

Topological Method for a Study of Discriminating Three Categories of Banks and its use in Attributes Reduction

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ABSTRACT

Article Info Volume 7 Issue 5 Page Number: 221-233 Publication Issue : September-October-2020 This work approaches the problem of knowledge extraction within the banking domain using rough set, rough set theory can be considered as a topological method. Our main goal is to separate of the accounting attributes to discriminate between Islamic, mixed, and conventional banks. To this end, we have used the positive region in the rough set framework is traditional uncertainty measurements, used usually as in attribute reduction. Attributes banks will be separated and we are classified with a given decision, then we theoretically analyze the variance of the rough set. In the actual application, we used the financial semantics based on the domain expertise of experts to determine between the competing approaches. The results show the value of shared financial information for distinguishing between the three types of banks with certain attributes. These results are helping us offer a new view of attribute reduction in knowledge. We used MATLAB for our applications in computing.

Article History

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I. INTRODUCTION

The Nobel Prize in Physics in 2016 was awarded because of topological uses in the theory of the transformation of the material in addition to international schools in Germany and America are using topological applications in science and engineering. Rough set theory [14] can be considered as a topological method because it basically depends on the partition generated by the equivalence relationship and the topology generated by the partition. Rough set is a legitimate mathematical method that deals with imprecise, unclear, ambiguous or incomplete decision-making information [6, 8]. This was successfully implemented in data mining where we use the reduction of attributes in the preprocessing phase of data and the reduction of the meaning in the inductive learning phase. The original rough set theory is from the perspective of algebra because all its basic concepts, such as lower and upper approximation and positive area, are the product of the indiscernible relationship between instances [13 -14]. However. introduce some researchers neighborhood method to attribute reduction [9 - 11].

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Then it gives the information view of attribute reduction. The information can be certain or have an uncertainty associated with it. We will make the decision under incompleteness or uncertainty, new mathematical tools were used for examples [16-17].

Specific techniques were employed for the purpose of classification or contrast in Islamic banking and finance. Many studies use the characteristics of accounting to compare Islamic and conventional banks [7, 15]. In the Logit model, papers provide specific accounting attributes and then two nonlinear classification methods (k-means nearest neighbors and neural networks) to differentiate between the two forms of banks [1, 12]. Previous work has been restricted to solving bi-class problems, while it is possible to differentiate three types of banks; traditional, Islamic, and mixed. Indeed, by opening Islamic windows and Islamic subsidiaries some banks shifted away from conventional activities towards Islamic financing activities. Such banks are known as mixed banks [2-4]. The current study aims to classify sixty-one banks operating in the Gulf Cooperation Council (GCC) region in the three categories of banks using 26 accounting attributes. Since there is no general consensus on financial ratios for this classification issue, it is important to analyze collected attributes for their attributes that discriminate. The current work falls entirely within the framework of data mining and information exploration, using rough set approaches. Rough set is an important step for data processing and the exploration of information in databases. Gaining information about the data and defining related attributes is helpful. We're planning this paper like the following. Section 2 contains some simple notions regarding decision-making method and rough set theory. In addition, the lower (respectively upper) approximation of any subset is exactly the interior (respectively closure) of the subset. Therefore the starting point for applying topological definition in the approximation method is the use of closure and interior design [5]. In section 3 we discuss the method of measuring uncertainty induced by the reduction method theoretically; these findings enable us to understand the quantitative relationships between different reductions of attributes in section 3. This paper is concluded and addressed in section 4.

II. METHODS AND MATERIAL

1. Rough sets and Approximations

Definition 1 [13] Let *U* be a finite set and *R* be an equivalence relation on *U*. This relation *R* will generate a partition $U/R = \{Y_1, Y_2, ..., Y_m\}$ on *U*, where $Y_1, Y_2, ..., Y_m$ are the equivalence classes generated by *R*. These equivalence classes are also called the elementary sets of *R*. For any $X \subset U$, we can describe *X* by the elementary sets of *R* and the following two sets

 $R(X) = \bigcup \{ Y_i \in U/R: \{ Y_i \} \subseteq X \}$ (called positive region), $R^*(X) = \bigcup \{ Y_i \in U/R: \{ Y_i \} \cap X \neq \emptyset \}$, which are called the lower and the upper approximation of *X*, respectively. Also, the lower (resp. upper) approximation of any subset $A \subseteq U$ is exactly the interior (resp. closure) of the subset *A*.

2. Reduction and Core

Every definition in the base of information can be expressed only in terms of simple categories. On the other hand, every fundamental category is made up of other elementary categories [16]. In the case of attributes and information, the concepts of core and reduct are two basic concepts of the rough set theory. The reduct is the integral element of which the original information structure renders all the objects discernible. The core of all reduct is a common element. The set of all attributes that are indispensable is called core. Logical rules based on experimental data can be used to facilitate new reductions [14]. We often face a question whether we can remove some data from a data table preserving its basic properties, that is, whether a table contains some superfluous data. The proposed algorithm introduces indeterminacy by removing conditional attributes in a controlled manner. The selection of attributes to be removed is made from the factors in the discernibility function, thereby removing information needed to discern classes in the original information system [11]

Definition 2. [9] If (*U*, *A*, *V*, *f*) is an information system defines an information function

f: $U \rightarrow V$, where *A* is the set of attributes, *V* is the domain of the particular attributes in which the values *V* are real numbers. We define a relation Ra_i for each attribute a_i , as follows: $x Ra_i y$ iff $|a_i(x) - a_i(y)| < \varepsilon$, where ε is determined by an expert of the field. For instance, if the knowledge comes from the medical field, the expert is an individual who is interested in medicine and in the problem making. Thus for each $a_i \in A$ we can get a classification O/Ra_i which is $\{xRa_i : x \in O\}$, where *O* is a finite set. $xRa_i = \{y : |a_i(x) - a_i(y)| < \varepsilon\}$.

Definition 3. [14] Let R be a family of equivalence relation and let $A \in R$. Then we will say that A is dispensable in R if IND (R) =IND(R-{A}), (superfluous). But it was remarked

A. IND (R) \neq IND(R-{A}), then we will say that A is indispensable in R (Core).

III. Data gathering

i) Data

Financial data are gathered from annual reports of sixty-one listed banks in the Gulf Cooperation Council (GCC) [2]. The GCC countries include Bahrain, the United Arab Emirates, Kuwait, Oman, Qatar, Saudi Arabia. Our preference for the banks operating in this area is inspired by a significant increase in the number of Islamic and mixed banks and in the number of transfers from conventional to Islamic. Every bank belongs to one of the three categories according to its activities:

• Class 1: Islamic banks providing interest-free loans under the principles of risk-sharing and sales.

• Class 2: mixed banks that are the traditional banks that have Islamic goods or open Islamic windows and subsidiary companies.

• Class3: conventional banks are driven by the concept of interest income-based profit maximization.

In this work, we introduce a reduction for Bank's data. Information technology and how areas of application of topology in modern theory of rough set presented by Pawlak [14] using information and data on an issue. By Pawlak work starts with an appropriate of the information system by translating as follows, $U = \{x_1, x_2, \dots, x_{61}\}$ denotes 61 listed Banks, the values of the attributes $R = \{R_1, R_2, \dots, R_{26}\} =$ **Capital adequacy** (R_1 =Total equity/Total assets and R_2 =Total equity/Total loans and advances), Assets quality (*R*₃=Total loans and advances/Total assets, and R_4 =Reserve for loan losses/Total loans and advances), Management quality and efficiency (R_5 =Net interest income/total loans and advances, R_6 =Operating expenses/Total assets, *R*7=Operating income/Total assets *R*⁸=Operating expenses/Operating income (revenue), R9=Personnel expenses/Total assets and R_{10} =Personnel expenses/Operating expenses), **Profit** ability and income structure (R_{11} =Net profit of the year/Total assets, R12=Net profit of the year/Total equity, R_{13} =Net profit of the year/Operating income, R_{14} =Net profit of the year/Total customer deposits, R_{15} =Net profit of the year/ Shareholder contributed capital, R₁₆=Net

interest income/Operating income and R17=Net noninterest income/Operating income), and Liquidity and **risk ratios** (*R*₁₈=Total loans and advances/Total liabilities. *R*19=Total loans and advances/Total customer deposits, $R_{20}=Cash/Total$ assets. R_{21} =Cash/Total customer deposits, R_{22} =Total customer deposits/total assets, R23=Total equity/Total customer deposits, R₂₄=Total liabilities / Total equity, R₂₅=Total liabilities/Share holder contributed capital and R_{26} =Retained earnings/Total assets), and the value of the decision attribute $\{d\}$ into qualitative terms. We have used MATLAB for our computational applications.

The data in question concern modeling of Bank's data,

where 61 Bank's data are in appendix-1, after converted the previous data by coded into three qualitative terms, The coded information system is given by converting each attribute value to a value from 0 to 1 as follows: $V_{new} = (V_{old} - V_{min}) / (V_{max} - V_{min})$, where V_{max} and V_{min} are the maximum and minimum value for each attribute, and dividing the interval [0, 1] into 3 parts as follows: [0, 0.33) = 1, [0.33, 0.66) = 2 and [0.66, 1] = 3, this is shown the coded and classification information system is given in appendix-2 and calculate the codding by the following

Algorithm appendix-2 codding and classification attributes based on the rough set

```
function [M] = coding(xapp,code);
 [nl,nc] = size(xapp);
M = zeros(nl,nc);
for i = 1:nc
  M(:,i) = (xapp(:,i) - 
min(xapp(:,i)))/(max(xapp(:,i)) - min(xapp(:,i)));
end
[I,J] = find(M \ge ((code-1)/code) \& M \le 1);
for i = 1:length(I)
  M(I(i),J(i)) = code;
end
for i = 1:(code-1)
  [I,J] = find(M \ge ((i-1)/code) \& M <
((i)/code));
  for t = 1:length(I)
  M(I(t),J(t)) = i;
  end
```

Fig. 1 Algorithm appendix-2 codding and classification attributes based on the rough set.

Now, we form the classification (elementary set) induced by indiscernibility relation IND(A) in appendix-2and we obtain the core attributes by **Algorithm appendix-2**.

Algorithm appendix-2 Core attributes one removal based on the rough set

```
function [core] = core_attributes_one_removal(M);
[pos] = object_reduction(M);
s = find(pos == 0);
pos(s) = [];
M = M(pos,:);
core = [];
M1 = M;
[nl,nc] = size(M1);
for i = 1:nc
M1(:,i) = [];
[pos] = object_reduction(M1);
if isempty(find(pos == 0)) == 0
    core = [core;[i,length(find(pos == 0))]];
end
```

Fig. 2 Algorithm appendix-3 Core attributes one removal based on the rough set.

The next following, by leaving out the attributes { R_1 , R_2 , ..., R_{26} } the result as follow in We notice in table 1, IND (R) \neq IND ($R - \{R_3\}$) and so..., then R_3 , R_4 , R_9 , R_{10} , R_{11} , R_{12} , R_{13} , R_{20} and R_{25} are indispensable. Otherwise R_1 , R_2 , R_5 , R_6 , R_7 , R_8 , R_{14} , R_{15} , R_{16} , R_{17} , R_{18} , R_{19} , R_{21} , R_{22} , R_{23} , R_{24} and R_{26} are superfluous.

		Removing Attributes												
Number	Non e	R 1	R	R₃	<i>R</i> 4	₽s	R ₀	R ₂	R_8	₽ø	R 10	R 11	R 12	R 13
0I olomontor	58	58	58	56	57	58	58	58	58	57	57	57	57	57
v sets	R_{14}	R 15	R 16	R 17	R 18	R 19	R 20	R 21	R 22	R 23	R 24	R 25	R 26	
y sets	58	58	58	58	58	58	55	58	58	58	58	57	58	

Table 1. Removing Attributes

ii) Results of data (Core)

We get the core of data as in table 2.

X	R3	<i>R</i> 4	Ro	R 10	R 11	R 12	R 13	R 20	R 25
Xi	3	1	1	1	2	2	2	2	1
X_2	3	1	2	2	2	2	2	3	1
<i>X</i> ₃	3	1	1	1	3	3	3	2	1
<i>X</i> 4	3	1	1	2	2	1	2	3	1
X_{5}	3	1	1	2	2	2	2	3	1
X6	3	2	2	2	2	2	2	3	1
<i>X</i> ₇	3	1	1	2	2	2	3	2	1
X8	2	1	1	2	2	2	3	3	1
Xo	3	1	1	2	2	3	3	2	1
X 10	3	1	1	2	2	3	3	3	1
X_{11}	3	1	1	1	2	2	3	3	1
X_{12}	3	1	1	2	2	2	2	3	2
X 13	2	1	1	2	2	2	3	3	1
X_{14}	3	1	1	2	2	3	3	2	1
X_{15}	3	1	1	1	2	3	3	3	2
X_{16}	3	1	1	1	2	2	3	2	2
X 17	3	1	1	1	2	3	3	3	1
X 18	2	1	1	2	2	2	3	2	1
X 19	3	1	1	1	2	2	3	2	1
X 20	3	1	2	2	2	2	2	2	1
X 21	3	1	1	2	2	3	2	2	1
X 22	2	1	1	1	2	1	2	2	1
X 23	3	1	1	1	2	2	2	3	2
X24	3	1	1	1	2	2	2	2	2
X 25	3	2	1	1	2	2	2	2	1
X 26	3	1	1	1	2	1	2	2	2
X27	3	2	1	1	2	2	2	2	1

X	R ₃	<i>R</i> 4	Ro	R 10	R 11	R 12	R 13	R 20	<i>R</i> 25
X28	3	2	1	1	2	2	2	3	2
X 29	2	2	1	1	2	2	2	2	2
X 30	3	1	1	1	2	1	2	2	1
X 31	3	1	1	1	2	2	2	3	1
X32	2	1	1	1	2	2	2	2	1
X 33	2	1	1	2	2	2	2	3	1
<i>X</i> 34	2	2	2	1	1	1	1	3	1
X 35	2	2	2	2	2	2	2	3	2
X 36	2	1	1	2	2	3	3	3	2
X 37	1	3	2	2	2	2	2	1	2
X38	3	1	2	2	2	1	2	2	1
X 39	1	2	1	3	3	2	3	2	1
X_{40}	3	2	1	1	2	2	2	3	1
X_{41}	3	3	1	1	2	2	2	2	1
X_{42}	3	2	1	1	2	2	2	1	3
X 43	2	2	2	1	2	2	2	3	1
<i>X</i> 44	2	3	1	1	2	1	2	2	1
X_{45}	3	2	1	1	2	2	2	2	2
X 46	3	2	2	1	2	2	2	3	2
X47	2	2	1	1	2	2	2	3	1
X48	3	3	2	1	2	2	2	1	1
X 49	2	1	2	3	2	3	2	2	1
X 50	3	1	1	1	2	2	3	2	3
X 51	3	2	1	1	3	2	3	3	1
X 52	2	1	1	2	2	2	2	3	3
X 53	3	2	2	2	2	2	2	3	1
<i>X</i> 54	2	1	1	1	3	2	3	3	1
X 55	3	1	3	1	3	3	2	2	1
X 56	3	1	2	2	2	2	2	3	1
X 57	3	1	1	2	3	3	3	2	1
X58	3	1	1	1	2	2	3	3	2

Table 2 continued

We can get a classification of data as follows by the next **Algorithm 3**

function [pos] = object_reduction(M);
[nl,nc] = size(M);
pos = [1:nl]';
for i = 1:(nl-1)
 for j = (i+1):nl
 if is equal(M(i,:),M(j,:)) == 1
 pos(j) = 0;

Fig. 3 Algorithm 3 object reduction based on the rough set

	Table 3. Classification of data												
Classes	R3	<i>R</i> 4	Ro	R 10	R 11	R 12	R 13	R 20	R 25				
$Y_1 = \{X_1\}$	3	1	1	1	2	2	2	2	1				
$Y_2 = \{X_2, X_{56}\}$	3	1	2	2	2	2	2	3	1				
$Y_3 = \{X_3\}$	3	1	1	1	3	3	3	2	1				
$Y_4 = \{X_4\}$	3	1	1	2	2	1	2	3	1				
$Y_5 = \{X_5\}$	3	1	1	2	2	2	2	3	1				
$Y_6 = \{X_6, X_{53}\}$	3	2	2	2	2	2	2	3	1				
$Y_7 = \{X_7\}$	3	1	1	2	2	2	3	2	1				
$Y_8 = \{X_8, X_{13}\}$	2	1	1	2	2	2	3	3	1				
$Y_9 = \{X_9, X_{14}\}$	3	1	1	2	2	3	3	2	1				
$Y_{10} = \{X_{10}\}$	3	1	1	2	2	3	3	3	1				
$Y_{11} = \{X_{11}\}$	3	1	1	1	2	2	3	3	1				
$Y_{12} = \{X_{12}\}$	3	1	1	2	2	2	2	3	2				
$Y_{13} = \{X_{15}\}$	3	1	1	1	2	3	3	3	2				
$Y_{14} = \{X_{16}\}$	3	1	1	1	2	2	3	2	2				
$Y_{15} = \{X_{17}\}$	3	1	1	1	2	3	3	3	1				
$Y_{16} = \{X_{18}\}$	2	1	1	2	2	2	3	2	1				
$Y_{17} = \{X_{19}\}$	3	1	1	1	2	2	3	2	1				
$Y_{18} = \{X_{20}\}$	3	1	2	2	2	2	2	2	1				
$Y_{19} = \{X_{21}\}$	3	1	1	2	2	3	2	2	1				
$Y_{20} = \{X_{22}\}$	2	1	1	1	2	1	2	2	1				
$Y_{21} = \{X_{23}\}$	3	1	1	1	2	2	2	3	2				
$Y_{22} = \{X_{24}\}$	3	1	1	1	2	2	2	2	2				
$Y_{23} = \{X_{25}, X_{27}\}$	3	2	1	1	2	2	2	2	1				
$Y_{24} = \{X_{26}\}$	3	1	1	1	2	1	2	2	2				
$Y_{25} = \{X_{28}\}$	3	2	1	1	2	2	2	3	2				
$Y_{26} = \{X_{29}\}$	2	2	1	1	2	2	2	2	2				
$Y_{27} = \{X_{30}\}$	3	1	1	1	2	1	2	2	1				
$Y_{28} = \{X_{31}\}$	3	1	1	1	2	2	2	3	1				
$Y_{29} = \{X_{32}\}$	2	1	1	1	2	2	2	2	1				
$Y_{30} = \{X_{33}\}$	2	1	1	2	2	2	2	3	1				
$Y_{31} = \{X_{34}\}$	2	2	2	1	1	1	1	3	1				
$Y_{32} = \{X_{35}\}$	2	2	2	2	2	2	2	3	2				
$Y_{33} = \{X_{36}\}$	2	1	1	2	2	3	3	3	2				
Y34 = {X37}	1	3	2	2	2	2	2	1	2				
Y35 = {X38}	3	1	2	2	2	1	2	2	1				
Y36 = {X39}	1	2	1	3	3	2	3	2	1				
$Y_{37} = \{X_{40}\}$	3	2	1	1	2	2	2	3	1				
$Y_{38} = \{X_{41}\}$	3	3	1	1	2	2	2	2	1				

The next table 3 obvious the classification of the application

$Y_{39} = \{X_{42}\}$	3	2	1	1	2	2	2	1	3
Table 3 continu	ıed								
Classes	R3	<i>R</i> 4	Ro	R 10	R 11	R 12	R 13	R 20	R 25
$Y_{40} = \{X_{43}\}$	2	2	2	1	2	2	2	3	1
$Y_{41} = \{X_{44}\}$	2	3	1	1	2	1	2	2	1
$Y_{42} = \{X_{45}\}$	3	2	1	1	2	2	2	2	2
$Y_{43} = \{X_{46}\}$	3	2	2	1	2	2	2	3	2
$Y_{44} = \{X_{47}\}$	2	2	1	1	2	2	2	3	1
$Y_{45} = \{X_{48}\}$	3	3	2	1	2	2	2	1	1
$Y_{46} = \{X_{49}\}$	2	1	2	3	2	3	2	2	1
$Y_{47} = \{X_{50}\}$	3	1	1	1	2	2	3	2	3
$Y_{48} = \{X_{51}\}$	3	2	1	1	3	2	3	3	1
$Y_{49} = \{X_{52}\}$	2	1	1	2	2	2	2	3	3
$Y_{50} = \{X_{54}\}$	2	1	1	1	3	2	3	3	1
$Y_{51} = \{X_{55}\}$	3	1	3	1	3	3	2	2	1
$Y_{52} = \{X_{57}\}$	3	1	1	2	3	3	3	2	1
$Y_{53} = \{X_{58}\}$	3	1	1	1	2	2	3	3	2

We get a classification of decision as follows in table 4.

Table 4. Classification of decision

D	Classification
D1(D=1)	$\{X_2, X_3, X_4, X_6, X_{12}, X_{13}, X_{14}, X_{30}, X_{32}, X_{33}, X_{34}, X_{36}, X_{37}, X_{41}, X_{42}, X_{44}, X_{47}, X_{49}, X_{59}\}.$
D2(D=2)	{X1, X5, X7, X8, X9, X10, X11, X26, X35, X43, X45, X46, X48, X53, X55, X60, X61}.
D₀(D–3)	{X15, X16, X17, X18, X19, X20, X21, X22, X23, X24, X25, X27, X28, X29, X31, X38, X39, X40, X50, X51, X52,
D3(D=3)	X54, X56, X57, X58 }.

In the previous Table 4 and the appendix 3, we get lower and upper approximations. The results get as the following by Algorithm 4,

<pre>function [core,Acc,MR,Lower5,Upper5,Class100]</pre>
<pre>= Lower_Upper(xapp,yapp,code);</pre>
[M] = coding(xapp,code);
M = xapp;
<pre>[core] = core_attributes_one_removal(M);</pre>
<pre>[posss] = object_reduction(M);</pre>
<pre>tt = find(posss==0);</pre>
M(tt,:) = [];MR = M;
yapp(tt) = [];
[MR] = coding(xapp,code);
<pre>[posss] = object_reduction(MR);</pre>

Algorithm 4 Lower, upper and accuracy based on rough set

<pre>tt = find(posss==0);</pre>
[nl,nc] = size(MR);
D = unique(yapp);
Acc = zeros(1,length(D));
for i = 1:length(D)
eval(['D' num2str(D(i)) '= find(yapp == D(i));']);
end
MR1 = MR;
obs = [1:n1]';
t = 0;
while isempty(obs) == 0

pos = [];

```
for i = 1:length(obs)
     if isequal(MR1(1,:),MR1(i,:)) == 1
       pos = [pos,i];
       t = t + 1;
  eval(['Class' num2str(t) '= obs(pos)']);
  obs(pos) = [];
  MR1(pos,:) = [];
end
for i = 1:length(D)
  eval(['Lower' num2str(i) '= []']);
  eval(['Upper' num2str(i) '= []']);
for i = 1:length(D)
  for j = 1:t
    j
     A = eval(['D' num2str(D(i))]);
     B = eval(['Class' num2str(j)]);
     if isequal(intersect(A,B),B) == 1
       L = eval(['Lower' num2str(i)]);
       eval(['Lower' num2str(i) '= [L;B]']);
          if isempty(intersect(A,B)) == 0
       U = eval(['Upper' num2str(i)]);
       eval(['Upper' num2str(i) '= [U;B]']);
     for i = 1:length(D)
  R = eval(['Lower' num2str(i)]);
  S = eval(['Upper' num2str(i)]);
  Acc(i) = length(R)/length(S);
end
```

Fig. 4 Algorithm 4 lower, upper By the all attributes, we get the lower and upper approximations.

First case: A class-1 (D =1) as follows:

 $D_1 = \{x_2, x_3, x_4, x_6, x_{12}, x_{13}, x_{14}, x_{30}, x_{32}, x_{33}, x_{34}, x_{36}, x$

 $x_{37}, x_{41}, x_{42}, x_{44}, x_{47}, x_{49}, x_{59}\},\$

then we get the lower $(L_{11}, L_{21}, ...)$ and upper $(U_{11}, ...)$

 $U_{21,...}$) approximations

 $L_{11} = \{x_2, x_3, x_4, x_6, x_{12}, x_{13}, x_{14}, x_{30}, x_{32}, x_{33}, x_{34}, x_{36}, x_{36}$

 $x_{37}, x_{41}, x_{42}, x_{44}, x_{47}, x_{49}, x_{59}\},\$

 $U_{11} = \{x_2, x_3, x_4, x_6, x_{12}, x_{13}, x_{14}, x_{30}, x_{32}, x_{33}, x_{34}, x_{36}, x_{34}, x_{36}, x_{36}$

 $x_{37}, x_{41}, x_{42}, x_{44}, x_{47}, x_{49}, x_{59}, x_1, x_{30}$

 $Acc_{11} = |L_{11}| / |U_{11}| = 90.5\%.$

A class-2 (D =2) as follows: $D_2 = \{x_1, x_5, x_7, x_8, x_9, x_{10}, x_{11}, x_{26}, x_{35}, x_{43}, x_{45}, x_{46}, x_{4$ $x_{48}, x_{53}, x_{55}, x_{60}, x_{61}$ $L_{21} = \{x_5, x_8, x_9, x_{10}, x_{11}, x_{26}, x_{35}, x_{43}, x_{45}, x_{46}, x_{48}, x_{53}, x_{45}, x_{46}, x_{48}, x_{53}, x_{45}, x_{45}, x_{46}, x_{48}, x_{53}, x_{45}, x_{46}, x_{48}, x_{53}, x_{45}, x_{54}, x_{56}, x_{$ x_{55}, x_{60}, x_{61} $\mathbf{U}_{21} = \{x_1, x_5, x_7, x_8, x_9, x_{10}, x_{11}, x_{26}, x_{35}, x_{43}, x_{45}, x_{46}, x_{46}$ $x_{48}, x_{53}, x_{55}, x_{60}, x_{61}, x_{30}, x_{18}$ $Acc_{21} = |L_{21}| / |U_{21}| = 78.95\%.$ A class-3 (D = 3) as follows: $D_3 = \{x_{15}, x_{16}, x_{17}, x_{18}, x_{19}, x_{20}, x_{21}, x_{22}, x_{23}, x_{24}, x_{25}, x_{24}, x_{25}, x_{26}, x_{26$ *X*27, *X*28, *X*29, *X*31, *X*38, *X*39, *X*40, *X*50, *X*51, *X*52, *X*54, *X*56, *X*57, x_{58} }, $L_{31} = \{x_{15}, x_{16}, x_{17}, x_{19}, x_{20}, x_{21}, x_{22}, x_{23}, x_{24}, x_{25}, x_{27}, x_{21}, x_{22}, x_{23}, x_{24}, x_{25}, x_{27}, x_{28}, x_$ $x_{28}, x_{29}, x_{31}, x_{38}, x_{39}, x_{40}, x_{50}, x_{51}, x_{52}, x_{54}, x_{56}, x_{57}, x_{58}$ $U_{31} = \{ x_7, x_{15}, x_{16}, x_{17}, x_{18}, x_{19}, x_{20}, x_{21}, x_{22}, x_{23}, x_{24}, \}$ *x*25, *x*27, *x*28, *x*29, *x*31, *x*38, *x*39, *x*40, *x*50, *x*51, *x*52, *x*54, *x*56, x_{57}, x_{58} } $Acc_{31} = |L_{31}| / |U_{31}| = 92.3\%.$ Second case: Now, we studied the core of

attributes in the previous Table 3 and Table 4 as the following:

A class-1 (D = 1) as follows:

 $D_1 = \{x_2, x_3, x_4, x_6, x_{12}, x_{13}, x_{14}, x_{30}, x_{32}, x_{33}, x_{34}, x_{36}, x$ $x_{37}, x_{41}, x_{42}, x_{44}, x_{47}, x_{49}, x_{59}$

Then we get the lower and upper approximations

$$|\mathbf{L}_{12}| = 15, |\mathbf{U}_{12}| = 23,$$

 $Acc_{12} = |L_{12}| / |U_{12}| = 65.2\%.$

A class-2 (D = 2) as follows:

 $D_2 = \{x_1, x_5, x_7, x_8, x_9, x_{10}, x_{11}, x_{26}, x_{35}, x_{43}, x_{45}, x_{46}, x_{4$

 $x_{48}, x_{53}, x_{55}, x_{60}, x_{61}$

 $|L_{22}| = 13, |U_{22}| = 23,$

 $Acc_{22} = |L_{22}| / |U_{22}| = 56.5\%.$

A class-3 (D = 3) as follows:

 $D_3 = \{x_{15}, x_{16}, x_{17}, x_{18}, x_{19}, x_{20}, x_{21}, x_{22}, x_{23}, x_{24}, x_{25}, x_{27}, x_{28}, x_{29}, x_{31}, x_{38}, x_{39}, x_{40}, x_{50}, x_{51}, x_{52}, x_{54}, x_{56}, x_{57}, x_{58}\},\$

$$\begin{split} | \ L_{32} | \ &= 23, \ | \ U_{32} | \ &= 27, \\ Acc_{32} = | \ L_{32} | \ / \ | \ U_{32} | = 85.2\%. \end{split}$$

The real data set is a tri-class problem consisting of 61 banks with 26 attributes (ratios). Each class refers to one class of banks; Islamic class 1; mixed class 2; and conventional banks class 3. The three-class ratios are 90.5 percent, 78.9 percent, respectively, and 92.3 percent. Indeed, the most important attributes (R_3, R_4) demonstrate the way banks handle loans. In addition, total shareholder capital commitments (R_{20} , R_{25}) should be for Islamic banks. This form of the bank generally does not use debt funding and relies on shareholder capital as the key source of funds. Consequently, these four attributes are observed to distinguish well between Islamic, mixed, and traditional banks. In addition, the key attributes of banks (R_{11} , R_{12} , and R_{13}) and the quality control attributes (R_9 , R_{10}) may be highly biased in distinguishing between the three types of banks.

iii) Results of data (Reminder)

Now, we studied the superfluous data of the next table 5, we get

Third case: We get the result of lower and upper approximation from Table 5 and Table 4 of data as follow:

A class-1 as follows:

 $\mathbf{D}_1 = \{x_2, x_3, x_4, x_6, x_{12}, x_{13}, x_{14}, x_{30}, x_{32}, x_{33}, x_{34}, x_{36}, x_{36}$

 $x_{37}, x_{41}, x_{42}, x_{44}, x_{47}, x_{49}, x_{59}\},\$

$$|L_{13}| = 13, |U_{13}| = 42,$$

 $Acc_{13} = |L_{13}| / |U_{13}| = 31\%.$

A class-2 as follows:

 $\mathbf{D}_2 = \{x_1, x_5, x_7, x_8, x_9, x_{10}, x_{11}, x_{26}, x_{35}, x_{43}, x_{45}, x_{46}, x$

 $x_{48}, x_{53}, x_{55}, x_{60}, x_{61}\},\$

$$|L_{23}| = 6, |U_{23}| = 34,$$

 $Acc_{23} = |L_{23}| / |U_{23}| = 17.6\%.$

A class-3 as follows:

 $\mathbf{D}_3 = \{x_{15}, x_{16}, x_{17}, x_{18}, x_{19}, x_{20}, x_{21}, x_{22}, x_{23}, x_{24}, x_{25}, x_{24}, x_{25}, x_{26}, x_$

 $x_{27}, x_{28}, x_{29}, x_{31}, x_{38}, x_{39}, x_{40}, x_{50}, x_{51}, x_{52}, x_{54}, x_{56}, x_{57}, x_{58}$

$$L_{33}| = 11, |U_{33}| = 42,$$

$$Acc_{33} = |L_{33}| / |U_{33}| = 26.2\%$$

Table 5.	Classification	of Data
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Classes	R 1	R ₂	₽₅	R 6	R 7	<i>R</i> 8	R 14	R 15	R 16	R 17	R 18	R 19	R 21	R 22	R 23	<i>R</i> 24	R 26
$Z_1 = \{X_1, X_5,$																	
X7, X9, X10,																	
X17, X20, X23,	1	1	1	1	1	1	C	C	2	1	1	1	1	2	1	C	1
X28, X32, X36,	1	1	1	1	1	1	Z	Z	5	1	1	1	1	5	1	Z	1
X40, X45, X46,																	
X49, X53, X57}																	
$Z_2 = \{X_2\}$	1	1	1	1	1	1	2	1	2	2	1	1	1	3	1	3	1
$Z_3 = \{X_3\}$	1	1	1	1	1	1	2	2	1	3	1	1	1	3	1	2	1
Z4 = {X4, X38,	1	1	1	1	1	1	Э	1	З	1	1	1	1	З	1	1	1
X47}	1	1	1	1	1	1	Z	1	5	1	1	1	1	5	1	1	1
$Z_5 = \{X_6\}$	1	1	1	2	2	1	2	1	2	2	1	1	1	3	1	2	1
$Z_6 = \{X_8, X_{24},$	1	1	1	1	1	1	Э	r	З	1	1	1	1	З	1	C	r
X58}	1	T	1	T	1	1	2	2	5	T	T	T	T	5	T	4	2
$Z_7 = \{X_{11},$	1	1	1	1	1	1	2	1	3	1	1	1	1	3	1	2	1

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X19, X22, X27, X30, X31}

Table 5 continued

Classes	R_1	R_2	R 5	R_6	R_7	R_8	R_{14}	R 15	R_{16}	R 17	R_{18}	R_{19}	R_{21}	R_{22}	R 23	R_{24}	R_{26}
$Z_8=\{X_{12}\}$	1	1	1	1	1	1	2	2	3	1	1	1	3	1	1	2	1
$Z_9 = \{X_{13}\}$	1	1	1	1	1	1	2	2	3	1	1	1	2	1	1	2	1
$Z_{10} = \{X_{14}\}$	1	1	1	1	1	1	3	1	3	1	1	3	3	1	2	2	1
$Z_{11} = \{X_{15},$	1	1	1	1	1	1	n	2	2	1	1	1	1	2	1	n	1
X 52}	1	1	1	1	1	1	Z	3	3	1	1	1	1	3	1	Ζ	1
$Z_{12} = \{X_{16}\}$	1	1	1	1	1	1	2	3	3	1	1	1	1	2	1	1	1
$Z_{13} = \{X_{18}\}$	1	1	1	1	1	1	2	1	2	2	1	1	1	2	1	2	1
$Z_{14} = \{X_{21},$	1	1	1	1	1	1	C	C	2	1	1	1	1	2	1	3	1
X35}	1	1	1	1	1	1	2	Z	3	1	1	1	1	5	1	5	1
$Z_{15} = \{X_{25}\}$	1	1	1	2	1	1	2	1	3	1	1	1	1	3	1	3	1
$Z_{16} = \{X_{26}\}$	1	1	1	2	1	2	2	1	3	1	1	1	1	3	1	2	1
$Z_{17} = \{X_{29}\}$	1	1	1	3	2	1	2	2	2	1	1	1	1	3	1	2	1
$Z_{18} = \{X_{33}\}$	1	1	1	1	1	1	2	1	1	3	1	1	3	1	1	1	2
$Z_{19} = \{X_{34}\}$	3	1	1	3	1	3	1	1	3	1	3	1	3	1	3	1	1
$Z_{20} = \{X_{37}\}$	1	3	3	1	1	1	2	2	3	1	1	1	1	2	1	2	2
$Z_{21} = \{X_{39}\}$	2	1	1	1	1	1	3	2	3	1	1	1	2	1	2	1	2
$Z_{22} = \{X_{41}\}$	1	1	1	1	1	1	2	2	2	2	1	1	1	3	1	2	1
$Z_{23} = \{X_{42}\}$	1	1	1	1	1	1	2	2	3	1	1	1	1	2	1	2	1
$Z_{24} = \{X_{43}\}$	1	1	1	2	1	1	2	2	2	2	1	1	1	2	1	2	3
$Z_{25} = \{X_{44}\}$	1	1	1	2	1	2	2	1	2	2	1	1	1	3	1	3	1
$Z_{26} = \{X_{48}\}$	1	1	1	2	2	1	2	1	3	1	1	1	1	3	1	2	1
$Z_{27} = \{X_{50}\}$	1	1	1	1	1	1	2	3	3	1	1	1	1	3	1	2	2
$Z_{28} = \{X_{51}\}$	1	1	1	1	1	1	2	2	3	1	1	1	1	3	1	1	2
$Z_{29} = \{X_{54}\}$	1	1	1	1	1	1	2	1	3	1	1	1	1	3	1	1	2
$Z_{30} = \{X_{55}\}$	1	1	1	3	3	1	2	3	3	1	1	1	1	3	1	1	2
$Z_{31} = \{X_{56}\}$	1	1	1	2	1	1	2	1	3	1	1	1	1	3	1	1	1

We obtained the final results in table 6 as shown

Table 0. Final results for accuracy													
		First ca	se		Second o	ase	Third case						
	Lower	Upper	Accuracy	Lower	Upper	Accuracy	Lower	Upper	Accuracy				
D1	L11	U11	Acc11	L12	U12	Acc12	L13	U13	Acc13				
	19	21	90.5%	15	23	65.2%	13	42	31%				
D2	L21	U21	Acc21	L22	U 22	Acc22	L23	U23	Acc23				
	15	19	78.9%	13	23	56.5%	6	34	17.6%				
D3	L31	U 3 1	Acc31	L32	U 32	Acc32	L33	U33	Acc33				
	24	26	92.3%	23	27	85.2%	11	42	26.2%				

Table 6. Final results for accuracy

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Through the previous tables, it was found that the main attributes of Islamic banks are R_3 , R_4 , R_9 , R_{10} , R_{11} , R_{12} , R_{13} , R_{20} and R_{25} , while the rest of the attributes belong to conventional and mixed banks. Therefore, bank employees are given a good opportunity to win new and more clients.

IV. CONCLUSION AND DISCUSSION

In this report, we investigate the impact of accounting attributes on discrimination within the GCC area between Islamic, mixed, and conventional banks. The enriching feedback provided by specialists to interpret the consistency of the selected attributes through the different rough approaches is one of the interesting aspects of this research. Thereby, our fair comparative study was fruitful to reveal a lot of technical and practical insights.

Finally, in response to the financial concerns raised in the implementation of this study, we proposed that regulators might use accounting attributes to differentiate between conventional, mixed, and Islamic banks in the GCC region. On the one hand, we illustrated the significance of the relationships between asset quality and credit risk indicator, and on the other, the quality attributes of management and the other attributes of banks. In addition, we have shown that certain attributes belong to Islamic banks without mixed or traditional banks; this result indicates that the client can choose any class of bank without difficulty or hardship with bank employees.

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Abbreviations

It's not applicable.

Availability of data and materials

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

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The authors are not declaring any conflict of interest. This article contains no studies with the author's performed human participants or animals.

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