

Research Article

An Application Of Fuzzy Expert Systems Using In Road Accident To Human Body Diseases Affected Details

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Abstract

The field of fuzzy sets and expert systems is a fascinating one. The majority of human tasks such as planning, designing, analyzing, and advising have been thought to be programmed in traditional software. Such tasks are incredibly difficult to define as a step-by-step procedure. So, using an expert method for medical diagnosis, find out how a road accident has impacted your body sickness.

Keywords: Expert System, Medical Diagnosis, Road Accident Details, Fuzzy Matrix, Fuzzy Relation

I. INTRODUCTION

Every year, nearly 1.35 million people's lives are cut short as a result of a car accident. Non-fatal events impact between 20 and 50 million more people, with many of them being disabled as a result of their injuries. Individuals, communities, and societies as a whole suffer significant economic losses as a result of road traffic accidents. Treatment expenses, lost productivity for those killed or injured, and family members who might take time off work or school to care for the wounded all contribute to the number of casualties.

Even a minor fender bender may result in a traumatic brain injury, requiring years of rehabilitation. Nobody expects their loved ones to be involved in a car accident, but it happens on Anderson's roads every day. Every year, thousands of people are killed or injured in traffic collisions that should have been avoided. Negligent drivers cost the state's economy more than \$1 billion per year. The emotional and financial toll on the state's economy and on innocent families is massive.

We support families advocate for all of their personal injury rights under South Carolina law at Harbin & Burnett. We will assist you in asserting your legal rights. The 2030 Agenda for Sustainable Development has set a lofty goal of halving the global number of road traffic

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fatalities and injuries by 2020. The majority of countries lose 3% of their GDP due to traffic accidents.

Pedestrians, cyclists, and motorcyclists account for more than half of all road traffic fatalities. Despite having roughly 60% of the world's cars, low- and middle-income countries account for 93 percent of all road fatalities. For children and young adults aged 5 to 29, road traffic accidents are the leading cause of demise.

Most Common Motor Vehicle Accident Injuries

The severity of injuries sustained in a car accident ranges from minor to fatal. Many car accident victims, regardless of the type of injury, are unable to return to work or go about their everyday lives. Injured drivers and passengers face hospital expenses, insurance costs, and missed income as a result of negligent driver.

Neck Fractures, Scarring, Broken Bones, Amputations & Lost Limbs, Traumatic Brain Injuries, Back Injuries, Disfiguring facial injuries and scars, Shoulder injuries, Wrist and hand injuries are all types of road accident injuries.

As a result of the road accident, fractures and diseases develop in the patient's body. So far, our study has focused on the symptoms and signs of accident injuries, as well as the number of diseases that are affected in the bodies of accident victims.

II. CADIAG-2, AN EXPERT SYSTEM FOR MEDICAL DIAGNOSIS

In medicine, expert expertise is largely ambiguous. And to a limited extent will objective measurements be used for diagnostic purposes. In borderline situations, label laboratory test findings as "natural" or "pathological" is arbitrary, and many conclusions are highly subjective.

The severity of pain, for example, can only be expressed verbally and is highly dependent on the patient's subjective assessment. Also the link between symptoms and diseases isn't always clear and distinct. Adlassnig and Kolarz present overviews of these applications.

They designed and implemented CADIAG-2, for which they stated the following objectives:

1. Medical experience should be organised as a logical sequence of symptoms and diagnoses.
2. The logic relationship may be ambiguous. They are not required to follow Boolean logic.
3. After observing the patient's symptom pattern, common and uncommon diseases are recommended.
4. The diagnosis procedure may be repeated many times.
5. Recommendations for further case investigations, as well as the explanations for all diagnosis outcomes, are made available upon request.

To sketch their system, let us the following symbols:

\tilde{S} = set of systems = $\{\tilde{S}_1, \dots, \tilde{S}_m\}$.

\tilde{D} = set of diseases or diagnoses = $\{\tilde{D}_1, \dots, \tilde{D}_n\}$.

\tilde{P} = set of patients = $\{\tilde{P}_1, \dots, \tilde{P}_q\}$.

$\tilde{S}_i, \tilde{D}_j, \tilde{P}_k$ = fuzzy sets characterized.

And there are membership functions is defined by

$\mu_{\tilde{S}_i}$ = expressed the intensity of symptoms \tilde{S}_i

$\mu_{\tilde{D}_j}$ = expressed the degree of membership of a patient to \tilde{D}_j

$\mu_{\tilde{P}_k}$ = assigns to each diagnosis a degree of membership for \tilde{P}_k .

Two aspects of system with respect to diseases are of particular interest:

1. Occurrence
2. Confirmability

Definition of two fuzzy sets is given by

$\tilde{O}(x)$, $x = \{0, 1, \dots, 100\}$ for occurrence of \tilde{S}_i at \tilde{D}_j

$\tilde{C}(x)$, $x = \{0, 1, \dots, 100\}$ representing frequency with which \tilde{S}_i has been confirmed for \tilde{D}_j

$$\left. \begin{aligned} \mu_{\tilde{O}(x)} &= f(x; 1, 50, 99) \quad x \in X \\ \mu_{\tilde{C}(x)} &= f(x, 1, 50, 99) \quad y \in Y \end{aligned} \right\} \text{Membership function for above two definition.}$$

Using certain linguistic variables for often, almost always, very frequently, often, unspecific, seldom, very seldom, almost never, and then never, the frequency and confirmability relationship is obtained empirically from medical experts.

Other relationships are characterised as fuzzy relations, such as symptom to symptom, disease to disease, and symptom to disease. The use of probabilistic interpretations is employed. The symptom to disease relationship, the symptom to combination disease relationship, and the disease to disease relationship all produce fuzzy diagnostic signs that can be used to determine conformed and excluded diagnoses, as well as diagnostic theories, based on a patient's symptom pattern.

Three binary fuzzy relations are then introduced:

$\tilde{R}_{\tilde{O}}$ = occurrence relation

$\tilde{R}_{\tilde{C}}$ = confirmability relation

$X \otimes Y$ = both in $\tilde{R}_{\tilde{O}}$, $\tilde{R}_{\tilde{C}}$

$\tilde{R}_{\tilde{S}_i}$ = symptoms relation

which is determined on the basis of the symptoms pattern of the patients.

Finally, four different fuzzy indications are calculated by means of fuzzy relation compositions.

1. $\tilde{S}_i \tilde{D}_j$ occurrence indication $\tilde{R}_1 = \tilde{R}_{\tilde{S}_i} \circ \tilde{R}_{\tilde{O}}$

$$\mu_{\tilde{R}_1}(p, \tilde{D}_j) = \max_{\tilde{S}_i} \min \{ \mu_{\tilde{R}_{\tilde{S}_i}}(p, \tilde{S}_i), \mu_{\tilde{R}_{\tilde{O}}}(\tilde{S}_i, \tilde{D}_j) \}$$
2. $\tilde{S}_i \tilde{D}_j$ confirmability indication $\tilde{R}_2 = \tilde{R}_{\tilde{S}_i} \circ \tilde{R}_{\tilde{C}}$

$$\mu_{\tilde{R}_2}(p, \tilde{D}_j) = \max_{\tilde{S}_i} \min \{ \mu_{\tilde{R}_{\tilde{S}_i}}(p, \tilde{S}_i), \mu_{\tilde{R}_{\tilde{C}}}(\tilde{S}_i, \tilde{D}_j) \}$$
3. $\tilde{S}_i \tilde{D}_j$ nonoccurrence indication $\tilde{R}_3 = \tilde{R}_{\tilde{S}_i} \circ (1 - \tilde{R}_{\tilde{O}})$

$$\mu_{\tilde{R}_3}(p, \tilde{D}_j) = \max_{\tilde{s}_i} \min \{ \mu_{\tilde{R}_3}(p, \tilde{s}_i), 1 - \mu_{\tilde{R}_0}(\tilde{s}_i, \tilde{D}_j) \}$$

4. $\tilde{S}_i \tilde{D}_j$ nonsymptom indication $\tilde{R}_4 = (1 - \tilde{R}_3) \circ \tilde{R}_0$

$$\mu_{\tilde{R}_4}(p, \tilde{D}_j) = \max_{\tilde{s}_i} \min \{ 1 - \mu_{\tilde{R}_3}(p, \tilde{s}_i), \mu_{\tilde{R}_0}(\tilde{s}_i, \tilde{D}_j) \}$$

Similar indications are determined for symptom to disease relationships, and we arrive at 12 fuzzy relationships \tilde{R}_j .

Three categories of diagnostic relationship are distinguished:

1. Confirmed diagnoses
2. Excluded diagnoses
3. Diagnostic hypotheses

Diagnoses are considered confirmed if

$$\mu_{\tilde{R}_j} = 1$$

or if the max-min composition of then yields 1.

For excluded diagnosis, the decision rules are more involved and for diagnostic hypotheses, all diagnoses are used for which the maximum of the following pairs of degree of membership are smaller than .5:

$$\max \{ \mu_{\tilde{R}_j}, \mu_{\tilde{R}_k} \} \leq .5$$

CADIAG – 2 can be used for different purposes.

III. METHODOLOGY

Let us consider the set of symptoms $\tilde{S} = \{ \tilde{s}_1, \tilde{s}_2, \tilde{s}_3 \}$ and the set of diseases $\tilde{D} = \{ \tilde{d}_1, \tilde{d}_2 \}$

\tilde{s}_1 = Brain damage

\tilde{s}_2 = Metabolism

\tilde{s}_3 = Backbone damage

\tilde{d}_1 = Coma

\tilde{d}_2 = Stroke

Let us assume that the following medical documentation exists concerning the relations of symptoms $\tilde{s}_1, \tilde{s}_2, \tilde{s}_3$ to diseases \tilde{d}_1 and \tilde{d}_2 :

- ❖ Symptom \tilde{s}_1 always occurs with disease \tilde{d}_1 and very often confirms the presence of disease \tilde{d}_1 .
- ❖ Symptom \tilde{s}_1 occurs very seldom in patients with disease \tilde{d}_2 and never confirms disease \tilde{d}_2 .
- ❖ Symptom \tilde{s}_2 always occurs with disease \tilde{d}_2 and always confirms the presence of disease \tilde{d}_2 .
- ❖ Symptom \tilde{s}_2 occurs very seldom in patients with disease \tilde{d}_1 .
- ❖ Symptom \tilde{s}_3 very often occurs in patients with disease \tilde{d}_1 and often confirms the presence of disease \tilde{d}_1 .
- ❖ Symptom \tilde{s}_3 seldom occurs in patients with disease \tilde{d}_2 .

- ❖ All missing relational pairs of symptoms and diseases are assumed to be unspecific and are given a membership grade of .5 from our medical documentation we construct the following matrices $\tilde{R}_{\tilde{D}}$, $\tilde{R}_{\tilde{C}} \in \tilde{S} \times \tilde{D}$.

$$\begin{array}{|c|c|c|} \hline & \tilde{d}_1 & \tilde{d}_2 \\ \hline \tilde{s}_1 & 1 & .1 \\ \hline \tilde{s}_2 & .3 & 1 \\ \hline \tilde{s}_3 & .8 & .15 \\ \hline \end{array} = \tilde{R}_{\tilde{D}} ; \quad \begin{array}{|c|c|c|} \hline & \tilde{d}_1 & \tilde{d}_2 \\ \hline \tilde{s}_1 & .9 & .1 \\ \hline \tilde{s}_2 & .4 & 1 \\ \hline \tilde{s}_3 & .65 & .4 \\ \hline \end{array} = \tilde{R}_{\tilde{C}}$$

We are given a fuzzy relation $\tilde{R}_{\tilde{S}}$ specifying the degree of presence of symptoms $\tilde{s}_1, \tilde{s}_2, \tilde{s}_3$ for three patients $\tilde{p}_1, \tilde{p}_2, \tilde{p}_3$ as follows:

$$\begin{array}{|c|c|c|c|} \hline & \tilde{s}_1 & \tilde{s}_2 & \tilde{s}_3 \\ \hline \tilde{p}_1 & .3 & .8 & .7 \\ \hline \tilde{p}_2 & .6 & .1 & .6 \\ \hline \tilde{p}_3 & .7 & .6 & 1 \\ \hline \end{array} = \tilde{R}_{\tilde{S}}$$

- (I) The matrix of $\tilde{S}_i \tilde{D}_j$ occurrence indication relation defined as $\tilde{R}_1 = \tilde{R}_{\tilde{S}} \circ \tilde{R}_{\tilde{D}}$ is given by

$$\mu_{\tilde{R}_1}(p, \tilde{D}_j) = \max_{\tilde{s}_i} \min \{ \mu_{\tilde{R}_{\tilde{S}}}(p, \tilde{S}_i), \mu_{\tilde{R}_{\tilde{D}}}(\tilde{S}_i, \tilde{D}_j) \}$$

$$= \begin{bmatrix} .3 & .8 & .7 \\ .6 & .1 & .6 \\ .7 & .6 & 1 \end{bmatrix} \circ \begin{bmatrix} 1 & .1 \\ .3 & 1 \\ .8 & .15 \end{bmatrix}$$

$$\tilde{R}_1 = \begin{array}{c} \tilde{p}_1 \\ \tilde{p}_2 \\ \tilde{p}_3 \end{array} \begin{array}{|c|c|} \hline \tilde{d}_1 & \tilde{d}_2 \\ \hline \begin{bmatrix} .7 & .8 \\ .6 & .6 \\ .8 & .6 \end{bmatrix} \\ \hline \end{array}$$

- (II) The matrix of $\tilde{S}_i \tilde{D}_j$ confirmability indication $\tilde{R}_2 = \tilde{R}_{\tilde{S}} \circ \tilde{R}_{\tilde{C}}$ is computed as

$$\mu_{\tilde{R}_2}(p, \tilde{D}_j) = \max_{\tilde{s}_i} \min \{ \mu_{\tilde{R}_{\tilde{S}}}(p, \tilde{S}_i), \mu_{\tilde{R}_{\tilde{C}}}(\tilde{S}_i, \tilde{D}_j) \}$$

$$= \begin{bmatrix} .3 & .8 & .7 \\ .6 & .1 & .6 \\ .7 & .6 & 1 \end{bmatrix} \circ \begin{bmatrix} .9 & .1 \\ .4 & 1 \\ .65 & .5 \end{bmatrix}$$

$$\tilde{R}_2 = \begin{matrix} & \tilde{d}_1 & \tilde{d}_2 \\ \tilde{p}_1 & \begin{bmatrix} .65 & .8 \end{bmatrix} \\ \tilde{p}_2 & \begin{bmatrix} .6 & .5 \end{bmatrix} \\ \tilde{p}_3 & \begin{bmatrix} .7 & .6 \end{bmatrix} \end{matrix}$$

(III) The matrix of $\tilde{S}_i \tilde{D}_j$ nonoccurrence indication $\tilde{R}_3 = \tilde{R}_{\tilde{S}} \circ (1 - \tilde{R}_{\tilde{D}})$

Where 'J' is the matrix with all its entries '1' is computed as

$$\mu_{\tilde{R}_3}(p, \tilde{D}_j) = \max_{\tilde{S}_i} \min \{ \mu_{\tilde{R}_{\tilde{S}}}(p, \tilde{S}_i), 1 - \mu_{\tilde{R}_{\tilde{D}}}(\tilde{S}_i, \tilde{D}_j) \}$$

$$= \begin{bmatrix} .3 & .8 & .7 \\ .6 & .1 & .6 \\ .7 & .6 & 1 \end{bmatrix} \circ \begin{bmatrix} 0 & .9 \\ .7 & 0 \\ .2 & .85 \end{bmatrix}$$

$$\tilde{R}_3 = \begin{matrix} & \tilde{d}_1 & \tilde{d}_2 \\ \tilde{p}_1 & \begin{bmatrix} .7 & .7 \end{bmatrix} \\ \tilde{p}_2 & \begin{bmatrix} .2 & .6 \end{bmatrix} \\ \tilde{p}_3 & \begin{bmatrix} .6 & .85 \end{bmatrix} \end{matrix}$$

(IV) The non-symptom indication relation

$$\tilde{R}_4 = (1 - \tilde{R}_{\tilde{S}}) \circ \tilde{R}_{\tilde{D}}$$

$$\mu_{\tilde{R}_4}(p, \tilde{D}_j) = \max_{\tilde{S}_i} \min \{ 1 - \mu_{\tilde{R}_{\tilde{S}}}(p, \tilde{S}_i), \mu_{\tilde{R}_{\tilde{D}}}(\tilde{S}_i, \tilde{D}_j) \}$$

$$= \begin{bmatrix} .7 & .2 & .3 \\ .4 & .9 & .4 \\ .3 & .4 & 0 \end{bmatrix} \circ \begin{bmatrix} 1 & .1 \\ .3 & 1 \\ .8 & .15 \end{bmatrix}$$

$$\tilde{R}_4 = \begin{matrix} & \tilde{d}_1 & \tilde{d}_2 \\ \tilde{p}_1 & \begin{bmatrix} .7 & .2 \end{bmatrix} \\ \tilde{p}_2 & \begin{bmatrix} .4 & .9 \end{bmatrix} \\ \tilde{p}_3 & \begin{bmatrix} .3 & .4 \end{bmatrix} \end{matrix}$$

IV. RESULTS

- ❖ From these four indication relation we may draw different types of diagnostic conclusions. For instance, If $\mu_{\tilde{R}_2}(\tilde{p}, \tilde{D}_j)=1$, then the \tilde{D}_j is confirmed diagnosis for the patient \tilde{p} . If the max-min composition of the yields 1. Since, \tilde{R}_2 relation we see that is not the case for any of our three patients. The disease \tilde{d}_2 is strongly confirmed for the patients \tilde{p}_1 .
- ❖ We may make an excluded diagnosis for a disease \tilde{d} in patient \tilde{p} . If $\mu_{\tilde{R}_3}(\tilde{p}, \tilde{D}_j)=1$, or if $\mu_{\tilde{R}_4}(\tilde{p}, \tilde{D}_j)=1$. In our sum proof for the disease \tilde{d}_2 may be excluded as a possible diagnosis for patients \tilde{p}_2 .
- ❖ We may include any disease \tilde{d} in the set of diagnostic hypothesis for patient \tilde{p} if it satisfies the inequality $.5 < \max.\{\mu_{\tilde{R}_1}(\tilde{p}, \tilde{D}_j), \mu_{\tilde{R}_2}(\tilde{p}, \tilde{D}_j)\}$. In both diseases \tilde{d}_1 and \tilde{d}_2 are suitable diagnostic hypothesis for patients \tilde{p}_1 and \tilde{p}_3 , whereas \tilde{d}_1 is the only acceptable diagnosis for patient \tilde{p}_2 .

V. CONCLUSION

The aim of this research paper is to determine the causes of road accidents and injuries, which are diseases. The disease is verified if the outcome of this article is greater than .5. Organ failure and chronic illness are common among young people aged 18 to 35(disease affected). As a result, the conclusion of this article is that driver's licences can be used to prevent accidents if the laws of the road and how to avoid accidents are well taught before the licence is given.

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