9663.86	15	757	88.99	516.39	0,98	11.01	20.39	37.06	9663.86
16	917	11.10	0.65	9.57	10.58	11.16	11.55	13.36	16	917	11.10	0.65	9.57	10.58	11.16	11.55	13.36
17	772	75.21	134.81	12.23	41.49	53.45	69.37	2236.36	17	772	75.21	134.81	12.23	41.49	53.45	69.37	2236.36
18	733	52.98	122.87	-	3.96	14.00	43.04	1195.75	18	733	52.98	122.87	-	3.96	14.00	43.04	1195.75
19	772	377.24	926.02	-	23.85	107.49	355.73	10,326.41	19	772	377.24	926.02	-	23.85	107.49	355.73	10,326.41
20	772	10,004.44	19,711.84	5.60	544.66	2911.71	11,474.16	243,773.31	20	772	10,004.44	19,711.84	5.60	544.66	2911.71	11,474.16	243,773.31
21	588	1546.88	3101.38	0.18	158.47	456.73	1670.36	34,069.07	21	588	1546.88	3101.38	0.18	158.47	456.73	1670.36	34,069.07
22	621	25.64	36.74	0.03	15.52	18.00	21.92	455.00	22	621	25.64	36.74	0.03	15.52	18.00	21.92	455.00
23	772	228.56	554.11	0.12	17.53	72.25	221.75	7264.13	23	772	228.56	554.11	0.12	17.53	72.25	221.75	7264.13
24	772	3.39	0.84	0.75	2.74	3.46	4.06	5.39	24	772	3.39	0.84	0.75	2.74	3.46	4.06	5.39
25	882	3.72	1.10	1.00	3.00	4.00	5.00	5.00	25	882	3.72	1.10	1.00	3.00	4.00	5.00	5.00
26	372	1.91	1.10	-	1.00	2.00	3.00	4.00	26	372	1.91	1.10	-	1.00	2.00	3.00	4.00
27	372	3.44	0.74	-	3.00	3.00	4.00	5.00	27	372	3.44	0.74	-	3.00	3.00	4.00	5.00
28	372	3.56	0.86	-	3.00	4.00	4.00	5.00	28	372	3.56	0.86	-	3.00	4.00	4.00	5.00
29	372	3.42	0.84	-	3.00	3.00	4.00	5.00	29	372	3.42	0.84	-	3.00	3.00	4.00	5.00
30	372	4.16	0.84	-	4.00	4.00	5.00	5.00	30	372	4.16	0.84	-	4.00	4.00	5.00	5.00
31	372	3.75	1.02	-	3.00	4.00	4.00	5.00	31	372	3.75	1.02	-	3.00	4.00	4.00	5.00
32	372	3.73	0.99	-	3.00	4.00	4.00	5.00	32	372	3.73	0.99	-	3.00	4.00	4.00	5.00
33	372	3.63	0.98	-	3.00	4.00	4.00	5.00	33	372	3.63	0.98	-	3.00	4.00	4.00	5.00
34	372	3.82	1.10	-	3.00	4.00	5.00	5.00	34	372	3.82	1.10	-	3.00	4.00	5.00	5.00
35	372	3.48	0.95	-	3.00	4.00	4.00	5.00	35	372	3.48	0.95	-	3.00	4.00	4.00	5.00
36	372	3.23	1.18	-	3.00	3.00	4.00	5.00	36	372	3.23	1.18	-	3.00	3.00	4.00	5.00
37	372	3.54	1.03	-	3.00	4.00	4.00	5.00	37	372	3.54	1.03	-	3.00	4.00	4.00	5.00
38	372	4.08	0.98	-	4.00	4.00	5.00	5.00	38	372	4.08	0.98	-	4.00	4.00	5.00	5.00
39	372	3.47	1.02	-	3.00	4.00	4.00	5.00	39	372	3.47	1.02	-	3.00	4.00	4.00	5.00
40	372	4.09	0.98	-	4.00	4.00	5.00	5.00	40	372	4.09	0.98	-	4.00	4.00	5.00	5.00

Table 3. *Cont.*

Before Random Forest Classifier									After Random Forest Classifier								
#	Count	Mean	Std	Min	25%	50%	75%	Max	#	Count	Mean	Std	Min	25%	50%	75%	Max
41	372	3.80	0.96	-	3.00	4.00	4.00	5.00	41	372	3.80	0.96	-	3.00	4.00	4.00	5.00
42	372	3.99	0.99	-	4.00	4.00	5.00	5.00	42	372	3.99	0.99	-	4.00	4.00	5.00	5.00
43	372	3.87	1.04	-	3.00	4.00	5.00	5.00	43	372	3.87	1.04	-	3.00	4.00	5.00	5.00
44	372	3.98	1.10	-	3.00	4.00	5.00	5.00	44	372	3.98	1.10	-	3.00	4.00	5.00	5.00
45	372	4.17	0.95	-	4.00	4.00	5.00	5.00	45	372	4.17	0.95	-	4.00	4.00	5.00	5.00
46	372	2.43	2.12	-	-	3.00	4.00	5.00	46	372	2.43	2.12	-	-	3.00	4.00	5.00
47	372	4.04	0.89	-	4.00	4.00	5.00	5.00	47	372	4.04	0.89	-	4.00	4.00	5.00	5.00
48	372	3.97	0.96	-	4.00	4.00	5.00	5.00	48	372	3.97	0.96	-	4.00	4.00	5.00	5.00
49	372	3.67	1.00	-	3.00	4.00	4.00	5.00	49	372	3.67	1.00	-	3.00	4.00	4.00	5.00
50	372	4.17	0.94	-	4.00	4.00	5.00	5.00	50	372	4.17	0.94	-	4.00	4.00	5.00	5.00
51	372	3.78	1.02	-	3.00	4.00	4.00	5.00	51	372	3.78	1.02	-	3.00	4.00	4.00	5.00
52	372	4.17	0.95	-	4.00	4.00	5.00	5.00	52	372	4.17	0.95	-	4.00	4.00	5.00	5.00
53	372	3.34	1.07	-	3.00	3.00	4.00	5.00	53	372	3.34	1.07	-	3.00	3.00	4.00	5.00
54	372	2.97	0.98	-	2.00	3.00	4.00	5.00	54	372	2.97	0.98	-	2.00	3.00	4.00	5.00
55	372	1.22	1.65	-	-	-	3.00	5.00	55	372	1.22	1.65	-	-	-	3.00	5.00
56	372	2.99	1.02	-	2.00	3.00	4.00	5.00	56	372	2.99	1.02	-	2.00	3.00	4.00	5.00
57	372	2.74	1.10	-	2.00	3.00	3.00	5.00	57	372	2.74	1.10	-	2.00	3.00	3.00	5.00
58	372	3.13	1.14	-	2.00	3.00	4.00	5.00	58	372	3.13	1.14	-	2.00	3.00	4.00	5.00
59	372	2.71	1.11	-	2.00	3.00	3.00	5.00	59	372	2.71	1.11	-	2.00	3.00	3.00	5.00
60	454	4.90	2.44	-	3.00	4.00	4.00	5.00	60	454	4.90	2.44	-	3.00	4.00	4.00	5.00
61	372	2.96	1.00	-	2.00	3.00	4.00	5.00	61	372	2.96	1.00	-	2.00	3.00	4.00	5.00
62	372	2.81	1.02	-	2.00	3.00	3.00	5.00	62	372	2.81	1.02	-	2.00	3.00	3.00	5.00
63	372	3.33	1.02	-	3.00	3.00	4.00	5.00	63	372	3.33	1.02	-	3.00	3.00	4.00	5.00
64	372	2.84	0.99	-	2.00	3.00	3.00	5.00	64	372	2.84	0.99	-	2.00	3.00	3.00	5.00
65	372	2.78	0.93	-	2.00	3.00	3.00	5.00	65	372	2.78	0.93	-	2.00	3.00	3.00	5.00
66	372	2.69	1.18	-	2.00	2.00	3.00	5.00	66	372	2.69	1.18	-	2.00	2.00	3.00	5.00
67	372	2.95	1.03	-	2.00	3.00	4.00	5.00	67	372	2.95	1.03	-	2.00	3.00	4.00	5.00
68	372	2.74	0.93	-	2.00	3.00	3.00	5.00	68	372	2.74	0.93	-	2.00	3.00	3.00	5.00
69	372	2.86	1.11	-	2.00	3.00	4.00	5.00	69	372	2.86	1.11	-	2.00	3.00	4.00	5.00
70	372	2.42	1.02	-	2.00	2.00	3.00	5.00	70	372	2.42	1.02	-	2.00	2.00	3.00	5.00
71	372	3.00	1.15	-	2.00	3.00	4.00	5.00	71	372	3.00	1.15	-	2.00	3.00	4.00	5.00

Figure 4 below is the correlation heatmap of the 72 variables after the random forest application. Denser colors are visible compared to the previous version of the heatmap, which means the correlation is positively or negatively higher after the improvement.

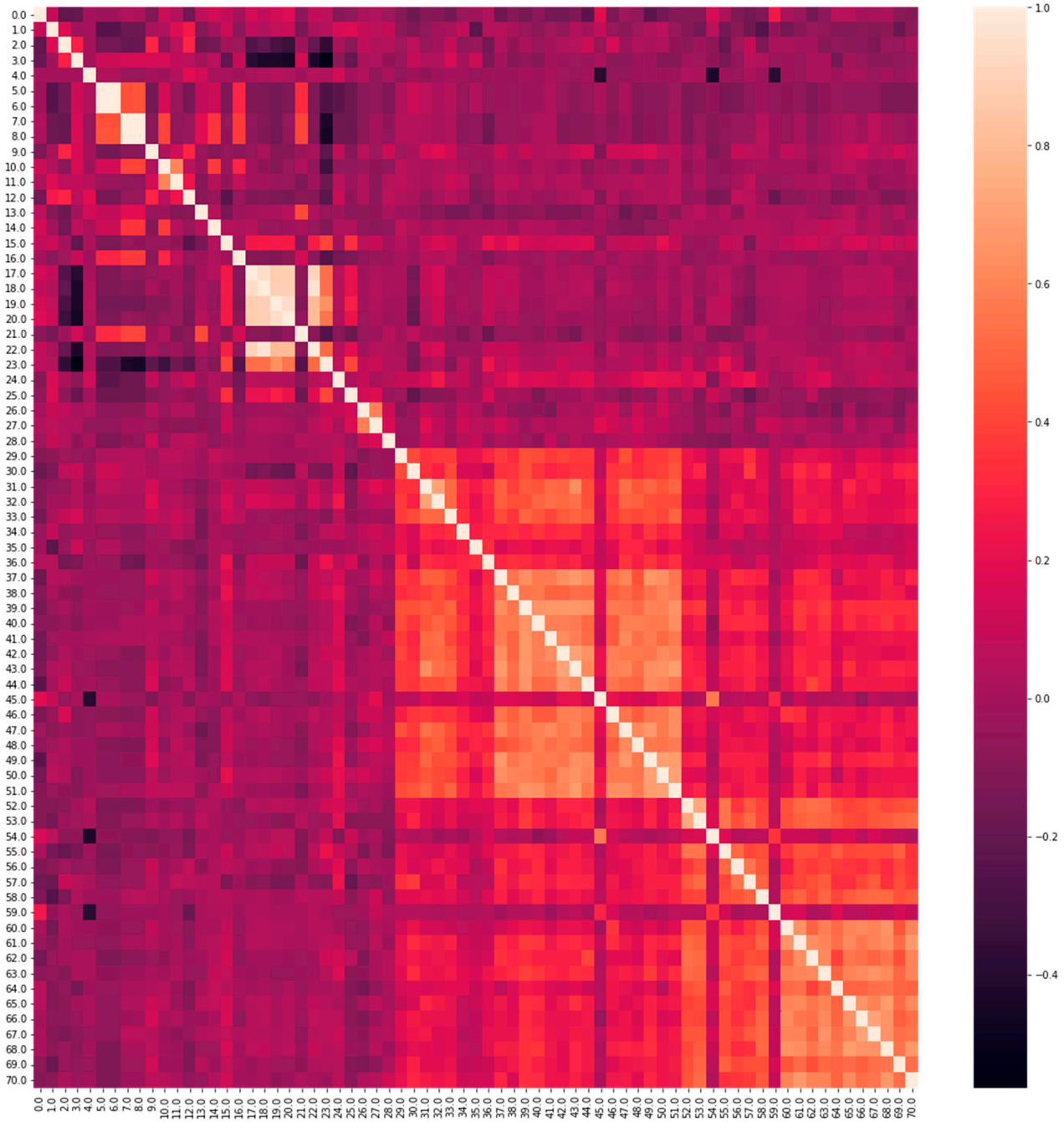

Figure 4. Correlation heatmap after the random forest application. Source: Author's Own.

Using bank-level data and a machine learning model in this work facilitates a comprehensive examination of the accuracy and reliability of the banks' survey responses. In the hypothetical scenario where a bank's survey response fails to align with its current performance average as determined by the aggregate average of comparable banks, an inquiry arises regarding the accuracy of the response provided in the survey. Furthermore, the disparity between the responses provided in the survey and the real-world circumstances allows for establishing a consistency metric for every bank. This model is imperative for establishments wherein surveys constitute a fundamental aspect of their operations, given

the substantial expenses associated with conducting such surveys in terms of temporal, financial, and human resources.

The heatmap reveals a positive relationship between consistency, bank size, country development, and bank profit. Regarding the size of banks, empirical findings indicate that larger banks tend to provide survey responses that more accurately align with their real operational circumstances. Although the existing literature does not provide much evidence on this outcome, major banks are expected to exhibit reduced apprehension in substantiating their institutional caliber and experience heightened confidence. Existing literature does not establish a direct correlation between the size of a bank and the quality of survey responses. Schiffer and Weder (2001) explained that larger institutions may employ more decentralized decision-making methods. Consequently, the response provided by a particular department may not accurately represent the views of other departments, resulting in a lack of uniformity in the survey responses. However, given that the upper management of these institutions responded to the GIBS Survey, a breakdown in communication between various sections is not expected. In contrast, larger financial institutions frequently possess a greater allocation of resources for conducting surveys, enabling the acquisition of more comprehensive and intricate data. This enhanced capacity facilitates the identification of incongruous responses. Furthermore, it can be seen that banks that generate substantial profits are often characterized by their advanced development and large-scale operations, hence reinforcing the correlation between bank size and profitability. Hence, a positive correlation exists between bank profitability and survey responses.

The second finding demonstrates a significant correlation between the level of national development and the overall quality of the responses obtained from the survey participants. Banks in nations characterized by robust gross domestic product (GDP), minimal inflation rates, and low interest rates tend to provide more accurate representations of their prevailing circumstances within the context of survey responses. Existing literature indicates that countries with higher levels of development tend to exhibit more educational attainment (Darwish et al. 2018), more robust moral frameworks (Schillinger 2006), and enhanced linguistic competency (Casale and Posel 2011). These characteristics may contribute to a higher level of consistency in the responses provided by banks in industrialized countries during surveys. On the other hand, it is worth noting that, in nations with lower levels of development, there may exist a lower degree of uniformity in the interpretation and response to survey questions. This can be attributed to variations in educational attainment, cultural practices, and linguistic obstacles.

The subsequent section of the study pertains to the hazards that are of concern to financial institutions. Upon analyzing the survey responses from 2016 to 2021, a notable decrease in risk-related apprehensions about Islamic banks is observed. One finding indicates a considerable reduction in the credit portfolio risk of Islamic banks during the years covered by the sample data. One plausible explanation can be attributed to the implementation of enhanced risk management strategies by Islamic financial institutions. Sophisticated credit scoring algorithms, early warning systems, and stress testing have efficiently identified and reduced potential credit problems. Implementing these techniques has led to enhancements in the risk management framework of Islamic banks, hence contributing to establishing a more secure and robust financial system.

Current global economic development and stability are additional aspects that contribute to mitigating credit risk for Islamic institutions. Consequently, there has been a notable upsurge in economic activity and investment prospects, fostering a more robust loan landscape for banks, particularly those adhering to Islamic principles. The enhancement of borrowers' creditworthiness has been facilitated by both economic growth and stability, resulting in a subsequent decrease in credit risk.

The involvement of regulatory frameworks has been crucial in mitigating credit risk for Islamic banks. Implementing stricter regulations and supervision requirements by regulatory authorities has resulted in a safer and more stable financial system for Islamic banks. According to Mahomed et al. (2021), implementing these standards has enhanced

governance, heightened transparency, and fostered a more efficient risk management structure within Islamic banks.

In conclusion, the practice of diversifying asset portfolios has proven to be effective in mitigating credit risk for Islamic banks. Islamic banks have effectively mitigated their overall credit risk by diversifying their investments across various assets, reducing their vulnerability to any single sector or borrower. Diversification has, additionally, facilitated the ability of Islamic banks to access novel investment prospects, hence leading to the establishment of an income stream characterized by enhanced stability and diversification.

In summary, the recent decline in credit risk for Islamic banks can be ascribed to a confluence of variables, encompassing the adoption of enhanced risk management methodologies, the presence of a stable and growing global economy, the establishment of regulatory frameworks, and the diversification of asset portfolios. These variables have played a role in enhancing the safety and stability of the banking sector, hence mitigating credit risk exposure for Islamic financial institutions. An essential aspect to consider within this discourse is incorporating responses in the dataset from 2016 to 2021. Hence, the impact of the COVID-19 pandemic may not be readily discernible in the available data. To eliminate the pandemic's influence, it is important to perform a distinct analysis, including 2022 and 2023.

Furthermore, the data above demonstrate a comparable decrease in terrorism funding and cybersecurity risk concerns across the Islamic banking sector. One potential factor is the heightened consciousness and implementation of legislation concerning anti-money laundering (AML) and counter-terrorism funding (CTF). Recently, regulatory bodies have implemented more stringent AML and CTF legislation. These restrictions have been extended to encompass financial institutions, including Islamic banks, to mitigate the risk of terrorist financing. The enhancement of due diligence and risk assessment procedures in Islamic banks has reduced the risk associated with terrorism financing.

Islamic financial institutions increasingly embrace a risk-based approach (RBA) to AML/CFT compliance, mitigating these apprehensions. RBA mandates that financial institutions conduct a comprehensive evaluation of the risks connected with their clients and transactions and adopt appropriate steps to minimize these risks. The implementation of a risk-based approach by Islamic banks has facilitated the enhanced identification and management of transactions with elevated risk levels. Consequently, this has led to a notable mitigation of the risk associated with supporting terrorism.

One plausible cause for the worries surrounding cybersecurity risks is the heightened allocation of resources toward developing and implementing cybersecurity infrastructure and technology. In response to the escalating cyberattack risks observed in the past seven years, Islamic banks have invested substantially in bolstering their cybersecurity infrastructure. These investments primarily encompass the implementation of various protective measures such as firewalls, intrusion detection and prevention systems, and data encryption technologies. These precautions have been implemented to safeguard their systems and data against cyber assaults.

In addition, enhancing cybersecurity threat awareness among staff and customers plays a significant role in mitigating cybersecurity risks within the context of Islamic banks. Islamic financial institutions have made strategic investments in cybersecurity training initiatives aimed at imparting knowledge to their workforce regarding the significance of cybersecurity and equipping them with the necessary skills to identify and mitigate cyber risks. Additionally, the organization has developed consumer education initiatives to enhance customer awareness regarding the potential hazards linked to Internet banking and provide guidance on safeguarding oneself against cyber threats.

Using machine learning techniques in financial risk analysis would be pointed as a direct implementation of fintech in risk management procedures. We hope this study will show that alternative advanced techniques would improve the survey-based risk analysis results, as the cost of these surveys is already sky-high for institutions. Moreover,

if surveys with missing data could be supported with the actual financial data under the right technique, results could still lead the financial institutions in the right direction.

It is important to consider that the data included in this study are derived from survey responses provided by senior executives in the banking industry. Surveys are frequently employed to acquire valuable insights into the performance and strategies of banks through the collection of responses from bank managers. Nevertheless, it is imperative to identify and consider the various limitations inherent in this study methodology. The present setting entails several constraints about surveys, which are outlined below:

Response bias can have an impact on the accuracy of survey responses, as participants may feel inclined to submit answers that are socially desirable or deliberately misleading information. Bank managers may hesitate to reveal sensitive or confidential information about their organizations, potentially jeopardizing the data's accuracy.

One of the study's main limitations is that the sample data have many blank cells, mostly repaired by the random forest classifier and regressor. However, it is important to remember that the model predicts the blank cells, not fills them with actual data. Therefore, the quality of the results may be slightly different than those that would appear from the original data. However, this study aims to prove that limited or damaged data can still produce an original result with the true machine learning techniques applied.

5. Conclusions

a. Future Research Recommendations

Future studies in the field of Islamic banking and risk management should endeavor to investigate several possible paths in order to enhance our comprehension of this pivotal domain. To begin with, implementing comprehensive case studies on distinct Islamic banks across various geographical areas can yield significant insights into the practical obstacles and optimal strategies for risk management. The case studies should consider the distinct cultural, regulatory, and economic settings within which these banks function.

Furthermore, there is a need to research the potential effects of emerging technologies, including blockchain and artificial intelligence, on the risk management strategies employed by Islamic banks. This particular domain presents a promising avenue for further investigation. This study has the potential to provide valuable insights into how these technologies can improve the processes of identifying, measuring, and mitigating risks inside Islamic financial institutions.

Moreover, there is a growing significance attached to the investigation of incorporating environmental, social, and governance (ESG) elements within the risk management techniques of Islamic banking. Examining the compatibility between Islamic banking principles and environmental, social, and governance (ESG) factors can offer valuable perspectives on the ability of Islamic banks to effectively handle both conventional financial risks and ethical and sustainability-related problems.

Furthermore, with the ongoing expansion of Islamic banking worldwide, it would be worthwhile to conduct comparative research examining the effectiveness, efficiency, and resilience of risk management practices between Islamic and conventional banks.

In conclusion, implementing longitudinal studies to monitor the progression of risk management techniques inside Islamic banks can facilitate the identification of industry trends, difficulties, and advancements. These studies can also provide significant insights for regulators, practitioners, and policymakers.

Future research should enhance our understanding of how Islamic banks effectively handle risks in a swiftly evolving financial environment. This can be accomplished by incorporating case studies, technological advancements, environmental, social, and governance (ESG) considerations, comparative analyses, and longitudinal studies. These approaches will contribute to a comprehensive understanding of this crucial domain.

b. Policy recommendations

Survey studies are common in practice. However, most of the time, their accuracy is questioned. Using advanced machine learning techniques would bring additional robustness to these academic studies. The main reason for this issue is not from the study but rather from the survey. The methodology in this research opens a new gateway to improving survey accuracy, especially in developing countries where this inaccuracy may be more apparent.

Another policy recommendation for the banks is to use advanced machine learning techniques to reduce the number of questions in each survey. As the cost of these surveys is already very high for institutions, asking fewer questions will save time in both the survey and subsequent research and analysis.

Lastly, as machine learning technology helps derive more results from the surveys, financial institutions must use them more to understand their performance levels and positioning in the industry.

c. Concluding remarks

In summary, the correlation between a bank's performance and risk management methods is indisputably complex and significantly influential. Implementing efficient risk management practices is not solely a mandated obligation but a crucial strategic necessity for financial institutions. The factor above significantly influences a bank's financial performance, resilience, and public perception. Prudent risk management strategies facilitate banks in maximizing profits on their investments, upholding the confidence of customers and investors, and ensuring adherence to regulatory norms. On the other hand, insufficient risk management practices can result in substantial monetary setbacks, harm one's reputation, and potentially even incur the threat of bankruptcy.

Moreover, the correlation between performance and risk management is particularly emphasized within the framework of Islamic banking. Under the guidance of Sharia rules, Islamic banks encounter a distinctive risk environment that necessitates specific methodologies for identifying, quantifying, and mitigating risks. Incorporating ethical and moral factors, adherence to Islamic law (Sharia), and excluding certain financial instruments present unique obstacles and prospects for risk management within Islamic banking institutions. Further investigation in this field ought to examine these particular characteristics to construct resilient risk management frameworks customized for the Islamic financial sector.

Furthermore, utilizing technological advancements, such as blockchain and artificial intelligence, alongside incorporating environmental, social, and governance (ESG) considerations, offers potential opportunities for improving risk management strategies in both conventional and Islamic banking institutions. The significance of proficient risk management persists as the financial sector undergoes continuous transformation. It is imperative to engage in ongoing research endeavors to adapt and innovate risk management techniques in response to the evolving landscape of risks and opportunities.

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Data Availability Statement: Private Data.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 948 entries, 0 to 947
Data columns (total 72 columns):
 #   Column                                                                                                                                  Non-Null Count  Dtype
---  ------                                                                                                                                  --------------  -----
 0   IDB                                                                                                                                     948 non-null    int64
 1   IDC                                                                                                                                     948 non-null    int64
 2   REGION                                                                                                                                  948 non-null    int64
 3   COUNTRYCODE                                                                                                                             948 non-null    object
 4   Fitch ID                                                                                                                                948 non-null    int64
 5   YEAR                                                                                                                                    948 non-null    int64
 6   A1                                                                                                                                      596 non-null    float64
 7   A2                                                                                                                                      596 non-null    float64
 8   C                                                                                                                                       772 non-null    float64
 9   E/TA                                                                                                                                    772 non-null    float64
 10  E1                                                                                                                                      747 non-null    float64
 11  E2                                                                                                                                      757 non-null    float64
 12  E3                                                                                                                                      751 non-null    float64
 13  INF                                                                                                                                     754 non-null    float64
 14  IR                                                                                                                                      421 non-null    float64
 15  L                                                                                                                                       757 non-null    float64
 16  LOGGDP                                                                                                                                  917 non-null    float64
 17  M                                                                                                                                       772 non-null    float64
 18  NFC                                                                                                                                     733 non-null    float64
 19  OIGS                                                                                                                                    772 non-null    float64
 20  TA_USD                                                                                                                                  772 non-null    float64
 21  TCAP                                                                                                                                    588 non-null    float64
 22  TCR                                                                                                                                     621 non-null    float64
 23  TOE                                                                                                                                     772 non-null    float64
 24  Z                                                                                                                                       772 non-null    float64
 25  SURVEY - Financial Performance                                                                                                          882 non-null    float64
 26  Size                                                                                                                                    372 non-null    float64
 27  Q1.1 What is your level of optimism on the state of the banking market in your jurisdiction this year?                                 372 non-null    float64
 28  Q 1.2 Score your optimism level in the future of the Islamic banking industry in your jurisdiction today compared to your confidence level in 2015.  372 non-null    float64
 29  Q 1.3 What is your expectation on the revenue growth of your institution relative to conventional banks in the year 2016 within your jurisdiction?  372 non-null    float64
 30  Q 1.4 Score your institution's main concerns regarding various issues and challenges facing your institution over the next 1-3 years (where 5 = extr  372 non-null    float64
 31  Political uncertainty                                                                                                                   372 non-null    float64
 32  Regulations concerning Islamic finance                                                                                                  372 non-null    float64
 33  Islamic financial market infrastructure                                                                                                 372 non-null    float64
 34  Capital adequacy, callable capital and reserve requirements                                                                             372 non-null    float64
 35  Competition from other Islamic financial institutions                                                                                   372 non-null    float64
 36  Competition from conventional financial institutions                                                                                    372 non-null    float64
 37  Margin pressure                                                                                                                         372 non-null    float64
 38  Service quality                                                                                                                         372 non-null    float64
 39  Back office operations                                                                                                                  372 non-null    float64
 40  Risk management                                                                                                                         372 non-null    float64
 41  Investment capability                                                                                                                   372 non-null    float64
 42  Product offering and innovation                                                                                                         372 non-null    float64
 43  Corporate governance                                                                                                                    372 non-null    float64
 44  Shariah standards, compliance, and governance framework                                                                                 372 non-null    float64
 45  Information technology                                                                                                                  372 non-null    float64
 46  Compliance (Anti-Money Laundering, Counter Terrorist Financing, etc.)                                                                   372 non-null    float64
 47  Human resources and talent development                                                                                                  372 non-null    float64
 48  Business growth and expansion                                                                                                           372 non-null    float64
 49  Financial inclusion, micro- and SME financing                                                                                           372 non-null    float64
 50  Consumer attraction, relation and retention                                                                                             372 non-null    float64
 51  Consumer protection                                                                                                                     372 non-null    float64
 52  Shareholder value and expectations                                                                                                      372 non-null    float64
 53  Q 2.1 Score the level of riskiness faced by your institution from the following types of risks in the next 1-3 years (where 5 = extreme risk and 1 =  372 non-null    float64
 54  Collateral risk                                                                                                                         372 non-null    float64
 55  Credit portfolio risk                                                                                                                   372 non-null    float64
 56  Rate of return risk                                                                                                                     372 non-null    float64
 57  Commodity price risk                                                                                                                    372 non-null    float64
 58  Currency risk                                                                                                                           372 non-null    float64
 59  Equity investment risk                                                                                                                  372 non-null    float64
 60  Liquidity risk                                                                                                                          454 non-null    float64
 61  Competencies of people risk                                                                                                             372 non-null    float64
 62  Misconduct and fraud risk                                                                                                               372 non-null    float64
 63  Technology risk and IT security                                                                                                         372 non-null    float64
 64  Transactions, process, and delivery risk                                                                                                372 non-null    float64
 65  Legal risk                                                                                                                              372 non-null    float64
 66  Shariah non-compliance risk                                                                                                             372 non-null    float64
 67  Strategic risk                                                                                                                          372 non-null    float64
 68  Enterprise/Managerial risk                                                                                                              372 non-null    float64
 69  Reputational risk                                                                                                                       372 non-null    float64
 70  Tax risk                                                                                                                                372 non-null    float64
 71  Money laundering and financing of terrorism risk                                                                                        372 non-null    float64
```

Figure A1. Non-null rows. Source: Author's Own, from Google Colab.

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