A distinct approach to diagnose dengue fever with the help of soft set theory

Fariha Iftikhar¹, Faiza Ghulam Nabi²

¹Department of Mathematics, University of Gujrat, Gujrat, Pakistan
²Department of Mathematics, Quaid-i-Azam University, Islamabad, Pakistan

Email: ¹Syedafarihabukhari86@gmail.com, ²Fiza.gnabi@gmail.com

http://doi.org/10.26782/jmcms.2019.10.00032

Abstract

Intelligent systems based on mathematical theories have proved to be efficient in diagnosing various diseases. In this paper we used an expert system based on “soft set theory” and “fuzzy set theory” named as soft expert system to diagnose tropical disease dengue. This study discuss the role of “Soft set theory” as system which worked on the basis of knowledge in medical field. Study used “soft expert system” to predict the risk level or chances of a patient causing dengue fever by using input variables like age, TLC, SGOT, platelets count and blood pressure. The proposed method explicitly demonstrates the exact percentage of the risk level of dengue fever automatically circumventing for all possible (medical) imprecisions.

Keywords: dengue fever, soft set theory, fuzzy set theory, intelligent systems.

I. Introduction

Now a day's dengue is an acute viral disease in tropics and subtropics like India, Egypt, Pakistan, West Indies and Indonesia. It is the most significant health problem in tropics. The septic disease dengue is transferred by the mosquito (usually the female Aedes aegypti). The infants, young children, and adults are affecting through this fatal disease. The signs and indications of dengue seem in 3-14 days after the infective bite. There has been a global increase in the morbidity rate of dengue fever, dengue hemorrhagic fever, and its epidemics in last two decades. Dengue fever dramatically increased in rate between 1960 and 2010 by 30 fold. The most prominent outbreak was in 2002 with more than one million reported cases [XII]. However, it is not easy to diagnose it. Dengue has the same symptoms like other viral infections such as fever, headache, vomiting, etc. This factor has become a difficulty for doctors to diagnose the exact illness. These variables induce some imprecision and uncertainties in diagnosing the disease. Consequently, medical researchers cannot accurately characterize how the disease is affecting the functionality of the human body [XI]. Therefore, diagnosing the disease is a critical issue due to enormous variables involved in a process.
Traditional mathematics cannot deal with such difficulties as it also yields various types of uncertainties. Subsequently, the question arises what method should be adopted to address such issues? Expert systems are helpful in eliminating uncertainty and imprecision [VII]. Intelligent systems are playing a significant role in solving many challenging human problems. An expert system is a smart computer program that solves the problem using the knowledge base of experts and different procedures [V]. Human experts find the solution of the issues with the help of facts and “reasoning ability”. It is presumed that an expert system, consist of two factors which are related to components: named as knowledge base and technique base system which enables the expert system to conclude.

Soft computing technology has been a subject of research in computational sciences. Several techniques in soft computing such as ESs, neural networks, fuzzy logic, genetic algorithm, Bayesian statistics, Khaos theory, etc. have been developed and implemented to resolve many issues and make possible to diagnosed different diseases in the field of medicine and engineering design.

In recent years some new techniques have been introduced to solve the substantial issues efficiently. These new techniques are involved with intuitionistic fuzzy soft sets, probability, vague sets, fuzzy set theory, the theory of interval mathematics, rough set theory, etc. These theories could be used as practical tools which proposed to handle the diverse sorts of uncertainties and deception experienced in a problem.

In 1965, to deal with the challenges of vagueness, L. A. Zadeh [6] introduced the theoretical approach known as "fuzzy set theory". The application of “fuzzy set theory” to medical diagnosis of dengue fever discussed in [XIII]. In this study, the choice of fuzzy logic is because it resembles with the human decision-making abilities. Later on, researchers observed some drawbacks of “fuzzy set theory” because there are different types of affiliation functions in “fuzzy set theory” and the accuracy level of each membership is different. In fact, all approaches mentioned above are linked with an inherent restraint, this shows the insufficiency of the “parameterization tool” related to these theories. Therefore a method was needed to eliminate such kind of flaws.

The solution to problem of the parameterization tool has led the researchers to seek out possible ways. Molodtsov (1999) demonstrated the idea of “soft set theory” as a new tool which functions according to mathematical rules to cope with an environment of imprecision [I]. The “soft set theory” allows the object to be defined without any hard and fast rules. Recently the establishment and development of soft set theory, augmented its applications in numerous fields.

In this paper, we use fuzzy set theory and soft set theory to diagnose dengue fever. The fuzzy set theory was constructive in the field of medical, engineering and economics. However, the actual challenge is how to choose a membership function to obtain significant results. The fuzzy set theory has various membership functions, and all of them have variations in accuracy which made crucial to choose a membership function. The soft set theory does not require any additional parameterization tool because it is a parameterized theory. Consequently, the purpose of the present study is to eliminate uncertainty in high percentage by using “soft set theory” with the “fuzzy sets”.
II. Literature Review

Artificial intelligent systems apply to address medical issues such as "dengue fever." Researchers make efforts on medical expert systems to find the solution of medical problems [III]. The diagnosis of tropical diseases involves different levels of imprecision and ambiguity [IV].

In 1999 Molodtso [I] put forward an idea of “soft set theory” as a novel tool of mathematical field to deal in an environment of imprecision which is very easy to use and absence from difficulties can be observed in “fuzzy set theory”. The soft set theory has several applications in different fields. The soft set firstly introduced by Molodtsov is a set linked with a “set of parameters” and application is observed with different directions. In “fuzzy set theory” to identify the membership function, some parameters are needed. The” soft set theory” allows the object to be defined without any hard and fast rules.

The “soft set theory” is normally linked with further mathematical methods. Some operations on soft set theory have been discussed [IX], but this research exhibited some drawbacks. Later on, in [VIII] points out the faults of [IX] and explain some rudimentary terms which part of theory are those includes “equality of two soft sets”, “subset and superset of a soft set”, “a complement of a soft set”, and “null soft set” with examples. “And”, “or”, “union” and “intersection” are the binary operations which also defined in this theory. “De Morgan's laws” and some results are verified in “soft set theory” context.

D. Chen et al. [II] investigated how to reduce parameters and highlighted the applications of soft sets. However it was noticed that the outcomes of soft sets are not feasible that were presented in [XV]. They verified it with the help of an example to measure the performance of the algorithms used in [XV], Finally, they presented a technique for the parameter reduction of “soft sets” deeply studied the algebraic structure of the “soft set theory” to deal with uncertainty and imprecision.

In [XIII], there is a detailed study of dengue fever and its epidemics. The authors used fuzzy expert system in their work to diagnose dengue fever somehow it was a better output. As mentioned earlier there are various types of membership functions in “fuzzy set theory” and the accuracy level of all functions is different. In this paper we used soft expert system to avoid from the difficulty in the selection of membership function. Our aim how we can use soft set theory in expert systems to eliminate even a little chance of imprecision. The consolidation of “fuzzy set theory” and soft theory known as a soft expert system is a good attempt in the field of medicine for the identification of tropical diseases. The role of an expert system is to improve the practitioner performance and it ultimately improves patient’s outcome. As a result, the standard of health care improved.

III. Material and Methodology

In this section, we discuss the soft expert system. It consists of 5 main steps. Fuzzification of data set, transforming fuzzy sets into soft sets, reduction of soft sets,
gaining “soft rules”, and analysis of “soft rules” are the steps of our system. Firstly we will fuzzify the data using membership function for each variable. To diagnose dengue fever using the soft expert system the data of dengue was collected from Holy Family Hospital Islamabad. The diagnosis of dengue fever using the soft expert system the actual dataset of 30 patients contain the essential factors that symbolize a person is suffering from dengue fever. In an expert system based on soft set theory; age, TLC, SGOT, Platelets count and Blood pressure are used as input variables and risk of dengue fever is used as an output variable.

III.i. Fuzzification of Data Set

In this section, we used fuzzy set theory and defined membership for all input variables. The data of 30 dengue patients was collected who were found treated at Holy Family Hospital Islamabad. Since the data set is not expedient for applying soft sets directly. Therefore we first fuzzify the data set for further procedure. For the fuzzification of input, linguistic variables are (for Age) child (C), young (Y), old (O), (for TLC, SGOT, Platelets count, Blood pressure) low (L), medium (M), high (H). Fuzzification of inputs is done by membership functions Age (A), TLC (B), SGOT (C), Platelets count (D), Blood pressure (E). Triangular membership functions are used to fuzzify the data set. The steps of the soft expert system are shown in figure 1.
\[
\mu_{\text{young}}(t) = \begin{cases} 
0 & ; \\ 
t - 15 & ; 15 \leq t \leq 30 \\ 
\frac{45 - t}{15} & ; 30 \leq t \leq 45 \\ 
0 & ; t > 45 
\end{cases}
\]

\[
\mu_{\text{old}}(t) = \begin{cases} 
0 & ; t < 44 \\ 
\frac{t - 44}{21} & ; 44 \leq t \leq 65 \\ 
\frac{90 - t}{25} & ; 65 \leq t \leq 90 \\ 
0 & ; t > 90 
\end{cases}
\]

\[
\mu_{\text{child}}(t) = \begin{cases} 
0 & ; t < 2 \\ 
\frac{t - 2}{7} & ; 2 \leq t \leq 9 \\ 
\frac{16 - t}{7} & ; 9 \leq t \leq 16 \\ 
0 & ; t > 16 
\end{cases}
\]
The membership function for TLC is separated into three sections, i.e. high, medium and low. The ranges of low medium and high are given below.

**(B): Membership function for TLC**

- 3500-4000 Low
- 3900-11000 Medium
- 10,000-15,000 High

$$
\begin{align*}
\mu_{\text{low}}(t) &= \begin{cases} 
0 & ; \quad t < 3500 \\
\frac{t - 3500}{250} & ; \quad 3500 \leq t \leq 3750 \\
\frac{4000 - t}{250} & ; \quad 3750 \leq t \leq 4000 \\
0 & ; \quad t > 4000
\end{cases} \\
\mu_{\text{medium}}(t) &= \begin{cases} 
0 & ; \quad t < 3900 \\
\frac{t - 3900}{3550} & ; \quad 3900 \leq t \leq 7450 \\
\frac{11000 - t}{3550} & ; \quad 7450 \leq t \leq 11000 \\
0 & ; \quad t > 11000
\end{cases}
\end{align*}
$$
SGOT is the third input variable. The membership function for SGOT is split into three sections, i.e. high, medium and low. The ranges of low, medium and high are mentioned below.

(C): Membership function for SGOT
- 0-40 Low
- 35-50 Medium
- 45-55 High

Fig. 3. Graph of the function of μ low, μ medium and μ high
The membership function for platelets is separated into three sections, i.e. high, medium and low. The range of low is 3500-150000, the range of medium is from 140000-450000 and high ranges from 440000-470000.

(D): Membership function for Platelets Count

\[
\mu_{\text{low}}(t) = \begin{cases} 
0 & ; \quad t < 10 \\
\frac{t - 10}{15} & ; \quad 10 \leq t \leq 25 \\
\frac{40 - t}{15} & ; \quad 25 \leq t \leq 40 \\
0 & ; \quad t > 40
\end{cases}
\]

\[
\mu_{\text{medium}}(t) = \begin{cases} 
0 & ; \quad t < 35 \\
\frac{t - 35}{7} & ; \quad 35 \leq t \leq 42 \\
\frac{50 - t}{8} & ; \quad 42 \leq t \leq 50 \\
0 & ; \quad t > 50
\end{cases}
\]

\[
\mu_{\text{high}}(t) = \begin{cases} 
0 & ; \quad t < 45 \\
\frac{t - 45}{5} & ; \quad 45 \leq t \leq 50 \\
\frac{55 - t}{5} & ; \quad 50 \leq t \leq 55 \\
0 & ; \quad t > 55
\end{cases}
\]
3500-1,50,000 Low
1,40,000-4,50,000 Medium
4,40,000-4,70,000 High

\[
\mu_{low}(t) = \begin{cases} 
0 & ; t < 3500 \\
\frac{t - 3500}{76500} & ; 3500 \leq t \leq 80,000 \\
\frac{1,50,000 - t}{70,000} & ; 80,000 \leq t \leq 1,50,000 \\
0 & ; t > 1,50,000 
\end{cases}
\]

\[
\mu_{med}(t) = \begin{cases} 
0 & ; t < 1,40,000 \\
\frac{t - 1,40,000}{1,55,000} & ; 1,40,000 \leq t \leq 2,95,000 \\
\frac{4,50,000 - t}{1,55,000} & ; 2,95,000 \leq t \leq 4,50,000 \\
0 & ; t > 4,50,000 
\end{cases}
\]

\[
\mu_{high}(t) = \begin{cases} 
0 & ; t < 4,50,000 \\
\frac{t - 4,40,000}{15,000} & ; 4,40,000 \leq t \leq 4,55,000 \\
\frac{4,70,000 - t}{15,000} & ; 4,55,000 \leq t \leq 4,70,000 \\
0 & ; t > 4,70,000 
\end{cases}
\]

Fig. 2. Graph of the function of μ low, μ medium and μ high
Blood pressure is the fifth and last input variable. The membership function for BP is separated into three sections, i.e. low, medium and high. The ranges of low medium and high are mentioned below.

(E): Membership function for Blood Pressure

- 120-134 Low
- 127-161 Medium
- 154-172 High

\[
\mu_{\text{low}}(t) = \begin{cases} 
0 & ; \quad t < 120 \\
\frac{t - 120}{7} & ; \quad 120 \leq t \leq 127 \\
\frac{134 - t}{7} & ; \quad 127 \leq t \leq 134 \\
0 & ; \quad t > 134 
\end{cases}
\]

\[
\mu_{\text{medium}}(t) = \begin{cases} 
0 & ; \quad t < 127 \\
\frac{t - 127}{17} & ; \quad 127 \leq t \leq 144 \\
\frac{161 - t}{17} & ; \quad 144 \leq t \leq 161 \\
0 & ; \quad t > 161 
\end{cases}
\]

\[
\mu_{\text{high}}(t) = \begin{cases} 
0 & ; \quad t < 154 \\
\frac{t - 154}{9} & ; \quad 154 \leq t \leq 163 \\
\frac{172 - t}{9} & ; \quad 163 \leq t \leq 172 \\
0 & ; \quad t > 172 
\end{cases}
\]

Fig.3. Graph of the function of $\mu$ low, $\mu$ medium and $\mu$ high
The data from Table 1 is fuzzified using the membership function mentioned earlier and given in Table 2 as follows:
Table 2
The fuzzy membership values of inputs

| Patient no (K) | Age       | TLC   | SGOT     | Platelets count | Blood pressure |
|---------------|-----------|-------|----------|-----------------|----------------|
| kkff1         | 0.57 C, 0 Y | 0.4 L, 0 M | 0.5 M, 0.2 H | 0.60 L, 0 M | 0.75 L, 0 M |
| kkff2         | 0 Y, 0.6 O | 0.6 L, 0 M | 0 M, 0.8 H  | 0.54 L, 0 M  | 0.85 L, 0 M  |
| kkff3         | 0 C, 0.33 Y | 0.4 L, 0 M | 0.37 M, 0.4 H | 0.46 L, 0 M | 0.57 L, 0.17 M |
| kkff4         | 0 C, 0.66 Y | 0 L, 0.30 M | 0.75 M, 0 H  | 0.21 L, 0 M  | 0 L, 0.70 M  |
| kkff5         | 0 C, 0.2 Y | 0.6 L, 0 M | 0.125 M, 0.8 H | 0.73 L, 0 M | 0.42 L, 0.23 M |
| kkff6         | 0.57 C, 0 Y | 0.8 L, 0 M | 0 M, 0.2 H  | 0.71 L, 0 M  | 0.75 L, 0.11 M |
| kkff7         | 0 C, 0.86 Y | 0.2 L, 0.01 M | 0 M, 1 H   | 0.07 L, 0.03 M | 0.14 L, 0.35 M |
| kkff8         | 0 Y, 0.28 O | 0 L, 0.05 M | 0.75 M, 0 H  | 0 L, 0.16 M  | 0.94 M, 0 H  |
| kkff9         | 0 Y, 0.52 O | 0.2 L, 0 M | 0 M, 0.2 H  | 0.64 L, 0 M  | 0.57 L, 0 M  |
| kkff10        | 0 Y, 0.4 O | 0.6 L, 0 M | 0.5 M, 0.2 H | 0.28 L, 0 M  | 0.85 L, 0 M  |
| kkff11        | 0.28 C, 0 Y | 0.4 L, 0 M | 0.25 M, 0.6 H | 0.92 L, 0 M | 0.75 L, 0.11 M |
| kkff12        | 0 Y, 0.23 O | 1 L, 0 M | 0 M, 0.4 H  | 0.28 L, 0 M  | 0.14 L, 0.35 M |
| kkff13        | 0 Y, 0.92 O | 0.28 M, 0 H | 0.26 L, 0.14 M | 0 L, 0.38 M | 0.64 M, 0 H  |
| kkff14        | 0 Y, 0.76 O | 0.6 L, 0 M | 0 M, 0.8 H  | 0.07 L, 0.03 M | 0.28 L, 0.29 M |
| kkff15        | 0 C, 0.86 Y | 0.8 L, 0 M | 0 M, 0.2 H  | 0.86 L      | 0.85 L, 0.05 M |
| kkff16        | 0 C, 0.4 Y | 0 M, 0.8 H | 0.86 L, 0 M | 0 L, 0.64 M  | 0.57 L, 0 M  |
| kkff17        | 0 Y, 0.8 O | 0.4 L, 0 M | 0.375 M, 0.4 H | 0.93 L, 0 M | 0.14 L, 0 M  |
| kkff18        | 0.14 C    | 0.8 L, 0 M | 0 M, 0.2 H  | 0.41 L, 0 M  | 0.85 L, 0 M  |
| kkff19        | 1 C, 0 Y  | 0.4 L, 0 M | 0 M, 0.6 H  | 0.34 L, 0 M  | 0.75 L, 0 M  |
| kkff20        | 0 C, 0.8 Y | 0.8 L, 0 M | 0.25 M, 0.6 H | 0.08 L, 0 M | 0.42 L, 0.23 M |
| kkff21        | 0 Y, 0.44 O | 0.8 L, 0 M | 0.5 M, 0.2 H | 0.09 L, 0 M  | 0.57 L, 0.17 M |
| kkff22        | 0 Y, 0.04 O | 0 L, 0.59 M | 0.75 L, 0 M | 0 L, 0.38 M  | 0 L, 0.70 M  |
| kkff23        | 0 C, 1 Y  | 0.2 L, 0.01 M | 0.125 M, 0.8 H | 0.47 L, 0 M | 0.42 L, 0 M  |
| kkff24        | 0.85 O    | 0.4 L, 0 M | 0 M, 0.2 H  | 0.54 L, 0 M  | 0.75 L, 0 M  |
| kkff25        | 0 C, 0.46 Y | 1 L, 0 M | 0 M, 0.4 H  | 0.87 L, 0 M  | 0.14 L, 0.35 M |
| kkff26        | 0 Y, 0.66 O | 0.4 L, 0 M | 0.125 M, 0.8 H | 0.85 L, 0 M | 0.28 L, 0.29 M |
| kkff27        | 0 Y, 1 O  | 0 L, 0.16 M | 0.33 L, 0 M | 0 L, 0.129 M | 0.28 L, 0 M  |
| kkff28        | 0.71 C, 0 Y | 0.5 L, 0.56 M | 0.53 L, 0 M | 0 L, 0.322 M | 0 L, 0.58 M  |
| kkff29        | 0 Y, 0.91 O | 0.4 L, 0 M | 0 M, 0.4 H  | 0.97 L, 0 M  | 0.57 L, 0 M  |
| kkff30        | 0 Y, 0.52 O | 0.8 L, 0 M | 0.25 M, 0.6 H | 0.85 L, 0 M | 0.85 L, 0.05 M |
III.ii. Transforming the fuzzy sets into soft sets

In this step, we will change fuzzy sets obtained in the first step into the soft sets. Since the soft sets are a generalization of fuzzy sets so by using the fuzzified values, we will make parameter sets applying the definition of \( \alpha \) – cut sets. Membership function gives us the parametric sets. Parameter sets provide the numerical costs so that we can apply soft set theory to that data.

Soft sets can be obtained from fuzzy sets by using the definition of \( \alpha \) – cut sets as follows:

\[
K = \{ kkff_1, kkff_2, kkff_3, \ldots, kkff_{30} \}, \\
E = \{ 0, 0.25, 0.5, 0.75, 1 \}
\]

These are the soft sets for the child age, derived from the fuzzified data. \( K \) denotes the set of patients and \( E \) is the set of parameters. The set of the parameter is different for each part of the input variable.

\[
(F_{C\text{Age}}, E) = \{ 0 = \{ kkff_1, kkff_2, kkff_3, kkff_4, kkff_5, kkff_6, kkff_7, kkff_11, kkff_15, kkff_16, kkff_18, kkff_19, kkff_20, kkff_22, kkff_25, kkff_28 \}, \\
0.25 = \{ kkff_1, kkff_6, kkff_11, kkff_19, kkff_28 \}, \\
0.5 = \{ kkff_1, kkff_6, kkff_19, kkff_28 \}, \\
0.75 = \{ kkff_19, kkff_28 \}, \\
I = \{ kkff_19 \} \}
\]

These are the soft sets for the child age, derived from the fuzzified data. \( F \) denotes the set of patients and \( E \) is the set of parameters. The set of the parameter is different for each part of the input variable.

\[
E = \{ 0.2, 0.4, 0.6, 0.8, 1 \} (F_{L\text{TLC}}, E) = \{ 0.2 = \{ kkff_1, kkff_2, kkff_3, kkff_5, kkff_6, kkff_7, kkff_9, kkff_10, kkff_11, kkff_12, kkff_14, kkff_15, kkff_17, kkff_18, kkff_19, kkff_20, kkff_21, kkff_23, kkff_24, kkff_25, kkff_26, kkff_29, kkff_30 \}, 0.4 = \{ kkff_1, kkff_2, kkff_3, kkff_5, kkff_6, kkff_7, kkff_9, kkff_10, kkff_11, kkff_12, kkff_14, kkff_15, kkff_17, kkff_18, kkff_19, kkff_20, kkff_21, kkff_23, kkff_24, kkff_25, kkff_26, kkff_29, kkff_30 \}, 0.6 = \{ kkff_1, kkff_2, kkff_3, kkff_5, kkff_6, kkff_7, kkff_9, kkff_10, kkff_11, kkff_12, kkff_14, kkff_15, kkff_17, kkff_18, kkff_19, kkff_20, kkff_21, kkff_23, kkff_24, kkff_25, kkff_26, kkff_29, kkff_30 \}, 0.8 = \{ kkff_1, kkff_2, kkff_3, kkff_5, kkff_6, kkff_7, kkff_9, kkff_10, kkff_11, kkff_12, kkff_14, kkff_15, kkff_17, kkff_18, kkff_19, kkff_20, kkff_21, kkff_23, kkff_24, kkff_25, kkff_26, kkff_29, kkff_30 \}, I = \{ kkff_1, kkff_2, kkff_25 \} \}
\]

These are the soft sets for the child age, derived from the fuzzified data. \( F \) denotes the set of patients and \( E \) is the set of parameters. The set of the parameter is different for each part of the input variable.

\[
E = \{ 0, 0.25, 0.5, 0.75, 1 \} (F_{M\text{SGOT}}, E) = \{ 0 = \{ kkff_1, kkff_2, kkff_3, \ldots, kkff_{30} \}, 0.25 = \{ kkff_1, kkff_3, kkff_4, kkff_5, kkff_6, kkff_7, kkff_10, kkff_11, kkff_17, kkff_20, kkff_21, kkff_30 \}, 0.5 = \{ kkff_1, kkff_3, kkff_4, kkff_5, kkff_6, kkff_7, kkff_10, kkff_11, kkff_17, kkff_20, kkff_21, kkff_30 \}, 0.75 = \{ kkff_4, kkff_6 \}, I = \emptyset \}
\]

Copyright reserved © J. Mech. Cont.& Math. Sci.
Fariha Iftikhar et al
The soft sets for the low platelets count given below, obtained from the fuzzified data.

\[ E = \{0.2, 0.55, 0.7, 0.85, 1\} \]

\[(F_{L,PC}, E) = \{0.2, 0.55, 0.7, 0.85, 1\} \]

\[= \{kkff_1, kkff_2, kkff_3, kkff_4, kkff_5, kkff_6, kkff_9, kkff_{10}, kkff_{11}, kkff_{12}, Kkff_{15}, kkff_{17}, kkff_{18}, kkff_{19}, kkff_{23}, kkff_{24}, kkff_{25}, kkff_{26}, kkff_{29}, kkff_{30}\}, \]

\[0.55= \{kkff_1, kkff_2, kkff_3, kkff_4, kkff_5, kkff_6, kkff_9, kkff_{11}, kkff_{15}, kkff_{17}, kkff_{24}, kkff_{25}, kkff_{26}, kkff_{29}, kkff_{30}\}, \]

\[0.7= \{kkff_5, kkff_6, kkff_{11}, kkff_{15}, kkff_{17}, kkff_{25}, kkff_{26}, kkff_{29}, kkff_{30}\}, \]

\[0.85= \{kkff_{11}, kkff_{15}, kkff_{17}, kkff_{25}, kkff_{26}, kkff_{29}, kkff_{30}\} \]

\[I = \emptyset \}

Here we have the soft sets for the low BP, obtained from the fuzzified data.

\[ E = \{0.2, 0.25, 0.5, 0.75, 1\} \]

\[(F_{L,BP}, E) = \{0.2, 0.25, 0.5, 0.75, 1\} \]

\[= \{kkff_1, kkff_2, kkff_3, kkff_4, kkff_5, kkff_6, kkff_7, kkff_9, kkff_{10}, kkff_{11}, kkff_{12}, kkff_{14}, kkff_{15}, kkff_{16}, kkff_{17}, kkff_{18}, kkff_{19}, kkff_{20}, kkff_{21}, kkff_{22}, kkff_{23}, kkff_{24}, kkff_{25}, kkff_{26}, kkff_{27}, kkff_{28}, kkff_{29}, kkff_{30}\}, \]

\[0.25= \{kkff_1, kkff_2, kkff_3, kkff_4, kkff_5, kkff_6, kkff_9, kkff_{10}, kkff_{11}, kkff_{15}, kkff_{16}, kkff_{18}, kkff_{19}, kkff_{20}, kkff_{21}, kkff_{22}, kkff_{23}, kkff_{24}, kkff_{26}, kkff_{27}, kkff_{28}, kkff_{29}, kkff_{30}\}, \]

\[0.5= \{kkff_1, kkff_2, kkff_3, kkff_5, kkff_{10}, kkff_{11}, kkff_{15}, kkff_{16}, kkff_{18}, kkff_{19}, kkff_{20}, kkff_{21}, kkff_{24}, kkff_{29}, kkff_{30}\}, \]

\[0.75= \{kkff_1, kkff_2, kkff_6, kkff_{10}, kkff_{11}, kkff_{15}, kkff_{18}, kkff_{19}, kkff_{24}, kkff_{29}, kkff_{30}\} \]

\[I = \emptyset \}

### III.iii. Parameter reduction of soft sets

In third step, we find reduced soft sets of the soft sets obtained above. In soft set theory, there are no limiting conditions when objects are described. One can choose parameters and their forms according to needs. The fact that setting parameters non bindingly helps significantly in the decision-making process and still, we can make effective decisions under the circumstances of less information.

The critical problem in soft set theory is parameter reduction. Some effort has been made on this problem. Ma et al. investigated standard parameter reduction in [XIV].

**Definition:** [XIV]

Let \((S, Z)\) be a soft set \(W = \{w_1, w_2, w_3, w_4, w_5, w_6\}\) and \(Z = \{z_1, z_2, z_3, \ldots, z_\chi\}\) be the set of parameters, if there exist a subset \(L = \{z'_1, z'_2, \ldots, z'_\chi\} \subseteq E\) satisfying \(f_L(w_1) = f_L(w_2) = \cdots = f_L(w_\chi)\), then \(L\) is dispensable, otherwise, \(L\) is indispensable. A subset \(M \subseteq Z\) is a normal parameter reduction of \(Z\), if the two conditions as follows are satisfied;
i. Mis indispeensable,
ii. \( f_{Z-M}(w_1) = f_{Z-M}(w_2) = \cdots = f_{Z-M}(w_x) \).

**Example:** [XIV]

Let a soft set \((S, Z)\) with tabular representation displayed as in table below, suppose that

\[
W = \{w_1, w_2, w_3, w_4, w_5, w_6\} \text{and } Z = \{z_1, z_2, z_3, z_4, z_5, z_6, z_7, z_8, z_9, z_{10}\},
\]

where \(n = 6\).

Then

| \(S/Z\) | \(z_1\) | \(z_2\) | \(z_3\) | \(z_4\) | \(z_5\) | \(z_6\) | \(z_7\) | \(z_8\) | \(z_9\) | \(z_{10}\) | \(f(\cdot)\) |
|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| \(w_1\) | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 6 |
| \(w_2\) | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 4 |
| \(w_3\) | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 3 |
| \(w_4\) | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 4 |
| \(w_5\) | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 5 |
| \(w_6\) | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 4 |
| \(Y(z_q)\) | 3 | 1 | 5 | 3 | 2 | 3 | 2 | 2 | 1 | 4 | \(Y_Z = 26\) |

It is obvious from table that the subsets \(\{z_1, z_2, z_5, z_6, z_8, z_9\}\), \(\{z_1, z_4, z_6, z_8, z_9\}\), or \(\{z_6, z_7, z_9\}\) can be deleted from \(Z\).

The subsets \(\{z_3, z_4, z_7, z_{10}\}\), \(\{z_2, z_3, z_5, z_7, z_{10}\}\), and \(\{z_1, z_2, z_3, z_4, z_5, z_8, z_{10}\}\) are normal parameter reduction of \(Z\).

As \(Y_{z_1,z_2,z_3,z_4,z_5,z_6} = 6 = 1 \times 6\) and \(Y_{z_1,z_2,z_3,z_4,z_5,z_6} = Y_{z_1,z_2,z_3,z_4,z_5,z_6} = 12 = 2 \times 6\), which are multiple of 6.

These are the reduced soft sets for the child age

\[
K = \{kkff1, kkff2, kkff3, \ldots, kkff30\},
\]

\[
E = \{0.25, 0.5, 0.75, 1\}
\]

\[
(F_{C,Age}, E) = \{0.25 = \{kkff1, kkff6, kkff11, kkff19, kkff28\}, \]

\[
0.5 = \{kkff1, kkff6, kkff19, kkff28\},
\]

\[
0.75 = \{kkff19, kkff28\},
\]

\[
l = \{kkff19\}
\]

These are the reduced soft sets for the low TLC.

\[
E = \{0.2, 0.4, 0.6, 0.8, 1\}(F_{L,TLC}, E) = \{0.2
\]

\[
= \{kkff1, kkff2, kkff3, kkff4, kkff5, kkff6, kkff7, kkff9, kkff10, kkff11, kkff12, kkff14, kkff15, kkff17, kkff18, kkff19, kkff20, kkff21, kkff22, kkff23, kkff24, kkff25, kkff26, kkff29, kkff30\} \cdot 0.4
\]

\[
= \{kkff1, kkff2, kkff3, kkff4, kkff5, kkff6, kkff7, kkff9, kkff10, kkff11, kkff12, kkff14, kkff15, kkff17, kkff18, kkff19, kkff20, kkff21, kkff22, kkff23, kkff24, kkff25, kkff26, kkff29, kkff30\} \cdot 0.6
\]

\[
= \{kkff2, kkff5, kkff6, kkff10, kkff12, kkff14, kkff15, kkff18, kkff20, kkff21, kkff22, kkff23, kkff25\}.
\]
III.iv. Obtaining soft rules

In this step, we will obtain soft rules by using the reduced soft sets of the previous step. We get the soft rules with the help of “AND” operation on reduced soft sets. We will use the definition of AND operation from [8] to obtain rules. After obtaining rules, we can observe that which patient provides which rule. Some rules are discussed as follows:

\[
E = \{0.25, 0.5, 0.75\}
\]

\[
(F_{\text{H.SGOT}}, E) = \{0.25
\]

\[
= \{kkf_f_1, kkf_f_3, kkf_f_4, kkf_f_5, kkf_f_6, kkf_f_9, kkf_f_{10}, kkf_f_{11}, kkf_f_{12}, kkf_f_{15}, kkf_f_{18}, kkf_f_{19}, kkf_f_{23}, kkf_f_{25}, kkf_f_{26}, kkf_f_{29}, kkf_f_{30}\},
\]

\[
0.5 = \{kkf_f_1, kkf_f_4, kkf_f_9, kkf_f_{10}, kkf_f_{11}, kkf_f_{12}, kkf_f_{15}, kkf_f_{18}, kkf_f_{20}, kkf_f_{21}, kkf_f_{22}, kkf_f_{25}\},
\]

\[
0.75 = \{kkf_f_4, kkf_f_6\},
\]

These are the reduced soft sets for the medium SGOT.

\[
E = \{0.2, 0.55, 0.7, 0.85\}
\]

\[
(F_{\text{L.PC}}, E) = \{0.2
\]

\[
= \{kkf_f_1, kkf_f_2, kkf_f_3, kkf_f_4, kkf_f_5, kkf_f_6, kkf_f_9, kkf_f_{10}, kkf_f_{11}, kkf_f_{12}, kkf_f_{15}, kkf_f_{18}, kkf_f_{19}, kkf_f_{23}, kkf_f_{25}, kkf_f_{26}, kkf_f_{29}, kkf_f_{30}\},
\]

\[
0.55 = \{kkf_f_1, kkf_f_2, kkf_f_3, kkf_f_4, kkf_f_5, kkf_f_6, kkf_f_9, kkf_f_{11}, kkf_f_{15}, kkf_f_{17}, kkf_f_{24}, kkf_f_{25}, kkf_f_{26}, kkf_f_{29}, kkf_f_{30}\},
\]

\[
0.7 = \{kkf_f_5, kkf_f_6, kkf_f_{11}, kkf_f_{15}, kkf_f_{17}, kkf_f_{24}, kkf_f_{25}, kkf_f_{26}, kkf_f_{29}, kkf_f_{30}\},
\]

\[
0.85 = \{kkf_f_{11}, kkf_f_{15}, kkf_f_{17}, kkf_f_{25}, kkf_f_{26}, kkf_f_{29}, kkf_f_{30}\}.
\]

These are the reduced soft sets for the low platelets count.

\[
E = \{0.25, 0.5, 0.75\}
\]

\[
(F_{\text{L.BP}}, E) = \{0.25
\]

\[
= \{kkf_f_1, kkf_f_2, kkf_f_3, kkf_f_5, kkf_f_6, kkf_f_9, kkf_f_{10}, kkf_f_{11}, kkf_f_{14}kkf_f_{15}, kkf_f_{16}, kkf_f_{18}, kkf_f_{19}, kkf_f_{20}, kkf_f_{21}, kkf_f_{22}, kkf_f_{23}, kkf_f_{24}, kkf_f_{26}, kkf_f_{27}, kkf_f_{29}, kkf_f_{30}\},
\]

\[
0.5 = \{kkf_f_1, kkf_f_2, kkf_f_3, kkf_f_6, kkf_f_{10}, kkf_f_{11}, kkf_f_{15}, kkf_f_{16}, kkf_f_{18}, kkf_f_{19}, kkf_f_{21}, kkf_f_{24}, kkf_f_{29}, kkf_f_{30}\},
\]

\[
0.75 = \{kkf_f_1, kkf_f_2, kkf_f_6, kkf_f_{10}, kkf_f_{11}, kkf_f_{15}, kkf_f_{18}, kkf_f_{19}, kkf_f_{24}, kkf_f_{30}\}.
\]

These are the reduced soft sets for the low BP.
1. \( F_{C_Age}(0.25) \land F_{LTLC}(0.2) \land F_{HSGOT}(0.2) \land F_{LPC}(0.2) \land F_{LBP}(0.25) \)
   = \{kkff_1, kkff_6, kkff_{11}, kkff_{19}, kkff_{28} \}
   \cup \{kkff_2, kkff_5, kkff_{15}, kkff_{17}, kkff_{19}, kkff_{20}, kkff_{21}, kkff_{23}, kkff_{24},
   kkff_{25}, kkff_{26}, kkff_{29}, kkff_{30} \}
   \cup \{kkff_3, kkff_4, kkff_6, kkff_{10}, kkff_{12}, kkff_{16}, kkff_{18}, kkff_{19},
   kkff_{20}, kkff_{22}, kkff_{23}, kkff_{24}, kkff_{26}, kkff_{27}, kkff_{29}, kkff_{30} \}
   \cup \{kkff_5, kkff_9, kkff_10, kkff_{11}, kkff_{12}, kkff_{15}, kkff_{17}, kkff_{18}, kkff_{19},
   kkff_{20}, kkff_{22}, kkff_{23}, kkff_{24}, kkff_{25}, kkff_{26}, kkff_{29}, kkff_{30} \}
   \cup \{kkff_6, kkff_{11}, kkff_{19} \}

2. \( F_{C_Age}(0.5) \land F_{LTLC}(0.2) \land F_{HSGOT}(0.2) \land F_{LPC}(0.25) \land F_{LBP}(0.25) \)
   = \{kkff_1, kkff_6, kkff_{19} \}

3. \( F_{C_Age}(0.75) \land F_{LTLC}(0.2) \land F_{HSGOT}(0.2) \land F_{LPC}(0.25) \land F_{LBP}(0.25) \)
   = \{kkff_{19} \}

4. \( F_{C_Age}(0.25) \land F_{M_TLC}(0.3) \land F_{HSGOT}(0.2) \land F_{M_PC}(0.2) \land F_{LBP}(0.5) \)
   = \emptyset

5. \( F_{C_Age}(0.25) \land F_{LTLC}(0.2) \land F_{HSGOT}(0.2) \land F_{LPC}(0.2) \land F_{M_BP}(0.4) \)
   = \emptyset

6. \( F_{C_Age}(0.25) \land F_{LTLC}(0.2) \land F_{M_SGOT}(0.25) \land F_{LPC}(0.2) \land F_{H_BP}(0) \)
   = \emptyset

7. \( F_{C_Age}(0.25) \land F_{LTLC}(0.2) \land F_{HSGOT}(0.2) \land F_{M_PC}(0.2) \land F_{LBP}(0.25) \)
   = \emptyset

8. \( F_{C_Age}(0.5) \land F_{LTLC}(0.4) \land F_{HSGOT}(0.4) \land F_{LPC}(0.55) \land F_{LBP}(0.5) \)
   = \emptyset

9. \( F_{C_Age}(0.75) \land F_{LTLC}(0.6) \land F_{HSGOT}(0.6) \land F_{LPC}(0.7) \land F_{LBP}(0.75) \)
   = \emptyset

10. \( F_{Y_Age}(0.3) \land F_{LTLC}(0.2) \land F_{HSGOT}(0.2) \land F_{LPC}(0.25) \land F_{LBP}(0.25) \)
    = \{kkff_3, kkff_{15}, kkff_{20}, kkff_{23} \}

11. \( F_{Y_Age}(0.6) \land F_{LTLC}(0.2) \land F_{HSGOT}(0.2) \land F_{LPC}(0.2) \land F_{LBP}(0.25) \)
\begin{align*}
&= \{kkf_{15}, kkf_{23}\} \\
12. \quad F_{Y,Age}(0.8) \land F_{LTLC}(0.2) \land F_{HSGOT}(0.2) \land F_{LPC}(0.2) \land F_{LBP}(0.25) \\
&= \{kkf_{15}, kkf_{23}\} \\
13. \quad F_{Y,Age}(01) \land F_{LTLC}(0.2) \land F_{HSGOT}(0.2) \land F_{LPC}(0.2) \land F_{LBP}(0.25) \\
&= \{kkf_{23}\} \\
14. \quad F_{Y,Age}(0.3) \land F_{LTLC}(0.4) \land F_{HSGOT}(0.2) \land F_{LPC}(0.2) \land F_{LBP}(0.25) \\
&= \{kkf_{3}, kkf_{15}\} \\
15. \quad F_{Y,Age}(0.3) \land F_{LTLC}(0.6) \land F_{HSGOT}(0.2) \land F_{LPC}(0.2) \land F_{LBP}(0.25) \\
&= \{kkf_{15}\} \\
16. \quad F_{Y,Age}(0.3) \land F_{LTLC}(0.6) \land F_{HSGOT}(0.4) \land F_{LPC}(0.55) \land F_{LBP}(0.5) \\
&= \emptyset \\
17. \quad F_{Y,Age}(0.6) \land F_{LTLC}(0.6) \land F_{HSGOT}(0.2) \land F_{LPC}(0.2) \land F_{LBP}(0.25) \\
&= \{kkf_{15}\} \\
18. \quad F_{Y,Age}(0.6) \land F_{LTLC}(0.6) \land F_{HSGOT}(0.4) \land F_{LPC}(0.55) \land F_{LBP}(0.25) \\
&= \{kkf_{15}\} \\
19. \quad F_{Y,Age}(0.6) \land F_{LTLC}(0.6) \land F_{HSGOT}(0.4) \land F_{LPC}(0.55) \land F_{LBP}(0.5) \\
&= \{kkf_{15}\} \\
20. \quad F_{Y,Age}(0.8) \land F_{LTLC}(0.8) \land F_{HSGOT}(0.6) \land F_{LPC}(0.7) \land F_{LBP}(0.5) \\
&= \emptyset \\
21. \quad F_{Y,Age}(0.8) \land F_{LTLC}(0.8) \land F_{HSGOT}(0.8) \land F_{LPC}(0.85) \land F_{LBP}(0.5) \\
&= \emptyset \\
22. \quad F_{Y,Age}(01) \land F_{LTLC}(0.2) \land F_{HSGOT}(0.2) \land F_{LPC}(0.2) \land F_{LBP}(0.25) \\
&= \{kkf_{23}\} \\
23. \quad F_{O,Age}(0.35) \land F_{LTLC}(0.2) \land F_{HSGOT}(0.2) \land F_{LPC}(0.2) \land F_{LBP}(0.25) \\
&= \{kkf_{2}, kkf_{9}, kkf_{10}, kkf_{24}, kkf_{29}, kkf_{30}\} \\
24. \quad F_{O,Age}(0.6) \land F_{LTLC}(0.2) \land F_{HSGOT}(0.2) \land F_{LPC}(0.2) \land F_{LBP}(0.25) \\
&= \{kkf_{2}, kkf_{24}, kkf_{29}, kkf_{30}\} \\
25. \quad F_{O,Age}(0.8) \land F_{LTLC}(0.2) \land F_{HSGOT}(0.2) \land F_{LPC}(0.2) \land F_{LBP}(0.25) \\
&= \{kkf_{2}, kkf_{26}, kkf_{29}, kkf_{30}\} \\
26. \quad F_{O,Age}(01) \land F_{LTLC}(0.2) \land F_{HSGOT}(0.2) \land F_{LPC}(0.2) \land F_{LBP}(0.25) \\
&= \emptyset \\
27. \quad F_{O,Age}(0.35) \land F_{LTLC}(0.4) \land F_{HSGOT}(0.4) \land F_{LPC}(0.2) \land F_{LBP}(0.25) \\
&= \{kkf_{2}, kkf_{26}, kkf_{29}, kkf_{30}\} \\
28. \quad F_{O,Age}(0.35) \land F_{LTLC}(0.4) \land F_{HSGOT}(0.4) \land F_{LPC}(0.55) \land F_{LBP}(0.5) \\
\end{align*}
We analyzed these soft sets and observe to what extent a patient in the set has dengue fever, i.e., what is the severity level of dengue fever a patient is having? To answer these questions, the soft set of patients against each rule was obtained in step four. We analyzed these soft sets and observe to what extent a patient in the set has dengue fever. In this way, we will obtain risk percentage of dengue fever for each

\[ F_{O,Age}(0.6) \land F_{L,TL}(0.6) \land F_{H,SGOT}(0.4) \land F_{L,PC}(0.55) \land F_{L,BP}(0.5) \]
\[ = \{kff_2, kff_3, kff_30\} \]

\[ F_{O,Age}(0.6) \land F_{L,TL}(0.6) \land F_{H,SGOT}(0.4) \land F_{L,PC}(0.7) \land F_{L,BP}(0.5) \]
\[ = \{kff_3, kff_30\} \]

\[ F_{O,Age}(0.8) \land F_{L,TL}(0.6) \land F_{H,SGOT}(0.2) \land F_{L,PC}(0.2) \land F_{L,BP}(0.25) \]
\[ = \emptyset \]

\[ F_{O,Age}(0.8) \land F_{L,TL}(0.6) \land F_{H,SGOT}(0.8) \land F_{L,PC}(0.85) \land F_{L,BP}(0.75) \]
\[ = \emptyset \]

\[ F_{C,Age}(01) \land F_{L,TL}(01) \land F_{H,SGOT}(01) \land F_{L,PC}(01) \land F_{L,BP}(1) \]
\[ = \emptyset \]

\[ F_{C,Age}(01) \land F_{L,TL}(01) \land F_{H,SGOT}(01) \land F_{L,PC}(01) \land F_{L,BP}(01) \]
\[ = \emptyset \]

\[ F_{C,Age}(0.5) \land F_{L,TL}(0.6) \land F_{M,SGOT}(0.5) \land F_{M,PC}(0.4) \land F_{M,BP}(0.4) \]
\[ = \emptyset \]

\[ F_{C,Age}(0.25) \land F_{L,TL}(0.2) \land F_{M,SGOT}(0.25) \land F_{L,PC}(0.2) \land F_{L,BP}(0.25) \]
\[ = \{kff_1, kff_11\} \]

\[ F_{C,Age}(0.5) \land F_{L,TL}(0.2) \land F_{M,SGOT}(0.25) \land F_{L,PC}(0.2) \land F_{L,BP}(0.25) \]
\[ = \{kff_1\} \]

By this method, we get many rules. After observing some rules have the same output, i.e., the same patients and some are null sets so neglecting that rules we are left with some rules.

### III.v. Analysis of soft rules

In this step, we synthesize the soft rules and calculate the exact risk percentage of dengue fever, i.e., what is the severity level of dengue fever a patient is having? To answer these questions, the soft set of patients against each rule was obtained in step four. We analyzed these soft sets and observe to what extent a patient in the set has dengue fever. In this way, we will obtain risk percentage of dengue fever for each
rule. If the data of a patient is expedient to more than one rule, then the highest value will be selected.

We have total 38 soft rules of dengue patients. However, we investigated particularly rule 1, 2, 3 and 24. The choice of analyzing these rules is not specific. We can analyze any rule from 38 rules mentioned above to get the exact risk percentage of dengue fever.

Now we calculate the risk percentage of rule one:

Rule 1:
\[ F_{\text{Age}(0.25)} \land F_{\text{TLC}(0.2)} \land F_{\text{SGOT}(0.2)} \land F_{\text{PC}(0.2)} \land F_{\text{BP}(0.25)} = \{k_ff_{5}, k_ff_{6}, k_ff_{11}, k_ff_{19}\} \]

Four patients have the properties of rule 1. Dengue fever is found in 2 patients. Hence the risk percentage for the rule 1 is given by \((2 \div 4) \times 100 = 50\%\)

By this calculation, we can realize that the patients whose inputs of Age, TLC, SGOT, Platelets count and Blood pressure are expedient to rule 1 have 50% risk of dengue fever.

Rule 2:
\[ F_{\text{Age}(0.5)} \land F_{\text{TLC}(0.2)} \land F_{\text{SGOT}(0.2)} \land F_{\text{PC}(0.2)} \land F_{\text{BP}(0.25)} = \{k_ff_{1}, k_ff_{6}, k_ff_{19}\} \]

There are 2 patients who have attributes of rule 2. Dengue fever is found in all three patients. Hence the risk percentage for the rule 2 is given by \((2 \div 3) \times 100 = 67\%\)

From above calculation the patient’s set of rule 2 has the 67% risk of dengue fever.

Rule 3:
\[ F_{\text{Age}(0.75)} \land F_{\text{TLC}(0.2)} \land F_{\text{SGOT}(0.2)} \land F_{\text{PC}(0.2)} \land F_{\text{BP}(0.25)} = \{k_ff_{19}\} \]

There is only 1 patient in the set of rule 3. The patient is suffering from dengue so risk for the rule 3 is 100%.

Similarly for...

Rule 24:
\[ F_{\text{Age}(0.6)} \land F_{\text{TLC}(0.2)} \land F_{\text{SGOT}(0.2)} \land F_{\text{PC}(0.2)} \land F_{\text{BP}(0.25)} = \{k_ff_{2}, k_ff_{24}, k_ff_{26}, k_ff_{29}, k_ff_{30}\} \]

In rule 24 there are 5 patients. Number of patients affected with dengue fever is 4. Hence the risk of rule 24 is 80%. Therefore the patients with the values of Age, TLC, SGOT, Platelets count and Blood pressure convenient to rule 24 have the 80% risk of dengue fever. Continuing the same procedure the risk percentage of each rule calculated. As the values of the patient \(k_ff_{19}\) is following the rules 1, 2 and 3. The observation makes it easy to say that rule 3 has highest value so the risk of dengue fever of patient is 100%.
IV. Results and Comparison

In this work, we used a soft expert system (SES) based on soft sets and fuzzy set theory to diagnose the dengue fever. We find out the exact percentage risk of dengue fever that will help an expert or practitioner to treat the patient according to its precise severity level. The patients with high percentage risk are having a high potential for dengue fever. This procedure determines the risk percentage for each soft rule.

After analysis, it is clear that some patients have dengue and some patients are not having dengue fever. We analyzed the data of 30 patients collected from the Holy Family Hospital Islamabad, Pakistan.

Subsequently, by applying the techniques of fuzzy soft set theory we can surely demonstrate the exact percentage of a patient having dengue fever. Our methodology exhibited the risk percentage for 13 patients out of 30. This risk percentage helps us to infer that 13 patients are having dengue while 17 patients are not suffering from dengue disease.

Some patients have high risk percentage and some with average risk percentage, but both are considered as victim of dengue fever.

We use same 5 features as input such as age, TLC, SGOT, Platelets count and blood pressure features similar the author [XIII] used. We used hybrid theory that is fuzzy soft set theory while the author [XIII] adopted fuzzy logic using different dataset. Since we have mentioned the limitations of fuzzy logic in the literature review. This is why we use fuzzy soft set theory which provides us exactly 100% accurate results in diagnostic of dengue fever as compared with fuzzy set theory [XIII].

Our competitor achieved “almost 100% results” [XIII], we can infer that achieved results are not exactly 100%. Additionally, the author did not demonstrate both the methodology and how he achieved the almost 100% results. Consequently, we are unable to make comparison with the methodology [XIII]. Our method in diagnostic dengue fever outperforms other methods with fuzzy logic.

For example, if a patient is suffering from fever, vomiting, headache and nausea, imagine for medical checkup he will visit two different practitioners say A and B. The practitioner A after examining the patient observes that patient is suffering from cold. However, it is likely to happen that the practitioner B observes that it is just because of fatigue. In this case too much ambiguity is present. As neither practitioner A can decide easily that the patient is suffering from dengue nor practitioner B. Mathematical theories can solve this problem. However, fuzzy set theory uses the dataset of a patient which involves values of some basic symptoms of dengue. After applying the methodology of fuzzy set theory the results are not satisfactory. Consequently fuzzy set theory fails here since fuzzy set theory has different types of membership functions. Therefore any individual has issue in selecting a membership function so ambiguity is still there in this case. To remove this kind of uncertainty soft set theory plays its role and
get succeed. The hybrid theory that includes fuzzy set theory and soft set theory can remove the ambiguity induced using only fuzzy set theory. Soft set theory is much better than fuzzy set theory due to its property that it is a parameterized theory and one can get best result in an environment of less information.

V. Conclusion

The main objective of this research is to help the doctor in examining the patient and diagnosing the disease severity without getting the chance of uncertainty and ambiguity. The results of our work are better than [XIII]. The best work done in this field using soft expert system was “the applications of soft set theory to diagnose the prostate cancer”. In this work the similar soft expert system is used to diagnose dengue fever. The execution of this work is more precise and useful as compared to [XIII]. We achieved 100% results, which can play significant role in examining the patient and diagnosing the dengue disease severity. This methodology in future may be prolonged to diagnose many other diseases and the conversion of this technique into software enables the patient to diagnose the disease himself at anywhere instead of visiting a medical expert.

References

I. D. A. Molodtsov, soft set theory- first results, Comput. Math. Appl. 37 (1999) 19-31.

II. D. Chen, E. C. C. Tsang, D. S. Yeung, X. Wang, the parameterization reduction of soft sets and its applications, Comput. Math. Appl. 49 (2005) 757-763.

III. F. M. E. Uzoka and K. Barker, Expert system and uncertainty in medical diagnosis: A proposal for fuzzy-AHP hybridization, an international journal of Medical Engg. And informatics, 2 (2010) 329-342.

IV. H. T. Nguyen and E. A. Walker, A first course in fuzzy logic, Application in intelligent systems Boston; Kluwer Academic.

V. J. Durkin, Expert System Design and Development, New Jersy: Prentice Hall (1994).

VI. L. A. Zadeh, Fuzzy sets, Inform. and Control 8 (1965) 338-353.

VII. L. Boullart, A. Krijgsman, R. A. Vingerhoeds, editors Applications of Artificial Intelligence in process control program press, (1992).

VIII. M. I. Ali, F. Feng, X. Liu, W. K. Min, M. Shabbir, On new operation in soft set theory. Comput. Math. Appl. 57 (2009) 1547-1553.
IX. P. K. Maji, R. Biswas, A. R. Roy, Soft set theory, Comput. Math. Appl. 45 (2003) 555-562.

X. P. Sharam, DBV. Singh, M. K. Bandil, and N. Mishra, Decision Support System for Malaria and Dengue Diagnosis, International Journal of information and Computational Technology, 3 (2013) 633-640.

XI. P. Szolovits, R. S. Patil and W. B. Schwartz, Artificial intelligence in medical diagnosis, Journal of international medicine, 108 (1988) 80-87.

XII. S. B. Halsted, V. A. Suaya, D. S. Shepard, The burden of dengue infection Lancet, 369 (2007) 1410-1411.

XIII. V. Pabbi: Fuzzy Expert System for Medical Diagnosis. IJSRP, 5 (2015).

XIV. X. Ma, N. Sulaiman, H. Qin, T. Herawan, V. M Zain, A new efficient normal parameter reduction algorithm of soft sets, Comput. Math. Appl. 62 (2011) 588-598.

XV. Y. Zou, Z. Xiao, Data analysis approaches of soft sets under incomplete information, known. Based Syst. 59 (2008) 2128-2137.