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Clustering Defensive Shariah-compliant Stocks Using Financial Performance as the Indicator

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Abstract*— Malaysian stocks, including Shariah-compliant stocks, have experienced turbulence last year. Although there are defensive stocks, the well-performing ones are not easily identified. Researchers have proposed various metrics to identify defensive stocks. However, most of the approaches require human intervention. In this study, we focus on Shariah-compliant stocks and propose to automate the labeling of stocks in terms of their financial performance via clustering. The study aims to identify the optimal clustering method to label the clusters. This was achieved by first employing *k*-Means, Agglomerative, and Mean Shift clustering to group similar stocks before labeling. When labeling, the criteria to distinguish well-performing defensive Shariah-compliant stocks were high dividend yield, low price-earnings ratio, low Beta value, and low price-to-book value. After labelling each stock with its financial performance (Low, Medium, High), we performed classification using Logistic Regression, *k*-Nearest Neighbors, Support Vector Machine, Decision Tree, and Random Forest to verify the credibility of the labels. Based on the results, the clusters created by k-Means clustering outperformed the rest in matching accuracy. Further investigation was conducted on the *k*-Means data set by dividing the data according to sector and classifying each sector's data separately. Logistic Regression outperformed other classification algorithms with an accuracy of 71.5%. The findings also suggested accuracy increased when stocks were classified according to sectors. Further considerations include performing outlier analysis on the data to select well-performing stocks.

***Keywords*— Defensive shariah-compliant stocks; clustering; weighted scores; profiling; classification.**

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I. INTRODUCTION

Stocks, including Shariah-compliant stocks, are often unpredictable since they are affected by internal and external factors. In particular, the Malaysian stock market suffered turbulence in 2022 due to geopolitical tensions, rising global interest rates, and inflation [1]. Though it is expected to have a turnaround by the latter half of the year 2023 [2], investors struggle to make suitable investments in the current state of the local stock market. In this unpredictable market, risk-averse investors are suited for stable stocks with minimal variance and low volatility. A suitable option for Malaysian investors is defensive Sharia-compliant stocks. Defensive Shariah-compliant stocks are (i) defensive or non-volatile (Beta Value < 1) stocks and (ii) Shariah-compliant or follow Islamic Principles [3]–[5].

Stocks listed on Bursa Malaysia are considered Shariah-compliant if they meet the screening requirements of the Securities Commission of Malaysia. A stock is not Shariah-compliant if (i) the firm mainly invests in prohibited business activities based on the Shariah law, which include producing or selling 'haram' goods (alcohol, pork, or pornography), and (ii) includes 'riba' or interest (conventional banking, gambling) [4]–[6]. Muslim investors are generally concerned about gaining income through 'halal' methods. Therefore, Shariah compliance is an important aspect to consider in-stock selection. In fact, non-Muslim investors may also be interested in Shariah-compliant stocks since these equities are usually defensive, leading to increased stability [7]. Defensive stocks are desirable, especially to risk-averse investors, as their price does not drop severely during a bear market. Thus, defensive Shariah-compliant stocks are suitable for Muslims, who make up a majority of Malaysian citizens [8].

This study contributes to easing the investor's burden since studying the characteristics of a well-performing defensive stock makes it possible to automate the stock selection. In addition, the use of data mining techniques can help to define the performance of a stock. Therefore, the main objective of this study was to identify the optimal clustering method to label the clusters. Labeling is crucial in determining each stock's performance to help investors identify well-performing stocks to avoid non-performing stocks. We accomplish this goal by testing several clustering methods to group similar stocks. To test the performance of each clustering method, we label the resulting clusters based on their financial performance before evaluating the fitness of the clustered stocks using classification algorithms.

II. Materials and Method

A. Indicators for Defensive Stocks

Risk-averse investors seek defensive stocks, which are considered safe since they minimize losses and provide steady returns. Defensive stocks possess low Beta values, minimal variance, and low volatility [9], [10]. As such, these stocks are usually stable even in a recession economic cycle, providing constant dividends to their shareholders.

Defensive stocks are associated with four financial ratios: dividend yield, price-earnings ratio, Beta value, and price-to-book value. **Dividend yield (DY)** calculates the percentage of a company's share market price that it pays as dividends to its stockholders annually [11]. The **Beta value** represents the stock price volatility relative to the stock market [12]. A stock with a Beta value of less than 1 is defensive in nature. **Price-earnings (PE) ratio** relates a stock's price to its earnings per share [13], whereas **Price-to-book value (PBV)** measures how much value the firm can generate for the company [14].

From the standpoint of risk-averse investors, they seek high DY stocks as they would want to receive steady profits while waiting. Thus, these investors prefer low-price fluctuation stocks (low Beta values). Furthermore, they would select stocks with low PE and low PBV. PE ratio and PBV are relative valuation metrics that contrast a company's value at a certain time with its rivals or peers in the industry [15]. Low PE or low PBV suggests that a stock is undervalued and may offer a high rate of return in the future [14].

Previous literature also supports that high DY and low PE ratios are traits usually linked to more defensive stocks [16]. In addition, Benjamin Graham's Defensive Investor Strategy is still used in recent literature in which stocks with PE < 15 and PBV < 1.5 are selected for investing [17]. Defensive stocks are also mainly defined by possessing low Beta values, which contrast with cyclical stocks' high Beta values [18]. Table I details recent studies from the last five years that have applied the following financial ratios about aggressive/defensive stocks.

TABLE I
FINANCIAL RATIOS USED IN STUDIES RELATED TO CYCLICAL/NON-CYCLICAL STOCKS

Author(s)	DY	PE	PBV	Beta
[16] Cardinali & Yasenchak	/	/		
[19] De Rossi et al.	/	/		
[20] Sharma et al.	/	/	/	
[17] Wirawan & Sumirat		/	/	
[21] Dhingra et al.		/	/	
[22] Backhaus at al.	/		/	
[18] Chen et al.				/
[23] Liao et al.				/
[9] Mestre				/
[24] Bukar & Daniel				/
[25] Loviscek & Xie				/

This shows that the mentioned financial ratios still apply to current research and are suitable for this study. Hence, we studied the behavior of risk-averse investors and the characteristics of defensive stocks to understand the background of the study.

B. Clustering Approach to Segmentation of Stocks

Various studies used clustering methods on stock or financial-related data to solve numerous problems. Palupi et al. [26] focused on decision efficiency in portfolio investment diversification using different clustering methods. They tested *k*-Means clustering, DBSCAN, Agglomerative clustering, and Mean Shift clustering on data of 175 assets from the Indonesia Stock Exchange in 2018. The experimental results showed that DBSCAN and Agglomerative clustering provided a higher portfolio return and reduced risk than the other two algorithms.

Vilas et al. [27] studied whether the inclusion and exclusion criteria of sustainability stock indices (FTSE4Good Global, FTSE4Good Developed 100, FTSE4Good US, FTSE4Good US 100, and FTSE4Good Europe) were different from the ones applied in conventional stock indices. The authors applied five clustering methods (*k*-Means, Agglomerative, Spectral, Mean Shift, and Affinity Propagation). They determined that four sustainability indices used a different inclusion process from the conventional indices. In addition, the clustering analysis validated the index classifications of four sustainability indices.

Putra et al. [28] proposed a method to form diversified stock portfolios on the weekly close price data of the KOMPAS-100 stocks from 2009-2018. The method used B-spline for dimensionality reduction of the data set, then grouped similar stocks using *k*-Means clustering. The portfolios consisted of stocks from different clusters for diversification and were formed using Mean-Variance and Equal-Weighted approaches. The back-testing showed that the Mean-Variance portfolio performed better (less volatility and higher Sharpe index) than KOMPAS-100. On the other hand, the Equal-Weighted portfolio performed worse than the index.

Dziuba et al. [29] reviewed 30 developed and emerging stock markets by examining their portfolios' risk, return, and level of international diversification. *k*-Means clustering was used to study the patterns of stock markets and portfolio investment flows. The paper confirmed its hypothesis whereby the level of international diversity in developed market investors' portfolios was higher than that in emerging market investors' portfolios.

TABLE II
SUMMARY OF STUDIES USING CLUSTERING METHODS

Author(s)	*k*-Means	Agglomerative	Mean Shift	DBSCAN	Affinity Propagation	Spectral	*k*-Medoids	Fuzzy based
[26] Palupi et al.	/	/	/	/				
[27] Vilas et al.	/	/	/		/	/		
[28] Putra et al.	/							
[29] Dziuba et al.	/							
[30] Owen & Oktariani		/						
[31] Xu et al.	/							
[32] Nakagawa et al.							/	
[33] Zainol Abidin et al.								/
[34] Buszko et al.	/							
[35] Salgado-Hernández & Vyas		/						
[36] Chaudhari & Thakkar	/							
[37] Chen & Rehman	/	/	/		/	/		

Owen and Oktariani [30] improved stock market prediction with stock data and sentiment scores derived from microblog text. In the initial phase of their research, they used Agglomerative clustering with distance matrix DTW to narrow the scope of their study. Due to limitations in time and API access, the researchers split the stocks listed on the Dow Jones Industrial Average Index during 2019 into 11 clusters and only accounted for the most volatile cluster.

The clustering methods used in the studies above and other related works are summarized in Table II. Most research used *k-means clustering, followed by Agglomerative* and Mean Shift clustering. These papers helped select different clustering methods for our study: *k*-Means, Agglomerative, and Mean Shift clustering. As they have distinct implementations, it will be interesting to note which method performs the best on our data set. Clustering methods have been used on various stock mining problems and could be implemented in our study to find a clustering method that optimizes the labeling of the clusters.

C. Methodology

The following are the steps taken to conduct our study: (i) data preparation and pre-processing, (ii) clustering, (iii) labeling clusters' performance with weighted scores, (iv) classification using the labeled clusters, and (v) evaluation. The flow chart of the method is shown in Figure 1 and is further explained in the following subsections.

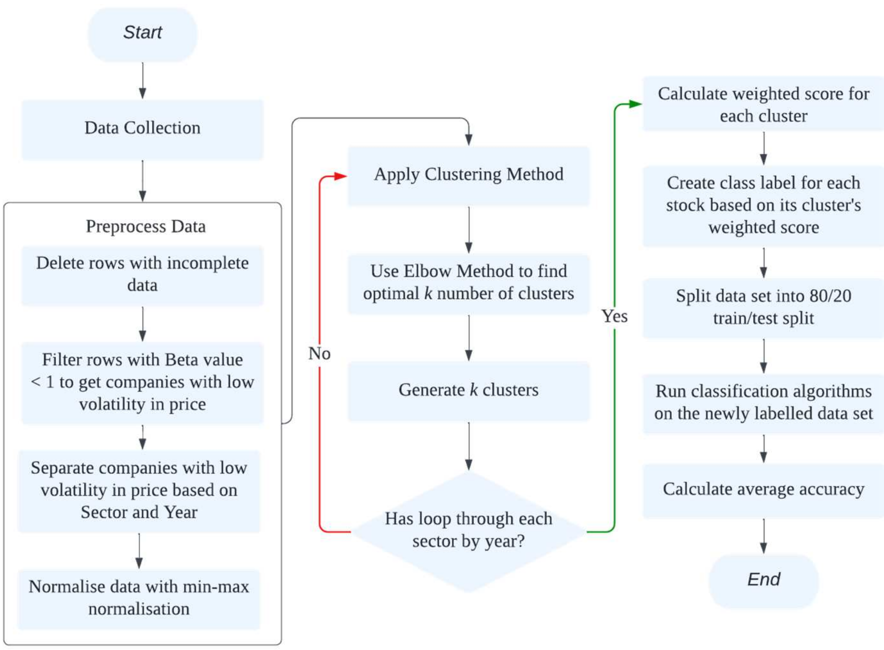

Fig. 1 Flow Chart of the Methodology

1) Data Set Description: A total of 3,359 Shariah-compliant stock financial data listed on Bursa Malaysia from 2018 until 2022 were collected using DataStream. The number of stocks in 2018, 2019, 2020, 2021, and 2022 are 648, 658, 671, 674, and 708, respectively. The data consisted of stock data from 10 different sectors: (i) Consumer Products & Services, (ii) Industrial Products & Services, (iii) Property, (iv) Construction, (v) Health Care, (vi) Technology, (vii) Telecommunications & Media, (viii) Transportation & Logistics, (ix) Plantation, and (x) Utility.

The initial data set consisted of company names, sectors, and annual data of four financial ratios. The financial ratios, their data type, and the formulae are shown in Table III. When pre-processing, we discarded stock data consisting of null values that cannot be found from other sources, such as the Bursa Malaysia portal. Additionally, it is noted that negative PE ratio values were set to zero.

TABLE III
THE FOUR FINANCIAL RATIOS USED IN THIS STUDY

Financial Ratio	DataStream Datatype	Formula
Dividend Yield	DY	Dividend per Share / Price per Share
Price to Book Value	PBV	Stock Market Price / Book Value per Share
Price-earnings Ratio	PE	Price per Share / Earnings per Share
Beta Value	WC09802	Covariance (Re, Rm) / Variance (Rm), Re = return on the stock & Rm = return on the market

We filtered the data set only to include stocks with a Beta value < 1 (a characteristic of defensive stocks) before moving on to the clustering stage. Since the range of values of the financial ratios varied, min-max normalization was applied to ensure that each financial ratio had the same value range [0, 1]. Thus, the variables do not outweigh other financial ratios with smaller ranges during the clustering process.

2) Clustering: *K*-Means, Agglomerative, and Mean Shift clustering were implemented to group stocks with similar financial characteristics. From the listed methods, ***k-means clustering is a commonly used clustering method with benefits such as being computationally efficient and easy to implement*** [26]. Before cluster generation, k clusters were set, and *k* number of centroids were randomly assigned to group data into clusters. Each data point was designated to its closest centroid according to a distance measure. The centroids were updated, and the process repeated until no more changes occurred. **Agglomerative clustering** is a hierarchical clustering method that follows a bottom-up approach when grouping clusters. It can be viewed as a dendrogram with all the data points at the bottom level. The method merged the closest sets of clusters at each level until the final number of clusters was satisfied. **Mean Shift clustering** is a non-parametric, density-based clustering method. The primary objective of the technique is to find the local maximum of the density function defined for all clusters within the specified radius. Each point underwent gradient ascent until convergence.

In this study, we set the initial clusters to be ranged [1, 10] using *k*-Means and Agglomerative clustering, respectively. The Elbow method was employed to determine the optimal number of clusters for the two clustering methods. The Elbow method is a common technique for choosing the optimal number of clusters. A graph would display the difference between each cluster's sum of square errors (SSE), whereby the point creating the graph's elbow angle denotes the number of clusters to select [38]. Although Mean Shift clustering does not require the user to set the number of clusters, the bandwidth parameter can be estimated using the sci-kit-learn package.

3) Labelling Clusters based on Weighted Scores: A weighted score was calculated for each generated cluster after clustering. This was accomplished by giving a score to each cluster's financial ratio, whereby a higher score denoted a better performance. This study prioritized high DY, low PE ratio, low Beta value, and low PBV. This assumption was considered when scoring the average of the financial ratios of a cluster.

Suppose there are three clusters. The cluster with the highest average DY receives the highest score (3), the second highest receives a medium score (2), and the last gets the lowest score (1). Conversely, the opposite holds for the PE ratio, Beta value, and PBV, prioritizing low values. The cluster with the lowest average PE ratio would receive the highest score (3) in the same scenario.

TABLE IV
THE WEIGHT ASSIGNED TO EACH FINANCIAL RATIO

Financial Ratio	Weight
Dividend Yield	3
Price to Book Value	2
Price-earnings Ratio	1
Beta Value	1

The scores would then be multiplied by the weights assigned to every variable. Each financial ratio was assigned a different weight based on its importance, as shown in Table IV. From the perspective of a risk-averse investor, DY is the most important financial ratio since it is related to the profits an investor earns. As such, it was assigned the most significant weight among the four financial ratios in the study. Beta value was assigned the second largest weight as it describes the volatility of a stock and is essential in defining a defensive stock. PE ratio and PBV are a company's value indicators and were given the lowest weight. The final weighted score of a cluster was the sum of the product of its assigned score and corresponding weight. The weighted score formula is described in Equation 1, whereby *x* represents the value of a financial ratio, and w denotes its corresponding weight.

$$Weighted\ Score = \sum_{i=1} x_i \cdot w_i \qquad (1)$$

4) Evaluation: We created class labels to indicate the performance of a stock for each clustering method. The previously calculated weighted scores were used as a basis to produce discrete values (High, Medium, and Low). The classification evaluated how well the clustering methods group the stocks according to their performance. Classification algorithms are supervised learning techniques that predict the class of the input data [39]. We selected five baseline traditional machine learning techniques: Logistic Regression, Support Vector Machine, *k*-Nearest Neighbor, Decision Tree, and Random Forest. Following an 80/20 train/test split, the data were normalized using min-max normalization, and then model training was conducted. The matching accuracy of each classification algorithm was recorded, and the average accuracy was calculated to be utilized as a comparison between clustering methods.

III. RESULTS AND DISCUSSION

This section discusses the (i) clustering results, the (ii) creation of class labels using weighted scores, and (iii) classification results. After filtering stocks with Beta value <

1, the total number of stocks in 2018, 2019, 2020, 2021, and 2022 were 213, 217, 220, 221, and 257, respectively.

Clustering was performed on the financial data for each stock sector by year to group similar stocks. The Elbow method determined the best number of clusters for *k*-Means Clustering and Agglomerative clustering. As for Mean Shift clustering, which does not require the number of clusters to be specified, the bandwidth parameter was determined using the sci-kit learn package. The number of clusters formed by each clustering method by sector and year are displayed in Tables V-VII.

TABLE V
THE OPTIMAL NUMBER OF CLUSTERS FOR THE SECTORS AND THE CORRESPONDING YEARS USING *K*-MEANS CLUSTERING

Sectors	2018	2019	2020	2021	2022
Consumer Products & Services	5	4	5	5	4
Industrial Products & Services	5	6	4	5	4
Property	4	5	4	4	5
Construction	4	5	5	4	5
Health Care	5	4	3	4	4
Technology	4	4	4	5	5
Telecommunications & Media	4	4	4	4	5
Transportation & Logistics	4	5	4	5	5
Plantation	4	4	4	4	4
Utility	5	4	4	6	4

As there were 150 distinct runs with different sets of data, we only highlighted the clustering results using data from the Property sector in Year 2018. We determined that the optimal number of clusters using *k*-Means clustering and Agglomerative clustering was four clusters based on the Elbow method, as shown in Figures 2-3. The graph shows the distortion score or SSE against the number of clusters, *k*. The optimal number of clusters is denoted by a vertical dotted black line, whereby the elbow of the graph is formed.

TABLE VI
THE OPTIMAL NUMBER OF CLUSTERS FOR THE SECTORS AND THE CORRESPONDING YEARS USING AGGLOMERATIVE CLUSTERING

Sectors	2018	2019	2020	2021	2022
Consumer Products & Services	5	5	5	5	4
Industrial Products & Services	5	5	4	5	4
Property	4	4	4	4	5
Construction	4	5	5	5	5
Health Care	5	4	4	4	4
Technology	4	4	4	4	6
Telecommunications & Media	4	4	4	4	5
Transportation & Logistics	3	5	5	5	4
Plantation	4	3	4	4	4
Utility	5	4	4	4	4

TABLE VII
THE OPTIMAL NUMBER OF CLUSTERS FOR THE SECTORS AND THE CORRESPONDING YEARS USING MEAN SHIFT CLUSTERING

Sectors	2018	2019	2020	2021	2022
Consumer Products & Services	6	5	3	6	4
Industrial Products & Services	3	6	6	6	4
Property	6	5	5	4	3
Construction	5	6	5	4	4
Health Care	5	4	4	4	5
Technology	5	4	5	6	4
Telecommunications & Media	4	6	4	4	5
Transportation & Logistics	4	6	6	6	6
Plantation	4	4	4	4	4
Utility	5	4	5	6	4

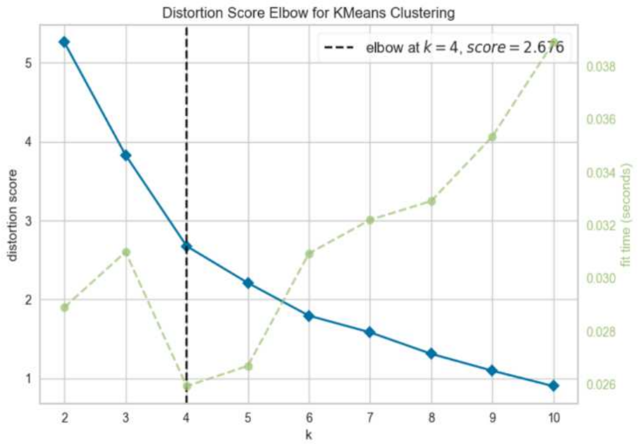

Fig. 2 Elbow Method for Property Sector Year 2018 Using *k*-Means Clustering

It is possible to conduct stock profiling based on the average financial ratios of each cluster using human judgment. Well-performing clusters were in **bold**, whereas non-performing clusters were in *italics*, as indicated in Tables VIII-X. It is noted that the labelling criteria assumed that well-performing defensive Shariah-compliant stocks possessed high DY, low PE ratio, low Beta value, and low PBV.

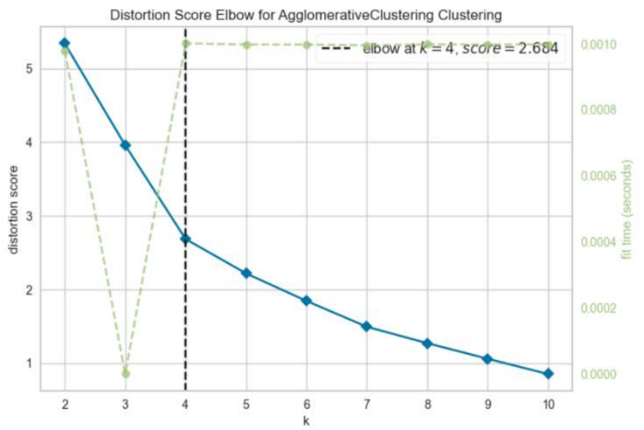

Fig. 3 Elbow Method for Property Sector Year 2018 Using Agglomerative Clustering

TABLE VIII
AVERAGE FINANCIAL RATIOS FOR PROPERTY SECTOR YEAR 2018 BY *K*-MEANS CLUSTERING

Cluster	DY	PE	BETA	PBV
0	**6.428**	**11.083**	**0.488**	**0.788**
1	0.724	11.244	0.461	0.717
2	2.025	2.83	0.911	0.555
3	*0*	*106.6*	*0.15*	*2.74*

TABLE IX
AVERAGE FINANCIAL RATIOS FOR PROPERTY SECTOR YEAR 2018 BY AGGLOMERATIVE CLUSTERING

Cluster	DY	PE	BETA	PBV
0	1.064	13.641	0.409	0.764
1	1.688	2.992	0.873	0.518
2	*0*	*106.6*	*0.15*	*2.74*
3	**6.706**	**5.88**	**0.582**	**0.794**

TABLE X
AVERAGE FINANCIAL RATIOS FOR PROPERTY SECTOR YEAR 2018 BY MEAN SHIFT CLUSTERING

Cluster	DY	PE	BETA	PBV
0	1.587	8.865	0.5987	0.676
1	**7.557**	**7.467**	**0.593**	**0.743**
2	*0*	*106.6*	*0.15*	*2.74*

Well-performing stocks such as Cluster 0 (Table VIII), Cluster 3 (Table IX), and Cluster 1 (Table X) had the highest average DY among the clusters, which were 6.428, 6.706, and 7.557, respectively. They also maintained a low PE ratio, Beta value, and PBV compared to the other clusters. In comparison, the non-performing clusters contained the 7105.KL stock, which was the direct opposite of our criteria. Though human judgment is reliable, we can automate this task by calculating weighted scores used in the study.

The scores assigned to each cluster by average financial ratio and its calculated weighted scores are shown in Tables XI-XIII. Each cluster was given scores based on the average of its financial ratios. For example, Cluster 2 (Table X) had the lowest DY, so it was assigned a 1 (lowest score) among the three clusters. It also obtained the highest PE ratio and PBV, prioritizing low values. Hence, it was given the lowest score for those particular financial ratios. However, its Beta value was the weakest among the clusters, so it was given a score of 3 (highest score).

TABLE XI
THE WEIGHTED SCORES OF PROPERTY SECTOR YEAR 2018 CLUSTERS USING *K*-MEANS CLUSTERING

Cluster	DY	PE	BETA	PBV	Weighted Score
0	4	3	2	2	21
1	2	2	3	3	17
2	3	4	1	4	19
3	1	1	4	1	13

TABLE XII
THE WEIGHTED SCORES OF PROPERTY SECTOR YEAR 2018 CLUSTERS USING AGGLOMERATIVE CLUSTERING

Cluster	DY	PE	BETA	PBV	Weighted Score
0	2	2	3	3	17
1	3	4	1	4	19
2	1	1	4	1	13
3	4	3	2	2	21

TABLE XIII
THE WEIGHTED SCORES OF PROPERTY SECTOR YEAR 2018 CLUSTERS USING MEAN SHIFT CLUSTERING

Cluster	DY	PE	BETA	PBV	Weighted Score
0	2	2	1	3	13
1	3	3	2	2	18
2	1	1	3	1	11

The scores in each column were multiplied by their corresponding weight in Table IV, then summed to calculate the weighted score. Although the stocks within the clusters differed, the weighted scores of the clusters formed by *k*-Means clustering and Agglomerative clustering were identical in this example.

Prior to classification, we created the class labels for each stock based on the weighted score of its cluster, as implemented in Table XIV. An intuitive binninga separates the clusters into three classes: High, Medium, and Low.

TABLE XIV
CLASS LABELS OF PROPERTY SECTOR YEAR 2018 CLUSTERS USING *K*-MEANS CLUSTERING

Cluster	Weighted Score	Label
0	21	High
1	17	Medium
2	19	Medium
3	13	Low

The number of stocks in each class differed for the three newly labeled data sets. The *k*-Means clustering data set consisted of 347 high stocks, 544 medium stocks, and 237 low stocks, whereas Aggregative clustering had 379 high stocks, 521 medium stocks, and 228 low stocks. Finally, Mean Shift clustering included 456 High stocks, 486 Medium stocks, and 186 Low stocks.

After an 80/20 train/test split, we trained five classification algorithms, which were Logistic Regression (LR), *k*-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF) on the separate data sets. The matching accuracy of the classification algorithms on data sets created by each clustering method was documented in Table XV, along with their average matching accuracy.

TABLE XV
MATCHING ACCURACY OF CLASSIFICATION ALGORITHMS

Clustering	LR	KNN	SVM	DT	RF	Average
k-Means	0.593	0.606	0.588	0.513	0.606	0.605
Agglomerative	0.543	0.493	0.546	0.465	0.525	0.545
Mean Shift	0.543	0.429	0.514	0.422	0.475	0.511

TABLE XVI
MATCHING ACCURACY OF CLASSIFICATION ALGORITHMS BY SECTOR

Number	Sector	LR	KNN	SVM	DT	RF	AVG
293	Consumer Products & Services	0.695	0.593	0.712	0.525	0.576	0.62
262	Industrial Products & Services	0.642	0.66	0.623	0.547	0.604	0.615
179	Property	0.75	0.75	0.806	0.806	0.75	0.772
62	Construction	0.769	0.769	0.769	0.692	0.769	0.754
39	Health Care	0.625	0.625	0.625	0.75	0.75	0.675
116	Technology	0.542	0.625	0.583	0.542	0.583	0.575
44	Telecommunications & Media	0.667	0.667	0.444	0.667	0.444	0.578
53	Transportation & Logistics	0.455	0.545	0.455	0.455	0.455	0.473
34	Plantation	1	0.857	1	0.857	1	0.943
46	Utility	1	0.7	0.9	0.4	0.8	0.76
	AVG	0.715	0.679	0.692	0.624	0.673	

From the results, the *k*-Means clustering data set had the best accuracy using all the classification algorithms and achieved the highest average accuracy (58.1%). The Agglomerative clustering data set obtained the second highest average accuracy (51.4%). In contrast, the Mean Shift Clustering data set acquired the lowest average accuracy (47.7%), though they obtained the same mean accuracy using Logistic Regression. It is noted that Logistic Regression had the best average accuracy (56%) while Decision Tree had the lowest average accuracy (46.7%) out of the five classification algorithms. Overall, *k*-Means clustering was the best clustering method in the study to optimize the labeling of the clusters.

Although the *k*-Means clustering data set performed the best, it only achieved an average accuracy of 58.1%. Further testing was conducted on the *k*-Means data set by separating the stocks by sector before classification. The number of stocks in each sector (Number) alongside the average accuracy (AVG) by sector and by classification algorithm are shown in Table XVI.

Logistic Regression obtained the highest average accuracy (71.5%) among the classification algorithms. It is closely followed by SVM (69.2%), KNN (67.9%), RF (67.3%), and DT (62.4%). The Plantation sector achieved the highest average accuracy (94.3%), much higher than the other sectors. However, it is also the sector with the fewest stocks (34). From our observation, the separation of sectors may affect the classification results since each sector has different ‘high' or 'low' values. For example, the average PBV of the Technology sector is 4.4, whereas the Construction sector has a significantly lower average PBV of 0.858. Hence, the classification algorithms would face more difficulty in classifying stocks by their stock performance when data from sectors of differing average financial ratios are combined. It is suggested that stocks are separated according to the sector before classification to increase the accuracy in predicting stock performance.

IV. CONCLUSION

This paper discusses the usage of clustering methods to automate the process of labeling stocks in terms of their financial performance. The results will assist investors in making investment decisions since the stocks are labeled straightforwardly (Low, Medium, High). The objective is to find the best clustering method for labeling the stocks; hence, we tested several clustering methods to label the clusters of defensive Shariah-compliant stocks according to their performance. We labeled the clusters generated by *k*-Means clustering, Agglomerative clustering, and Mean Shift clustering based on the weighted score of their average financial ratios. The stocks within each cluster were labelled based on the clusters’ weighted score as Low, Medium, or High. After training the models using the newly labelled data set, we calculated the average matching accuracy of five classification algorithms to determine the best clustering method in the study. In this work, we employed the Elbow method to determine the best number of *k* clusters and each sector obtained different optimal *k* values.

The results showed that the *k*-Means clustering data set achieved the best average accuracy (60.5%), followed by Agglomerative clustering (54.5%), then Mean Shift Clustering (51.1%). This shows that *k*-Means clustering performs better than Agglomerative and Mean Shift clustering in optimizing the labelling of the clusters. Further testing was conducted on the *k*-Means data set after being separated by sector. As a result, Logistic Regression achieved the highest average accuracy of 71.5% among the classification methods. The study is limited by the few numbers of stocks in certain sectors. Future research considerations include utilizing outlier analysis to select well-performing defensive Sharia-compliant stocks.

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