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**Topological Modeling for Symptom Reduction of Corona virus**

M. A. El Safty
Department of Mathematics, College of Science
Taif University, P.O. Box 11099, Taif 21944,Saudi Arabia
Email: elsafty010@yahoo.co.uk or m.elsafty@tu.edu.sa

Samirah AlZahrani
Department of Mathematics, College of Science
Taif University, P.O. Box 888, Taif 21944,Saudi Arabia
Corresponding Author Email: elsafty010@yahoo.co.uk or m.elsafty@tu.edu.sa

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**Abstract.**World Health Organization announced Coronavirus as a global epidemic virus, and the search for approximating uncertain concepts and measuring the accuracy of the approximation is an important goal for researchers in many theoretical and applied fields. Therefore this paper suggested a specific mathematical approach with the support of the confidence and strength of an association to determine the most important attribute. Our approach is based on removing redundant attributes to produce the successfully reduced set and formulate the core set of attributes. Additionally, we give new insight into the attribute reduction application and in order to get the result, we use MATLAB programming. We want you to know that this research paper lasted more than two months, in order to confirm the results reached.

**AMS (MOS) Subject Classification Codes: 54Axx, 54Bxx, 54Hxx**
**Key Words:** Rough set, Generation of rule, Discovery of intelligence, Decision making.

## 1. INTRODUCTION

The 2016 Nobel Prize in Physics was awarded, in addition to international schools in Germany and America, for topological uses of material transformation theory using topological applications of science and engineering [5]. We believe that the topological structure would provide a significant foundation for the modification of information extraction and processing [[1]-[2], [6]]. The Fuzzy topology is generalized to the fundamental concepts of the general topology which is very helpful to solve several issues of our life [14]. Rough set theory can be called a topological approach since it essentially depends on the partition generated by the partition's relationship of equivalence and the topology generated by it. In the case of attributes and information, concepts of the core and the reduced are two central concepts of the rough set theory [12]- [13] . For many decades people when making and taking his decisions usually depend on the results of analyzing the available data about their problems of interest [3] -[4]. Nowadays is characterized by the revolution of communications and computer technology, but this implies that collected data may be incomplete, having missing, uncertain and vague values [[8] - [10]]. The analyses of such data need the use of intelligent computational methods such as rough sets, fuzzy sets and hybrid methods [[15] -[16]]. Rough set has been developed in many ways as a technique for the management of ambiguity for both information and queries in relational databases. The theory of topological spaces is a well-known theory that was combined with rough set theory to develop new topological approximations for uncertain concepts in information systems [11].

The main objectives of this work are to establish the structure of the approximation of a target concept by a reduction [9]. These measures will open up the way for a wide range of choices to decision - makers because topological approximations decompose the boundary region to a set of multi sub- regions while approximations based on equivalence relations look to the boundary as a single region. The rest of this article consists of: section two issues with the fundamental principles of the rough set theory and the topological construction of information systems, and section three was concerned with introducing application of corona virus (COVID-19) for each subclass of attributes in the information systems. Also, the relationship between the attributes was clarified as well as the knowledge of any attribute of importance in the epidemic of corona virus (COVID-19). We would like to note that the knowledge gathered in this research on Coronavirus is from 500 patients. Because of the similarity of the attributes in rows (objects), 500 patients were reduced to 10 patients identify the most extreme symptoms of a corona virus. This was studied using the different methods described in the study.

## 2. BASIC CONCEPTS

This paper was carried out to present basic definitions of some rough set and topological approximations.

### 2.1. **Topological Approximations.**

In the initial rough set model, the approximation space $(U, R)$ with equivalence relation $R$ describes a special topological space $(U, \tau_R)$, when $\tau_R$ is a list of all cl-open in $(U, \tau_R)$ and $Y/R$ is a base. The upper (resp. lower) approximation of any sub-set $B \subseteq U$ is also precisely the closure (resp. interior) of the $B$ sub-set. Thus the starting point of applying topological concepts in the approximation process is the use of closure and interior [[5]-[6]].

**Definition 2.2.** [15] *If $U$ is a universe and $R$ is a binary relationship on $U$, we define:*

*i.* "After set" as follows: $xR = \{y : xRy\}$**.**

**Definition 2.3.** [7] *Let $(U, R_1)$ be a space, where $U \neq \phi$ be a finite sea aid $R_1$ be a binary relation on $U$, and $\tau_{R_1}$ be a topology generated by $R_1$. Then the triple $(U, R_1, \tau_{R_1})$ is called "topological approximation space", in briefly "topological space".*

**Definition 2.4.** [12] *Let $S \subseteq U$ and $(U, R_1, \tau_{R_1})$ be a topological space, then the lower (resp. upper) approximation of $S$ is defined by $\underline{R}S = S^0$(resp. $\bar{R}S = \bar{S}$ For a topological space $(U, R_1, \tau_{R_1})$.*

New definability concepts for subset $S \subseteq U$ are presented in the following remark.

**Remark 2.5.** *In general $\bar{R}(\underline{R}S) \neq \underline{R}S$and $\underline{R}(\bar{R}S) \neq \bar{R}S$. The following is an example that illustrates this idea and also, using topological approximations, computes the degree of certainty of uncertain concepts.*

**Example 2.6.** *Let* $B = \{b_5, b_4, b_3, b_2, b_1\}$ *and R be a relation defined as follows:*

$$R = \{(b_1, b_2), (b_1, b_4), (b_2, b_5), (b_2, b_1), (b_3, b_3), (b_3, b_2), (b_4, b_5), (b_5, b_5), (b_5, b_1)\},$$

$$S = \{\{b_2, b_4\}, \{b_1, b_5\}, \{b_2, b_3\}, \{b_5\}\},$$

$$V = \{\phi, \{b_2\}, \{b_5\}, \{b_1, b_5\}, \{b_2, b_3\}, \{b_2, b_4\}\},$$

$$\tau = \{B, \phi, \{b_2\}, \{b_5\}, \{b_1, b_5\}, \{b_2, b_3\}, \{b_2, b_4\}, \{b_2, b_5\}, \{b_2, b_3, b_4\}, \{b_2, b_4, b_5\}, \{b_2, b_1, b_5\}, \{b_2, b_3, b_5\}, \{b_1, b_2, b_4, b_5\}, \{b_1, b_2, b_3, b_5\}, \{b_4, b_2, b_3, b_5\}\}.$$

$$\tau^c = \{B, \phi, \{b_1\}, \{b_3\}, \{b_4\}, \{b_1, b_4\}, \{b_4, b_3\}, \{b_1, b_3\}, \{b_1, b_5\}, \{b_1, b_3, b_4\}, \{b_1, b_4, b_5\}, \{b_2, b_3, b_4\}, \{b_1, b_3, b_5\}, \{b_1, b_2, b_4, b_3\}, \{b_1, b_4, b_3, b_5\}\}.$$

*Let $D = \{b_4, b_5\}$, then*

$$\underline{R}\,D = \{b_5\}, \overline{R}\,(\underline{R}\,D) = \{b_1, b_5\} \neq \underline{R}\,D.$$

$$\overline{R}\,D = \{b_1, b_2, b_4, b_5\}, \underline{R}(\overline{R}\,D) = \{b_1, b_2, b_3, b_4, b_5\} \neq \overline{R}\,D.$$

2.7. **Rough set theory.**

A modern, incomplete mathematical knowledge technique, that is, vagueness, is implied by the rough set. Vagueness is represented by a defined boundary region in that strategy.

**Definition 2.8.** [11] *Topological operations, interiors, and closures may describe a rough description, are called approximations.*

i) Information systems ( IS ) is a pair $(U, D)$, in which the finite sets are $U$ and $D$.
ii) For every $c \in D$, $c : U \to K_c$, the value set of $c$ *is* $K_c$ .
iii) The equivalence class $R$-indiscernibility relation $[Y]_R$of an element $x \in Y$ consists of all objects $y \in Y$such that $xRy$.
iv) Let $IS = (U, D)$, then with any $C \subseteq D$ there is an associated equivalence relation:$IND_{IS}(C) = \{(b, b'^2 : \forall a \in C, a(b) = a(b')\}$,where $IND_{IS}(C)$is the $C$-indiscernibility relation.
v) If objects$(b, b') \in IND_{IS}(C)$, then $b$ and $b$' are indiscernible from each other by attributes from $C$.

**Definition 2.9.** [12] *:*

i) Let $T = (U, D)$, $C \subseteq D$and $y \in Y \subseteq U$, we can approximate $y$ using only the information contained in $C$ by constructing the $C$-lower ($\underline{C}Y$)and $C$-upper $(\overline{C}Y)$ approximations of $Y$, where

$$\underline{C}Y = \{y : [y]_C \subseteq Y\}, \overline{C}Y = \{y : [y]_C \cap Y \neq \phi\}.$$

ii) $C$-boundary region of $Y$, $CN_C(Y) = \overline{C}Y - \underline{C}Y$, consists of those objects that we cannot decisively classify into $Y$ in $C$.
iii) If its border region is empty, a set is seen to be crisp; otherwise, the set is rough.
iv) Accuracy of approximation, $\alpha_c(Y) = \left|\underline{C}Y/\overline{C}Y\right|$, where $|Y|$denotes the cardinality of $Y \neq \phi$,obviously $0 \leq \alpha_C(Y) \leq 1$, if $\alpha_C(Y) = 1$, $Y$ is crisp with respect $C$ and if $\alpha_C(Y) < 1$, $Y$ is rough with respect to $C$.

**Definition 2.10.** [12]*:*

Let $F = \{Y_1, \ldots, Y_n\}$ be a family of sets such that the set $Y_i \subseteq U, i = 1, 2, \ldots, n$ and $\{d\}$ is an attribute for decision. $Y$ is dispensable in $F$, if $\cap(F - Y_i) \subseteq [Y_i]_d$; otherwise the set $Y_i$ is indispensable in $F$.

**Definition 2.11.** [13] *:*

A fuzzy soft topological space $(Z,\ \tau,\ I)$and fuzzy soft set $(F,\ I)$ over $Z$. Then

i) Fuzzy soft $\alpha$–open, if $(F,\ I) \leq (((F,\ I)^o)^-)^o$.
ii) Fuzzy soft $\alpha-$closed, if $(((F,\ I)^-)^o)^- \leq (F,\ I)$.

**Theorem 2.12.** *The intersection of fuzzy soft $\alpha$-open set and fuzzy soft $\beta$-open set is fuzzy soft $\beta$- open set.*

*Proof.* Let $(F, I)$ be fuzzy$\alpha$- open set and $(G, I)$ is fuzzy soft$\beta$- open set, then □

$(F, I)\,\widetilde{\wedge}(G, I) \leq (((F, I)^{FS-})^{FSo}\,\widetilde{\wedge}(((G, I)^{FS-})^{FSo})^{FS-}$
$\leq ((F, I)^{FSo})^{FS-}\,\widetilde{\wedge}(((G, I)^{FS-})^{FSo})^{FS-} \leq ((F, I)^{FSo}\,\widetilde{\wedge}(\ (G, I)^{FS-})^{FSo})^{FS-}$
$\leq ((F, I)^{FSo}\,\widetilde{\wedge}((G, I)^{FS-})^{FSo})^{FS-} \leq (((F, I)^{FSo}\,\widetilde{\wedge}(G, I)^{FS-})^{FSo})^{FS-}$
$\leq ((((F, I)\,\widetilde{\wedge}(G, I))^{FS-})^{FSo})^{FS-}$.
Thus the $(F, I)\widetilde{\wedge}(G, I)$is fuzzy -soft $\beta$- open set.

## 3. APPLICATION

In this application, we introduce the proposed method, and the application of corona virus (COVID-19) can be described as follows; we would like to mention that the information obtained in this Corona-virus analysis is from 500 patients. Since the attributes in rows (objects) were identical, 500 patients were reduced to 10 patients, where the objects as; $U = \{X_1, X_2, ..., X_{10}\}$ denotes 10 listed patients, the attributes as $\{a_1,\ a_2,\ ...,\ a_6\}$ = {Difficulty breathing, Chest pain, Temperature, Dry cough, Headache, Loss of taste or smell}and decision COVID-19 corona virus $\{d\}$, as follows in information was collected by the World Health Organization as well as through medical groups specializing in corona virus (COVID-19).
Considering the following information system in the Table 1:

**Table 1** Information's decisions data set

| **Objects** | **Serious symptoms** | | | **Most common symptoms** | | | **Decision covid-19** |
|---|---|---|---|---|---|---|---|
| | **Difficulty breath-ing** | **Chest pain** | **Temperature** | **Dry cough** | **Headache** | **Loss of taste or smell** | |
| **X1** | yes | yes | v. high | yes | yes | yes | yes |
| **X2** | yes | yes | high | yes | yes | yes | yes |
| **X3** | yes | yes | normal | yes | no | yes | no |
| **X4** | yes | yes | normal | no | no | no | no |
| **X5** | yes | yes | normal | yes | no | no | no |
| **X6** | yes | no | high | yes | yes | no | yes |
| **X7** | no | no | v. high | yes | yes | no | yes |
| **X8** | no | no | normal | yes | yes | no | no |
| **X9** | no | no | v. high | no | no | yes | yes |
| **X10** | no | no | high | yes | yes | no | yes |

We are again drawing the consistent part of Table 1 by the next Table 2

**Table 2** Consistent part of Table 1

| **Objects** | **Attributes** | | | | | | **Decision** |
|---|---|---|---|---|---|---|---|
| | $a_1$ | $a_2$ | $a_3$ | $a_4$ | $a_5$ | $a_6$ | **d** |
| **X1** | 2 | 2 | 3 | 2 | 2 | 2 | 2 |
| **X2** | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| **X3** | 2 | 2 | 1 | 2 | 1 | 2 | 1 |
| **X4** | 2 | 2 | 1 | 1 | 1 | 1 | 1 |
| **X5** | 2 | 2 | 1 | 2 | 1 | 1 | 1 |
| **X6** | 2 | 1 | 2 | 2 | 2 | 1 | 2 |
| **X7** | 1 | 1 | 3 | 2 | 2 | 1 | 2 |
| **X8** | 1 | 1 | 1 | 2 | 2 | 1 | 1 |
| **X9** | 1 | 1 | 3 | 1 | 1 | 2 | 2 |
| **X10** | 1 | 1 | 2 | 2 | 2 | 1 | 2 |

Next, by leaving out the $a_1$ attribute in Table 3 as follows

**Table 3** Removes from Table 2 attribute $a_1$

| ***U / A*** **-** $\{\boldsymbol{a}_1\}$ | **Attributes (** ***A*** **-** $\{\boldsymbol{a}_1\}$**)** | | | | |
|---|---|---|---|---|---|
| | $\boldsymbol{a}_2$ | $\boldsymbol{a}_3$ | $\boldsymbol{a}_4$ | $\boldsymbol{a}_5$ | $\boldsymbol{a}_6$ |
| $\boldsymbol{W}_1$ **=**{ X1} | 2 | 3 | 2 | 2 | 2 |
| $\boldsymbol{W}_2$**=**{ X2} | 2 | 2 | 2 | 2 | 2 |
| $\boldsymbol{W}_3$**=**{ ***X3***} | 2 | 1 | 2 | 1 | 2 |
| $\boldsymbol{W}_4$ **=** { ***X4***} | 2 | 1 | 1 | 1 | 1 |
| $\boldsymbol{W}_5$ **=** { ***X5***} | 2 | 1 | 2 | 1 | 1 |
| $\boldsymbol{W}_6$ **=** { ***X6, X10***} | 1 | 2 | 2 | 2 | 1 |
| $\boldsymbol{W}_7$ **=** { ***X7***} | 1 | 3 | 2 | 2 | 1 |
| $\boldsymbol{W}_8$ **=** { ***X8***} | 1 | 1 | 2 | 2 | 1 |
| $\boldsymbol{W}_9$ **=** { $\boldsymbol{X}_9$} | 1 | 3 | 1 | 1 | 2 |

We note that, $IND(A) \neq IND(A-\{a_1\}), \ldots.$, then $a_1, a_3, a_4$ and $a_6$ are indispensable. Also, we get $a_2$ removed then we obtain $IND(A) = IND(A-\{a_2\})$, and superfluous are $a_{2,} a_5$.

**Algorithm 1** 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
M1 = M;
```

Then, we get the removal of attributes as the next Table 4,

**Table 4** Eliminating Attributes

| | **Removal of attributes** | | | | | | |
|---|---|---|---|---|---|---|---|
| **Number of Basic Sets** | **None** | $a_{\mathbf{1}}$ | $a_{\mathbf{2}}$ | $a_{\mathbf{3}}$ | $a_{\mathbf{4}}$ | $a_{\mathbf{5}}$ | $a_{\mathbf{6}}$ |
| | 10 | 9 | 10 | 7 | 9 | 10 | 9 |

Table 5 therefore presents a new information table based on this reduct.

**Table 5** Reduced information table

| $U/A^{'}$ | **Attributes ($A^{'}$)** | | | | **Decision** |
|---|---|---|---|---|---|
| | $a_1$ | $a_3$ | $a_4$ | $a_6$ | $d$ |
| $T_1$ | 2 | 3 | 2 | 2 | 2 |
| $T_2$ | 2 | 2 | 2 | 2 | 2 |
| $T_3$ | 2 | 1 | 2 | 2 | 1 |
| $T_4$ | 2 | 1 | 1 | 1 | 1 |
| $T_5$ | 2 | 1 | 2 | 1 | 1 |
| $T_6$ | 2 | 2 | 2 | 1 | 2 |
| $T_7$ | 1 | 3 | 2 | 1 | 2 |
| $T_8$ | 1 | 1 | 2 | 1 | 1 |
| $T_9$ | 1 | 3 | 1 | 2 | 2 |
| $T_{10}$ | 1 | 2 | 2 | 1 | 2 |

In our application, the set {Difficulty breathing, Temperature, Headache, Loss of taste or smell} is a reduct of attributes original set {Difficulty breathing, Chest pain, Temperature, Dry cough, Headache, Loss of taste or smell}but { Chest pain, Dry cough}are redundant.

3.1. **Generate the rules for data.** In fact, the following rules can be derived from Table 5:

i) (Difficulty breathing, no), (Temperature, normal), (Headache, yes) and (Loss of taste or smell, no) →(COVID-19, no),
ii) (Difficulty breathing, yes) and (Temperature, normal) →(COVID-19, no),
iii) (Difficulty breathing, yes), (Temperature, high), (Headache, yes) and (Smell or Loss of taste, yes) →(COVID-19, yes),
iv) (Loss of taste or smell, yes) and (Temperature, v. high) →(COVID-19, yes),
v) (Temperature, high) and (Headache, yes) →(COVID-19, yes).

3.2. **Set Approximation.** The $B$-lower: $\underline{B}\,X = \cup\{Y \in IND(B) : Y \subseteq X\}$
The $B$-upper: $\overline{B}\,X = \cup\{Y \in IND(B) : Y \cap X \neq \phi\}$
Now, we're trying to find a connection between the main (indispensable) attributes,
**Discussion-** $a_1$
Removed attribute $a_1$: we get the results shown in the following
For $a_1[(d = yes, X_{Yes} = \{T_1, T_2, T_6, T_7, T_9, T_{10}\}), (d = No, X_{No} = \{T_3, T_4, T_5, T_8\}$ )]

$$X = X_{Yes} + X_{No}$$

**Table 6** Indispensable $a_1$

| $U/A'$-{ $a_1$ } | Attributes ($A'$-{ $a_1$ }) | | |
|---|---|---|---|
| | $a_3$ | $a_4$ | $a_6$ |
| $t_1$={ $T_1$} | 3 | 2 | 2 |
| $t_2$={ $T_2$} | 2 | 2 | 2 |
| $t_3$={ $T_3$} | 1 | 2 | 2 |
| $t_4$={ $T_4$} | 1 | 1 | 1 |
| $t_5$={ $T_5$, $T_8$ } | 1 | 2 | 1 |
| $t_6$={ $T_6$, $T_{10}$ } | 2 | 2 | 1 |
| $t_7$={ $T_7$} | 3 | 2 | 1 |
| $t_8$={ $T_9$} | 3 | 1 | 2 |

For $a_1$[(d= yes, $X_{Yes} = \{T_1, T_2, T_6, T_7, T_9, T_{10}\}$)]
Lower approximation is donated as { $T_1, T_2, T_6, T_7, T_9, T_{10}$}, then $|L_{Yes}| = 6$
Upper approximation is { $T_1, T_2, T_6, T_7, T_9, T_{10}$}, then $|U_{Yes}| = 6$
Accuracy of approximation is $\mu(a_1) = |L_{Yes}| / |U_{Yes}| = 1 = 100\%$
For $a_1$[(d= No, $X_{No} = \{T_3, T_4, T_5, T_8\}$)]
Lower approximation is donated as { $T_3, T_4, T_5, T_8$}, then $|L_{No}| = 4$
Upper approximation is { $T_3, T_4, T_5, T_8$}, then $|U_{No}| = 4$
Accuracy of approximation is $\mu(a_1) = |L_{No}| / |U_{No}| = 1 = 100\%$
**Discussion-** $a_3$
Removed attribute $a_3$: We'll get the results shown Table 7 below,

**Table 7** Indispensable $a_3$

| $U/A'$-{ $a_3$ } | Attributes ($A'$-{ $a_3$ }) | | |
|---|---|---|---|
| | $a_1$ | $a_4$ | $a_6$ |
| $t_1$={ $T_1$, $T_2$, $T_3$} | 2 | 2 | 2 |
| $t_2$={ $T_4$} | 2 | 1 | 1 |
| $t_3$={ $T_5$, $T_6$} | 2 | 2 | 1 |
| $t_4$={ $T_7$, $T_8$, $T_{10}$} | 1 | 2 | 1 |
| $t_5$={ $T_9$} | 1 | 1 | 2 |

For $a_3$[(d= yes, $X_{Yes} = \{T_1, T_2, T_6, T_7, T_9, T_{10}\}$)]
Lower approximation is donated as $\{T_9\}$, then $|L_{Yes}| = 1$
Upper approximation is { $T_1, T_2, T_3, T_5, T_6, T_7, T_8, T_9, T_{10}$}, then $|U_{Yes}| = 9$
Accuracy of approximation is $\mu(a_3) = |L_{Yes}| / |U_{Yes}| = 1/9 = 11\%$
For $a_3$[(d= No, $X_{No} = \{T_3, T_4, T_5, T_8\}$)]
Lower approximation is donated as $\{T_4\}$, then $|L_{No}| = 1$
Upper approximation is { $T_1, T_2, T_3, T_5, T_6, T_7, T_8, T_4, T_{10}$}, then $|U_{No}| = 9$
Accuracy of approximation is $\mu(a_3) = |L_{No}| / |U_{No}| = 1/9 = 11\%$
**Discussion-** $a_4$
Removed attribute $a_4$: we have the following Table 8,

**Table 8** Indispensable $a_4$

| $U/A'$-{ $a_4$ } | Attributes ($A'$-{ $a_4$ }) | | |
|---|---|---|---|
| | $a_1$ | $a_3$ | $a_6$ |
| $t_1$={ $T_1$} | 2 | 3 | 2 |
| $t_2$={ $T_2$} | 2 | 2 | 2 |
| $t_3$={ $T_3$} | 2 | 1 | 2 |
| $t_4$={ $T_4$, $T_5$} | 2 | 1 | 1 |
| $t_5$={ $T_6$ } | 2 | 2 | 1 |
| $t_6$={ $T_7$ } | 1 | 3 | 1 |
| $t_7$={ $T_8$} | 1 | 1 | 1 |
| $t_8$={ $T_9$} | 1 | 3 | 2 |
| $t_9$={ $T_{10}$} | 1 | 2 | 1 |

For $a_4$[(d= yes, $X_{Yes} = \{T_1, T_2, T_6, T_7, T_9, T_{10}\}$)]
Lower approximation is donated as $\{ T_1, T_{2,} T_{6,} T_7,\ T_9, T_{10}\}$, then $|L_{Yes}| = 6$
Upper approximation is $\{ T_1, T_{2,} T_{6,} T_7,\ T_9, T_{10}\}$, then $|U_{Yes}| = 6$
Accuracy of approximation is $\mu(a_4) = |L_{Yes}|/|U_{Yes}| = 1 = 100\%$
For $a_4$[(d= No, $X_{No} = \{T_3, T_4, T_5, T_8\}$)]
Lower approximation is donated as $\{T_{3,} T_{4,} T_{5,} T_8\}$, then $|L_{No}| = 4$
Upper approximation is $\{T_{3,} T_{4,} T_{5,} T_8\}$, then $|U_{No}| = 4$
Accuracy of approximation is $\mu(a_4) = |L_{No}|/|U_{No}| = 1 = 100\%$

**Discussion- $a_6$**

Removed attribute $a_6$: we obtain the following Table 9,

**Table 9** Indispensable $a_6$

| $U/A'$-{ $a_6$ } | Attributes ($A'$-{ $a_6$ }) | | |
|---|---|---|---|
| | $a_1$ | $a_3$ | $a_4$ |
| $t_1$={ $T_1$} | 2 | 3 | 2 |
| $t_2$={ $T_2$, $T_6$} | 2 | 2 | 2 |
| $t_3$={ $T_3$, $T_5$} | 2 | 1 | 2 |
| $t_4$={ $T_4$} | 2 | 1 | 1 |
| $t_5$={ $T_7$ } | 1 | 3 | 2 |
| $t_6$={ $T_8$ } | 1 | 1 | 2 |
| $t_7$={ $T_9$} | 1 | 3 | 1 |
| $t_8$={ $T_{10}$} | 1 | 2 | 1 |

**Algorithm 2** Lower, upper and accuracy based on rough set

```
function [core,Acc,MR,Lower5,Upper5,Class100] =
Lower_Upper(xapp,yapp,code);
[M] = coding(xapp,code);
M = xapp;
[core] = core_attributes_one_removal(M);
[posss] = object_reduction(M);
tt = find(posss==0);
M(tt,:) = [];MR = M;
yapp(tt) = [];
[MR] = coding(xapp,code);
[posss] = object_reduction(MR);
tt = find(posss==0);
[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:nl]';
t = 0;
while isempty(obs) == 0
pos = [];
for i = 1:length(obs)
if isequal(MR1(1,:),MR1(i,:)) == 1
pos = [pos,i];
end
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) '= []']);
end
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]']);
end
if isempty(intersect(A,B)) == 0
U = eval(['Upper' num2str(i)]);
eval(['Upper' num2str(i) '= [U;B]']);
end
for i = 1:length(D)
R = eval(['Lower' num2str(i)]);
S = eval(['Upper' num2str(i)]);
Acc(i) = length(R)/length(S);
end
```

For $a_6$[(d= yes, $X_{Yes} = \{T_1, T_2, T_6, T_7, T_9, T_{10}\}$)]
Lower approximation is donated as $\{ T_1, T_{2,} T_{6,} T_7, T_9, T_{10}\}$, then $|L_{Yes}| = 6$
Upper approximation is $\{ T_1, T_{2,} T_{6,} T_7, T_9, T_{10}\}$, then $|U_{Yes}| = 6$
Accuracy of approximation is $\mu(a_6) = |L_{Yes}| / |U_{Yes}| = 1 = 100\%$
For $a_6$[(d= No, $X_{No} = \{T_3, T_4, T_5, T_8\}$)]
Lower approximation is donated as $\{T_{3,} T_{4,} T_{5,} T_8\}$, then $|L_{No}| = 4$
Upper approximation is $\{T_{3,} T_{4,} T_{5,} T_8\}$, then $|U_{No}| = 4$
Accuracy of approximation is $\mu(a_4) = |L_{No}| / |U_{No}| = 1 = 100\%$

3.3. **Reduction Method.** Next, in every decision rule, we need to reduce the superfluous values of the condition. The core values of the condition attribute have been computed using definition 6, The families of sets in Table 2 are $F_{1,...,} F_{10}$, since $F_1 = \{[T_1]_{a1}, [T_1]_{a3}, [T_1]_{a4}, [T_1]_{a6}\} = \{\{T_6, T_2, T_1, T_4, T_3, T_5\}, \{T_1, T_7, T_9\}, \{T_{10}, T_6, T_3, T_5, T_2, T_7, T_{10}, T_8\}, \{T_1, T_9, T_3, T_2\}\}$,
$[T_1]_d = \{T_1, T_2, T_{10}, T_7, T_9, T_6\}$, since $a_1(T_1) = 2, a_3(T_1) = 3, a_4(T_1) = 2, a_6(T_1) = 2$.
In order to find dispensable,

$$\cap(F_1 - [T_1]_{a1}) = \{T_1\} \subseteq [T_1]_d, \cap(F_1 - [T_1]_{a3}) = \{T_1, T_2, T_3\} \not\subset [T_1]_d,$$
$$\cap(F_1 - [T_1]_{a4}) = \{T_1\} \subseteq [T_1]_d, \cap(F_1 - [T_1]_{a6}) = \{T_1\} \subseteq [T_1]_d,$$

This means that the core value is $a_3(T_1) = 3$.
Also, we find
$F_2 = \{[T_2]_{a1}, [T_2]_{a3}, [T_2]_{a4}, [T_2]_{a6}\}$
$= \{\{T_4, T_6, T_3, T_1, T_5, T_2\}, \{T_2, T_6, T_{10}\}, \{T_1, T_8, T_3, T_5, T_6, T_2, T_7, T_{10}\}, \{T_1, T_2, T_3, T_9\}\}, [T_2]_d = \{ T_1, T_2, T_6, T_7, T_9, T_{10}\}$, since $a_1(T_2) = 2$, $a_3(T_2) = 2, a_4(T_2) = 2, a_6(T_2) = 2$.
In order to find dispensable,

$$\cap(F_2 - [T_2]_{a1}) = \{T_2\} \subseteq [T_2]_d, \cap(F_2 - [T_2]_{a3}) = \{T_1, T_2, T_3\} \not\subset [T_2]_d,$$
$$\cap(F_2 - [T_2]_{a4}) = \{T_2\} \subseteq [T_2]_d, \cap(F_2 - [T_2]_{a6}) = \{T_2, T_6\} \subseteq [T_2]_d,$$

This means that the core value is $a_3(T_2) = 2$.
Also, we find $F_3 = \{[T_3]_{a1}, [T_3]_{a3}, [T_3]_{a4}, [T_3]_{a6}\} = \{\{T_6, T_5, T_3, T_4, T_2, T_1\}, \{T_3, T_8, T_5, T_4\}, \{T_1, T_8, T_3, T_5, T_{10}, T_7, T_2, T_6\}, \{T_1, T_2, T_3, T_9\}\}, [T_3]_d = \{T_3, T_4, T_5, T_8\}$,since $a_1(T_3) = 2, a_3(T_3) = 1, a_4(T_3) = 2, a_6(T_3) = 2$.
In order to find dispensable,

$$\cap(F_3 - [T_3]_{a1}) = \{T_3\} \subseteq [T_3]_d, \cap(F_3 - [T_3]_{a3}) = \{T_1, T_2, T_3\} \not\subset [T_3]_d,$$
$$\cap(F_3 - [T_3]_{a4}) = \{T_3\} \subseteq [T_3]_d, \cap(F_3 - [T_3]_{a6}) = \{T_3, T_5\} \subseteq [T_3]_d,$$

This means that the core value is $a_3(T_3) = 1$.
Also, we find by similar and algorithm intersection method $F_4, F_5, \ldots, F_{10}$.
From these calculations, it was shown that attributes $a_1, a_3, a_4$ and $\boldsymbol{a}_6$ are indispensible, also we find the power $\boldsymbol{a}_3$ attribute of the rules is maximized. Table 5 can be reduced to Table 10 as follows
**Algorithm 3** Intersection method based on rough set.

**Algorithm 3** Intersection method based on rough set

```
function [MR] = intersection_method(M);
[nl,nc] = size(M);
for i = 1:nl
eval(['F' num2str(i) '= []']);
U = eval(['F' num2str(i)]);
for j = 1:nc
eval(['F' num2str(i) num2str(j) '= find(M(:,j) == M(i,j))']);
V = eval(['F' num2str(i) num2str(j)]);
eval(['F' num2str(i) '= [U,[V;NaN(nl-length(V),1)]]']);
U = eval(['F' num2str(i)]);
longueur(1,j) = length(V);
end
s = max(longueur);
U = eval(['F' num2str(i)]);
eval(['F' num2str(i) '= U(1:s,:)']);
end
for i = 1:nl
[I] = intersection_multiple(eval(['F' num2str(i)]));
eval(['Inter_F' num2str(i) '= I']);
end
for i = 1:nl
A = eval(['F' num2str(i)]);
B = A;
for j = 1:nc
A(:,j) = [];
[II] = intersection_multiple(A);
eval(['Inter_F' num2str(i) num2str(j) '= II']);
A = B;
end
MR = M;
for i = 1:nl
AA = eval(['Inter_F' num2str(i)]);
for j = 1:nc
BB = eval(['Inter_F' num2str(i) num2str(j)]);
if isequal(AA,BB) == 1
MR(i,j) = 0;
end
```

**For the** Algorithm 3 Intersection method based on rough set, we obtain table 10

**Table 10** Decision Table 5

| **Objects** | $\cap(F_i - [a_k]) \subseteq d_i$ | | | | **Decision** |
|---|---|---|---|---|---|
| | $a_1$ | $a_3$ | $a_4$ | $a_6$ | $d$ |
| $T_1$ | $-$ | 3 | $-$ | $-$ | 2 |
| $T_2$ | $-$ | 2 | $-$ | $-$ | 2 |
| $T_3$ | $-$ | 1 | $-$ | $-$ | 1 |
| $T_4$ | $-$ | $-$ | $-$ | $-$ | 1 |
| $T_5$ | $-$ | 1 | $-$ | $-$ | 1 |
| $T_6$ | $-$ | 2 | $-$ | $-$ | 2 |
| $T_7$ | $-$ | 3 | $-$ | $-$ | 2 |
| $T_8$ | $-$ | 1 | $-$ | $-$ | 1 |
| $T_9$ | $-$ | $-$ | $-$ | $-$ | 2 |
| $T_{10}$ | $-$ | 2 | $-$ | $-$ | 2 |

Reduce Table 10 by removing the same decision values and condition attributes, i.e. by combining separate rows that attribute the same conditions and decision values. This method is referred to as the Row Reduction (See Table 11).

**Table 11** Reduced decision Table 10

| **Objects** | $\cap(F_i - [a_k]) \subseteq d_i$ | | | | **Decision** |
|---|---|---|---|---|---|
| | $a_1$ | $a_3$ | $a_4$ | $a_6$ | $d$ |
| $\{T_1, T_7\}$ | $-$ | 3 | $-$ | $-$ | 2 |
| $\{T_2, T_6, T_{10}\}$ | $-$ | 2 | $-$ | $-$ | 2 |
| $\{T_3, T_5, T_8\}$ | $-$ | 1 | $-$ | $-$ | 1 |
| $T_4$ | $-$ | $-$ | $-$ | $-$ | 1 |
| $T_9$ | $-$ | $-$ | $-$ | $-$ | 2 |

It is clear from the previous tables that the temperature is the main power attributes that causes coronavirus (COVID-19) infection, followed by difficulty breathing, dry cough and also loss of taste and smell

## 4. CONCLUSION

Our work clearly presents a new approach to the determination of the most important coronavirus attributes (COVID-19). It is one of the most exciting and modern theoretical approaches, the idea of a rough collection that can be used to frame modern rules for decision-making. Method is very important in finding a reduction for any data, in enabling us to remove any unnecessary knowledge base, and thus preserving only the real useful information. In the fields of information discovery, data mining, or any other area relating to the reduction of attributes and best feature selection, the application of this method can be used extensively. Also, we will provide new evidence in further releases of

these guidelines. In the future, we will use the fuzzy method on the research to get the best of accuracy and test this method to compare it with other existing methods.
Author Contributions:
This paper is written through all contributions' efforts. The individual contributions and obligations of both authors can be summarized as follows: **M. A.** brought up the entire manuscript concept, and finish the preparatory work for the paper.
**Samirah** analyzed the existing work of Topological modeling, and revised the paper.
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