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Module Convenor:	**Prof. Christian Wagner**	**Seminar Tutor** (if applicable)	
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FUZZY INFERENCE SYSTEMS FOR MEDICAL EMERGENCY

ABSTRACT

The goal of the coursework is to create hypothetical fuzzy inference systems that will advise a doctor on how serious the patient is and whether to send for emergency investigations to a hospital or not, based on the given three inputs—the patient's age, the intensity of their headache, and the patient's temperature.

INTRODUCTION

Fuzzy Logic, a sophisticated multi-valued system, extends beyond binary logic by assigning truth values between 0 and 1. It excels in managing imprecise data, providing a mathematical foundation for decision-making ambiguity. Operating on fuzzy rules, it articulates nuanced relationships between input and output variables through if-then statements, yielding fuzzy sets that express membership degrees for potential output values.

1. JUSTIFICATION OF FUZZY MODELS

We have created two models **- Mamdani** and **Sugeno** for each case.

Case 1: In this case, we are expected to take all the inputs in its numeric form. We have used min operator as t-norm for implication and max operator as aggregator. Further we get the defuzzified output using the defuzzification methods.

Case 2[3]: Here as we know the inputs are uncertain, so we develop membership functions for these, and to tackle the interval-based inputs we took intersection between the input and the antecedent membership functions. Thereafter the centroid will be calculated for the intersected area where these centroids for each linguistic term are used in the rules in order to calculate the defuzzified output.

Model 1 [Mamdani][1]: Mamdani fuzzy inference system involves set of fuzzy rules where both its antecedent is fuzzy and the output of each of the rules is a fuzzy logic set and through defuzzification of those rules the consequent crisp result is achieved. ***Why Mamdani?*** Since it is most suitable when the link between the input and output variables is complicated and difficult to define quantitatively. Linguistic rules provide interpretability, which is useful in various medical applications where human comprehension is critical difficult to quantify.

Model 2 [Sugeno][2]: Sugeno model employs fuzzy rules with a fuzzy antecedent and a non-completely fuzzy consequent, unlike Mamdani. Each fuzzy if-then rule has a consequent represented by a fuzzy set with a monotonically increasing/decreasing membership function. The rule's output is a crisp value, corresponding to its firing strength. The overall output is determined as the weighted average of individual rule outputs, eliminating the need for the time-consuming defuzzification process. ***Why Sugeno?*** Since Sugeno is appropriate when exact numerical output is desired and more computationally efficient, making it appropriate for real-time applications.

1.1 Antecedents with their linguistic variables along with their ranges

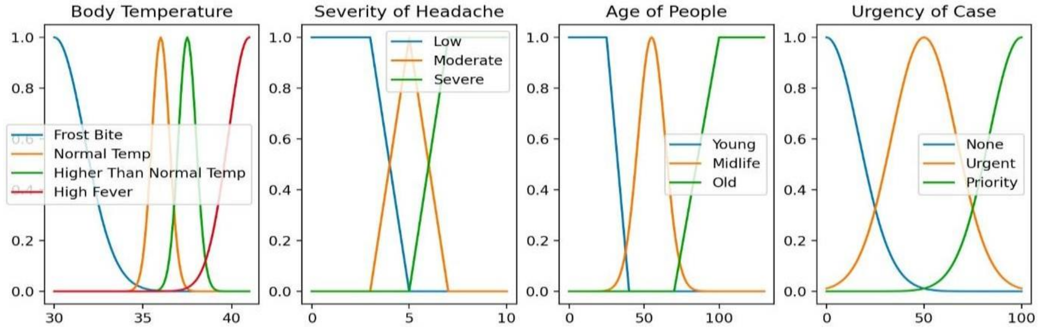

Figure 1 - Mamdani Inference System

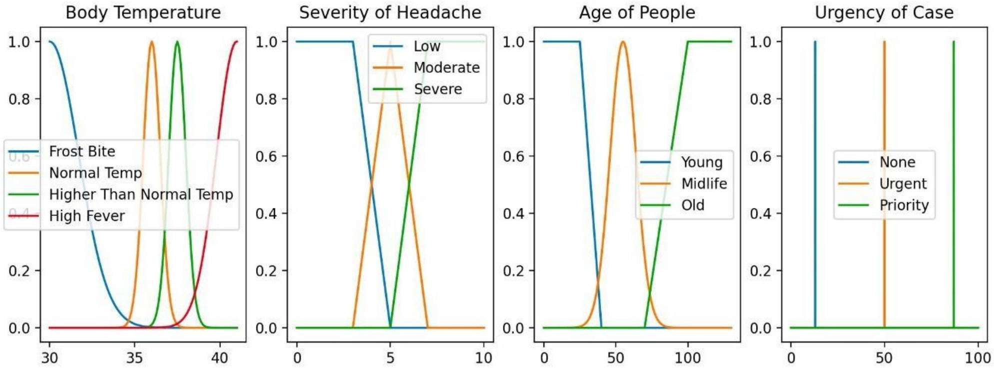

Figure 2 - Sugeno Inference System

Body Temperature[4]: The antecedent is body temperature which is one of the determining factors to get the output ranging from 30-41 Degree Celsius. Its linguistic variables are:

- **Frost-bite:** When the temperature is too low
- **Normal:** When the temperature is well enough
- **Higher than Normal:** The temperature is slightly higher than the normal range
- **Fever:** The temperature is quite high making the person sick

Headache: The second antecedent is headache which is another deciding factor for the urgency that ranges between 0-10. Its linguistic variables are:

- **Less:** Having headache in less intensity which is tolerable enough
- **Moderate:** Having a moderate level intensity
- **Severe:** Suffering from an extreme headache

Age: The final antecedent with its linguistic variables that is between the range of 0-130 are:

- **Young:** One can be between his/her infant life till the beginning of his/her's mid-life
- **Midlife:** The central period of one's' life
- **Old:** The person is aged and belongs to the category of senior citizens in the society

Body Temperature	Membership Function	Range (in Celcius)
Frost-bite	Gaussian	30 - 35.5
Normal	Gaussian	34 - 37.5
Higher than Normal	Gaussian	36 - 38
Fever	Gaussian	38 - 41
Headache	**Membership Function**	**Range**
Less	Open-left Trapezoidal	0 - 5
Moderate	Triangular	3 - 7
Severe	Open-right Trapezoidal	5 - 10
Age	**Membership Function**	**Range**
Young	Open-left Trapezoidal	0 - 40
Midlife	Gaussian	30 - 80
Old	Open-right Trapezoidal	70 - 130

Table 1: Antecedents with their linguistic variables and ranges

1.2 Membership Functions and its parameters:

Antecedent	Membership Function	Parameters
Body Temperature	Gaussian	Standard Deviation, Mean
Headache	Left-Open Trapezoidal	a,b,c,d
	Triangular	a,b,c
	Right-Open Trapezoidal	a,b,c,d
Age	Left-Open Trapezoidal	a,b,c,d
	Gaussian	a,b,c
	Right-Open Trapezoidal	a,b,c,d

Table 2: Parameters of each membership functions

1) **Body Temperature -** The **membership function** used here is **Gaussian** which is the same for all of its linguistic variables. **Why?** Gaussian is used because it represents a Normal Distribution which is most fitted for Temperature to show its linguistic variables in a proper way.

$$\mu(x) = \exp\left(-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right)$$

Parameters defined for each linguistic variables are:

	Standard Deviation	Mean
Frost-bite	1.7	30
Normal	0.5	36
Higher than Normal	0.5	37.5
Severe	1.2	41

Table 3: Parameters for Body Temperature

2) **Headache -** Here, we have used **Open-left Trapezoidal Triangular** and **Open- Right Trapezoidal** membership functions for the variables as mentioned below. **Why?** Because Gaussian is less strict than that of Triangular or Trapezoidal membership and since we need some values of headache to be strictly 1 and strictly 0, so we decided to take these functions accordingly.

   Parameters for each linguistic variables are:

$$\mathrm{trapezoid}(x; a, b, c, d) = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \qquad \mathrm{triangle}(x; a, b, c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right)$$

	a	b	c	d
Less	0	0	3	5
Moderate	3	5	7	-
Severe	5	7	10	10^+

Table 4: Parameters for Headache

3) **Age -** The **membership functions** used here are **Open-left Trapezoidal, Gaussian and Open-Right Trapezoidal** for the linguistic variables young, midlife and old consecutively. **Why?** We took Gaussian for midlife but for the other two as we need to represent two extremes, that is either it should be 1 or 0, we took trapezoidal functions.

   Parameters for each linguistic variables are:

	a	b	c	d	Standard Deviation	Mean
Young	0	0	25	40	-	-
Midlife	-	-	-	-	9	55
Old	70	100	130	130^+	-	-

Table 5: Parameters for Age

1.3 Consequent with its membership functions and parameters:

Model 1

The Consequent of our model is Urgency i.e., the level of urgency or severity of a person and depending on that, further actions needs to be taken. The level of urgency is based on the antecedents mentioned above. Its linguistic variables are:

- **None:** The person is fine and there is no such urgency

- **Urgent:** The person is quite serious and needs to be taken care so that it does not deteriorate further
- **Priority:** The person is very serious and needs to be taken care in a prior basis

The membership function used here is **Gaussian**. **Why?** Because it represents a Normal Distribution which is most fitted for Urgency here to show its linguistic variables in a proper way. The parameters are:

Urgency	Membership Function	Range
None	Gaussian	0 - 50
Urgent	Gaussian	25 - 75
Priority	Gaussian	50 - 100

	Standard Deviation	Mean
None	16.67	0
Urgent	16.67	50
Priority	16.67	100

Table 6: Consequent description for model 1

Model 2

In model 2, the key difference lies in the consequent, specifically in the use of Singleton membership functions in Sugeno. These functions, concentrated at a single point, simplify modelling and rule building, providing crisp outputs. This stands in contrast to Mamdani, where both antecedent and consequent are fuzzy. Parameters for each term are outlined below.

Urgency	Membership Functions	Range
None	**Singleton**	**0 - 50**
Urgent	**Singleton**	**25 - 75**
Priority	**Singleton**	**50 - 100**

	z
None	12.986
Urgent	50
Priority	87.014

Table 7: Consequent description for model 2

1.4 Fuzzification Approach for both models:

- **Intuition:** Fuzzification in Mamdani systems involves an intuitionistic approach, using expert knowledge to define membership functions for linguistic terms tied to input variables, often visualised with linguistic variables. While Sugeno systems influences singleton membership functions for antecedents through expert judgement, focusses on determining numerical values associated with singletons.
- **Inference:** In Mamdani systems, the inference-based technique gauges the degree of membership by applying mathematical or rule-based criteria, derived from logical rules and expert knowledge. Conversely, Sugeno emphasises functional links between input and output variables, translating input variables to crisp values using mathematical or rule-based relationships, often linear or nonlinear equations.

1.5 Defuzzification Methods:

- **Centroid Defuzzification** calculates the weighted average position of the membership function, providing a measure of central tendency for the fuzzy output providing a balanced output

- **First, Mean and Last of Maxima,** which computes the average of the maximum membership values across different linguistic terms, on the other hand first selects the smallest maximum membership value and last identifies the largest maximum membership value, reflecting an optimistic perspective by favouring the most influential rule

2. DESCRIPTION OF FINAL MODELS WITH EXAMPLES

2.1 Ruleset:

For both of our cases we have created the same rule set which contains all-total of **24 rules** using **AND** operator since we require the minimum from each of the rules.

For instance - If we consider our Body Temperature to be **Normal AND** Headache to be **less AND** the age of the person to be **old**, then there is **no such urgency**, as the person is fit. Similarly, we have deduced other rules too.

Body Temp	Headache	Age	Urgency
-	Moderate	Old	Urgent
-	Severe	Old	Priority
Frost-bite	-	-	Priority
Fever	-	Old	Priority
Normal	Less	Old	None
Higher than Normal	-	Old	Urgent
Normal	Less	Young	None
Normal	Moderate	Young	None
Normal	Severe	Young	Urgent
Higher than Normal	Less	Young	None
Higher than Normal	Moderate	Young	None
Higher than Normal	Severe	Young	Urgent
Fever	Less	Young	Urgent
Fever	Moderate	Young	Urgent
Fever	Severe	Young	Priority
Normal	Less	Midlife	None
Normal	Moderate	Midlife	None
Normal	Severe	Midlife	Urgent
Higher than Normal	Less	Midlife	None
Higher than Normal	Moderate	Midlife	None
Higher than Normal	Severe	Midlife	Urgent
Fever	Less	Midlife	Urgent
Fever	Moderate	Midlife	Urgent
Fever	Severe	Midlife	Priority

Table 8: Ruleset

2.2 Operators used:

Min operator: In fuzzy logic, the "min" operator selects the lowest degree of membership for each output term, implicating rule strengths conservatively. **Why?** This method prevents overestimation by constraining the output with the weakest contributing rule, particularly in the presence of an AND in the rule.

Max operator: In aggregation, the "max" operator selects the highest degree of membership, combining contributions from various linguistic terms. It calculates the overall degree an element belongs to each term, especially when an OR is present in the rule.These operators affect the way inputs are processed and the outputs that are produced.

How the processed inputs impact on the outputs generated? Using the processed inputs, we can calculate the firing strength for each rule, enabling the plotting of alpha cuts on the output. Subsequently, these cuts are aggregated to derive an output membership, which is then subjected to defuzzification to obtain clear, crisp outputs.

2.3 Examples demonstrating both the cases:

As we have seen above what basically we did, how we and why we did it in describing our fuzzy modelling process, now, we will take some examples for a better understanding

Case 1:

Body Temperature	Headache	Age	Centroid Defuzzification-Mamdani	Weighted Average-Sugeno
35.5	7.5	75	61.458	74.727
30.0	6	40	42.775	31.861
40.0	8	68	82.990	87.013

Case 2:

Body Temperature	Headache	Age	Centroid Defuzzification-Mamdani	Weighted Average-Sugeno
30 - 41	5 - 10	50 - 100	52.313	48.681
35 - 39	4 - 8	10 - 70	43.679	39.839
39 - 41	6 - 10	50 - 86	66.795	71.756

Table 8: Examples for each case

In Case 1 we can see that **-** If body temp is 40, headache is 8 and age is 68 then as per the defuzzified output the severity is extreme. Although we took the mean of the interval inputs in Case 1, the output might still vary since the intersection of input range and antecedent range in Case 2 might vary from the actual centroids.

3. COMPARISON AND CONTRAST BETWEEN CASES INCLUDING THEIR STRENGTHS AND WEAKNESSES

3.1 Comparative Analysis

In **Case 1**, inputs are viewed as singleton functions, facilitating the determination of firing strength and rule evaluation due to consistent values across linguistic terms. The intersection of singleton membership functions with antecedent membership functions always results in a single output. While this approach ensures **accuracy, computational efficiency, and easy implementation**, its **drawbacks** include **ineffectiveness with uncertain and real-world data, limiting its overall efficiency**.

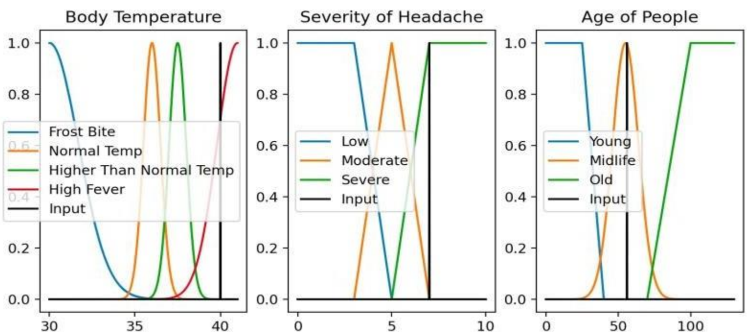

Figure 3 : Antecedents and consequents for singleton inputs

But **Case 2[3]** uses non-singleton membership functions, introducing input intervals to address uncertainty. Rule analysis hinges on the intersection of input and linguistic term membership functions. The centroid of this intersection serves as input for associated rules, offering **human interpretability, high applicability, and expert knowledge integration**. However, it entails **computational expenses**, **fuzzification challenges, and input range dependency**, constituting both **strengths and weaknesses** of this system.

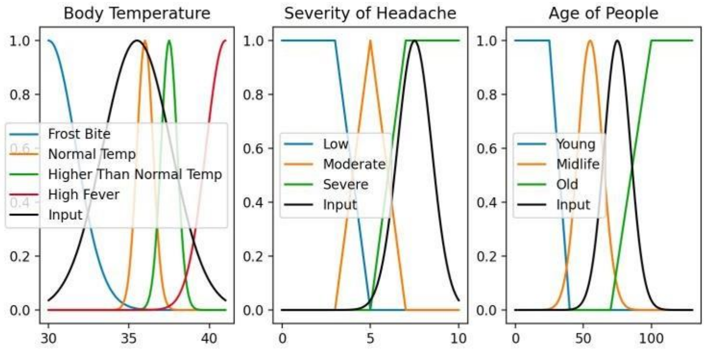

Figure 4 : Antecedents and consequents for non-singleton inputs

3.2 Personal Reflection on the work:

I grasped the significance of fuzzy systems in data comprehension, discerning their varying effectiveness in different scenarios illustrated by the two cases and also how can the systems be implemented when the data is uncertain as this can be seen in most of the medical operations where the data produced from sensors and the machines are very uncertain, we need to imply many rules in order to define the data and calculate the output for the patient to be looked after carefully.

4. BRIEF SELF-REFLECTION INCLUDING GROUP AND INDIVIDUAL WORK

From my perspective, Fuzzy Systems excel in managing model uncertainty by skillfully navigating real-world ambiguity through partial membership. Utilising varied membership functions and linguistic variables, they provide a versatile framework for handling uncertain information. This proves especially valuable in contexts where human expertise and subjective judgments play a crucial role, effortlessly integrating linguistic terms and rules reflecting human decision-making.

Therefore, we have created two models for each of the cases and analysed the rules and derived the rules together. My teammate Aditya Purswani has worked on the development of the fuzzification approach for both the cases and I have worked on defuzzifying the output aggregate for both the models in both cases. I think we did a great job as a group.

Conclusion:

In summary, our medical fuzzy system project effectively showcases the utility of fuzzy logic in managing inherent uncertainty in medical data. Through the incorporation of linguistic variables and rules, the system offers a nuanced, adaptable approach, informing doctors about patient urgency to tailor preferences accordingly.

References:

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[3] C. Wagner, A. Pourabdollah, J. McCulloch, R. John and J. M. Garibaldi, "A similarity-based inference engine for non-singleton fuzzy logic systems," 2016 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Vancouver, BC, Canada, 2016, pp. 316-323, doi: 10.1109/FUZZ-IEEE.2016.7737703.

[4] Nurhadiansyah, M.Y., Sudibyo, R.W., & Hadi, M.Z.S. (2022). Body Temperature and Heart Rate Monitoring System Using Fuzzy Classification Method. International Journal of Artificial Intelligence & Robotics (IJAIR), 4(2), 86-96. http://dx.doi.org/10.25139/ijair.v4i2.5290