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FUZZY BASED (MAMDANI) MODEL FOR IDENTIFICATION OF "LONG HAUL COVID PROBLEMS"

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Abstract: A COVID-infected person having a past health history is susceptible to developing "Long –haul COVID" problems. After a year of COVID, a model is designed in this article using Fuzzy Inference system-Mamdani Type, based on the health problems developed or reoccurrence of the past health problems in case of post-COVID issues. The focus is to construct a model based on a Fuzzy Inference System (FIS) where we analyze the data and identify the chances of developing "Long-haul COVID" problems.

Index Terms **- Fuzzy Logic, Fuzzy Inference System(FIS), COVID-19, Long Haul**.

I. INTRODUCTION

In late 2019, a novel corona virus, called COVID-19, an acute infection of the respiratory tract was discovered in Wuhan, China, and has spread to different cities in China as well as to 24 other countries. The majority of COVID patients are of age 50 above and having a health history. The after effect of COVID, symptoms continued to persist for months or years. The virus can damage the lungs, heart and brain, which increases the risk of long term health problems or reoccurrence of severe health problems like cancer, diabetes, migraine, blindness, etc. According to the findings of Mayo clinic staff, the COVID patients showing Long term health problems are described as "long haulers" and this condition is called as POST COVID-19 SYNDROME or "LONG COVID -19". The general symptoms which are present for long time are fatigue, shortness of breath, cough, joint pains, etc. COVID mainly affects lungs as well as it can damage other organs like heart, brain, liver, etc. Post COVID also showed issues regarding mood, psychology, etc. A study was performed as long term affects of severe acute respiratory syndrome (SARS), the corona virus that emerged in 2003, which showed that 40% or more reported fatigue symptoms for 3.5 years after diagnosis. Since it is hard to assess long term affects off the pandemic, there is a necessity to perform detailed study on the long term effects of COVID-19 or the post COVID-19 conditions.

Times of India, August 12th, 2020, a study report of UK found that 10% people may suffer from symptoms of viral infection even after successful recovery. The term "Long COVID", a study conducted by university of Leads, published in the Journal of Medical Virology, reported that array of symptoms ranging from fatigue, muscle aches, etc. As on 6th September 2020, multi state phone study in USA reported that symptoms like fatigue, cough, heart related issues, etc may linger among the patients for weeks, months or years. WHO reported that COVID-19 can result in prolonged illness and persistent symptoms even in young adults and persons with no underlying conditions. More time and research is needed to understand the long term affects of COVID, also the reasons for symptoms to persist or recur, treatment and likelihood of full recovery, etc.

In some cases, the COVID affected person could not recognize the symptoms as a Long Haul problem. At this juncture, common man is unaware of the possible threats ahead for him due to the pandemic. The "long-haul COVID" awareness and identifying the most risked issue out of a list is vital, which is not now in focus. Extreme caution is needed, as the long term effects of COVID 19 is still unknown.

A Fuzzy Logic Inference System(FLIS) is developed with the selected conditions of Covid-19 patients "long-haul COVID" symptoms. The result of the model for selected attributes for any country may be to adopted and implemented. In this respect, fuzzy logic mimics the crucial ability of the human mind to summarize data and focus on decision-relevant information.

II. THEORETICAL FRAMEWORK

Based on the different symptoms/health issues faced by affected/treated patients of COVID, a Fuzzy Inference System is designed by following steps: 1) Define the input, output variables, Linguistic Variables and their range, 2) Define the Input/output variables Membership Functions, 3) Construction of the fuzzy rule base, 4) Fuzzification, 5) Fuzzy Inference Engine, 6) Defuzzification.

Fuzzification, the process of decomposing a systems input and/or output variables into fuzzy sets mostly using a triangular or trapezoidal-shaped membership functions. The membership function of a Fuzzy set is associated with linguistic term. Using the rule base the, the inference engine combines the measurements of input variables with relevant fuzzy information rules and makes inferences regarding the output variable, as a Fuzzy set. Then by defuzzification, the fuzzy output obtained by inference engine, is converted to a single real number, the crisp output.

A Fuzzy Inference System (FIS) involves input and output membership functions, fuzzification, fuzzy inference engine, Fuzzy rule base and defuzzification, illustrated in Fig. 1:

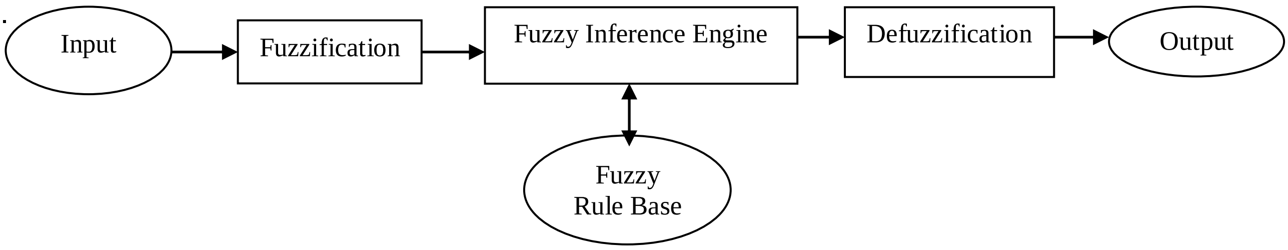

Fig.1:Fuzzy Inference System

Step1: Define the input, output variables, Linguistic Variables and their range:

The input variables are defined as I1:Lungs related (LR), I2: Heart related(HR), I3:Brain related (BR) , I4:Other Health Problems (OHP). Based on the parameters like type of chronic disease, age, type of treatment, place of residence, average monthly income, health history, etc. The linguistic variables for input variables are defined as “Low effected”, “Medium effected”, “High effected”. The output variable is defined as “Long Hauled COVID Problem (LHCP)” with 3 linguistic variables defined as “Highly Hauled COVID Problem (HH)”, “Medially Hauled COVID Problem (MH)”, “Lowly Hauled COVID Problem (LH)”. The range of input and output variables are defined in 0-10.

Step-2: Define the Input/output variables Membership Functions:

The membership functions for all the 4 input variables are defined as follows and presented in Fig.2:

$$\mu_{\text{LE}}(\text{x}) = \frac{4-\text{x}}{4}, 0 \le \text{x} \le 4,\ \ \mu_{ME}(x) = \begin{cases} \frac{x}{4}, & 0 \le \text{x} \le 4 \\ \frac{8-\text{x}}{4}, 4 \le \text{x} \le 8 & \end{cases},\ \ \mu_{HE}(x) = \begin{cases} \frac{x-4}{4}, 4 \le \text{x} \le 8 \\ 1, \quad 8 \le \text{x} \le 10 \end{cases}.$$

The membership functions for the output variable are defined as follows and presented in Fig.3:

$$\mu_{\text{LH}}(\text{x}) = \frac{4-\text{x}}{4}, 0 \le \text{x} \le 4,\ \ \mu_{MH}(x) = \begin{cases} \frac{x}{4}, & 0 \le \text{x} \le 4 \\ \frac{8-\text{x}}{4}, 4 \le \text{x} \le 8 & \end{cases},\ \ \mu_{HH}(x) = \begin{cases} \frac{x-4}{4}, 4 \le \text{x} \le 8 \\ 1, \quad 8 \le \text{x} \le 10 \end{cases}.$$

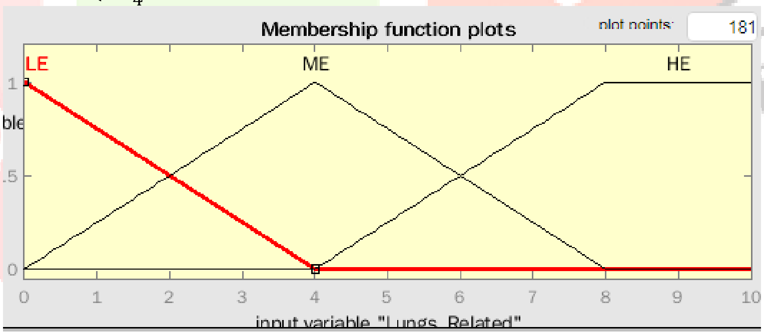

Fig.2: Membership functions for input variables I_i.

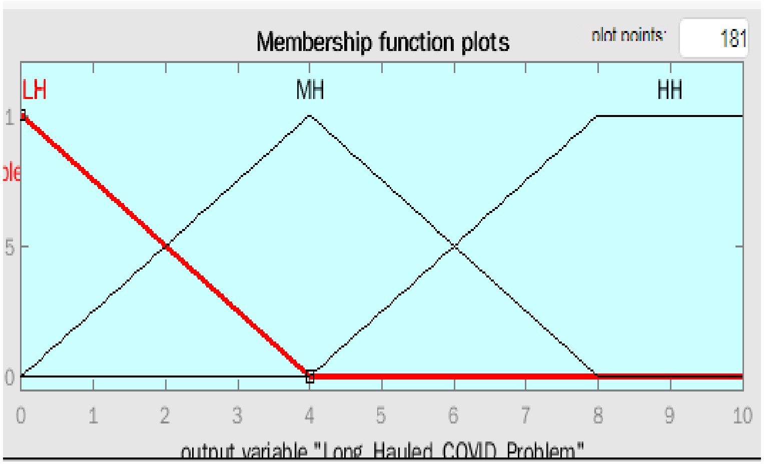

Fig.3: Membership functions for the output variable O.

Step-3: Construction of the fuzzy rule base:

The Fuzzy Rule Base drives the Fuzzy Inference Engine to calculate the output. Here, we construct the possible Rules for 3 input membership functions defined for each of the 4 inputs and 3 membership functions defined for one output variable. Then the numbers of rules generated are 3x3x3x3=81 fuzzy rules are presented and only 22 rules are considered in Table.1:

Table.1: Fuzzy Inference Rules (Fuzzy Rule Base)

Rule No.	If				Long Hauled COVID Problem (LHCP) is
	I_1	I_2	I_3	I_4	
1	L	L	M	M	Lowly Hauled COVID Problem (LH)
2	L	M	M	L	Lowly Hauled COVID Problem (LH)
3	M	M	L	L	Lowly Hauled COVID Problem (LH)
4	M	L	L	M	Lowly Hauled COVID Problem (LH)
5	L	M	L	M	Lowly Hauled COVID Problem (LH)
6	M	L	M	L	Lowly Hauled COVID Problem (LH)
7	M	M	M	M	Medially Hauled COVID Problem (MH)
8	M	M	M	H	Medially Hauled COVID Problem (MH)
9	M	M	H	M	Medially Hauled COVID Problem (MH)
10	M	H	M	M	Medially Hauled COVID Problem (MH)
11	H	M	M	M	Medially Hauled COVID Problem (MH)
12	M	M	H	H	Medially Hauled COVID Problem (MH)
13	H	M	M	H	Medially Hauled COVID Problem (MH)
14	M	H	H	M	Medially Hauled COVID Problem (MH)
15	M	H	M	H	Medially Hauled COVID Problem (MH)
16	H	M	H	M	Medially Hauled COVID Problem (MH)
17	H	H	H	H	Highly Hauled COVID Problem(HH)
18	H	H	H	M	Highly Hauled COVID Problem(HH)
19	H	H	M	H	Highly Hauled COVID Problem(HH)
20	H	M	H	H	Highly Hauled COVID Problem(HH)
21	M	H	H	H	Highly Hauled COVID Problem(HH)
22	H	H	M	M	Highly Hauled COVID Problem(HH)

Step-4: Fuzzification**:**

In this process the crisp input variables are decomposed into fuzzy sets using Fuzzy membership functions already defined as:

$$\mu_{LE}(x) = \frac{4-x}{4}, 0 \le x \le 4, \quad \mu_{ME}(x) = \begin{cases} \frac{x}{4}, & 0 \le x \le 4 \\ \frac{8-x}{4}, & 4 \le x \le 8 \end{cases}, \quad \mu_{HE}(x) = \begin{cases} \frac{x-4}{4}, & 4 \le x \le 8 \\ 1, & 8 \le x \le 10 \end{cases}.$$

Step 5: Fuzzy Inference Engine:

The fuzzy inference engine identifies the suitable rules from the Rule base for the fuzzy inputs, calculates the Fuzzy Output applying the Max Min Composition Rule of Mamdani Fuzzy Model. In this case, Mamdani Model for Multiple Rules and Multiple Antecedents is required to apply. The rule is described as:

Rule 1: If x_1 is A_{11} and x_2 is A_{12} and x_3 is A_{13} and x_4 is A_{14} then y is C_1.
Rule2: If x_1 is A_{21} and x_2 is A_{22} and x_3 is A_{23} and x_4 is A_{24} then y is C_1.
Rule3: If x_1 is A_{31} and x_2 is A_{32} and x_3 is A_3 and x_{34} is A_4 then y is C_1.
....i rules............
Fact (Input): If x_1 is A_1 and x_2 is A_2 and x_3 is A_3 and x_4 is A_4
…………………………..………………………..
Conclusion: y is C.
…………………………………………………

Step 6: Defuzzification:

The Fuzzy output obtained from the Mamdani Fuzzy Model is required to be converted to crisp output using the Defuzzification process by using Centroid Method. In Centroid method, the defuzzified value is defined as the value within the range of the output variable O for which the area under the graph of membership function obtained by truncating the fuzzy output. It is divided into sub-areas, Centroid method derives the output value as the centre of the area occupied by the Fuzzy set 'C' of the output variable O, given by

$$x^* = dc_A(x) = \frac{\int_{-c}^{c} c(z).\, z.dz}{\int_{-c}^{c} c(z).\, dz} \quad \text{for continuous membership function}$$

III. RESULTS AND DISCUSSION

Consider I_1= 1, I_2 = 9, I_3=1, I_4=1, then membership functions that are characterizing the corresponding fuzzy sets of the input variables, the relevant rules out of the 22 rules and the corresponding output is obtained using the Fuzzy toolbox of MATLAB. The defuzzified output using Centroid Method is 4 in the 10 point scale implying a Medially Hauled COVID Problem as shown in the following Fig.4. If a COVID patient has lower levels of the input variables i.e I1:Lungs related (LR), I2: Heart related(HR), I3:Brain related (BR), I4:Other Health Problems (OHP) then the level of the output variable "Long Hauled COVID Problem (LHCP)" would be low. If any one of the input variable is high i.e I_1= 1, I_2 = 9, I_3=1, I_4=1 then the value of the output variable is 4 i.e the "Long Hauled COVID Problem (LHCP)" related I2: Heart related(HR) is medial.

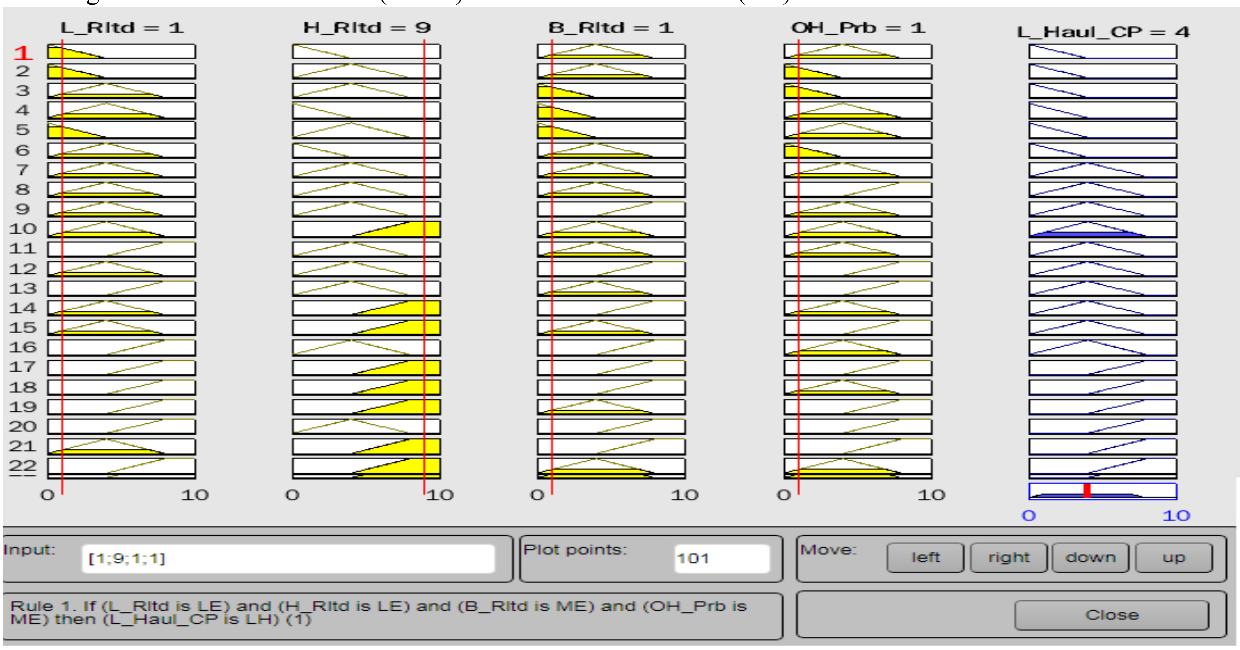

Fig.4: 22 rules and Defuzzified Output

IV. CONCLUSIONS

The estimated chance of having a "Long Hauled COVID Problem (LHCP)" related to heart related is 40%. Hence the person is aware of the chance of post effect of COVID. Using the Fuzzy logic tool of MATLAB, we can analyze the chances of having a "Long Hauled COVID Problem (LHCP)" and hence protect ourselves by managing all the possible factors.

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