Fuzzy Regression Based Patient Life Risk Rate Prediction Using Oxygen Level, Pulse Rate And Respiration Rate In Covid-19 Pandemic (FRPRPS)

Gaurav Kant Shankhdhar[1], Himanshu Pandey[2], Atul Kumar Pal[3], Sumit Mishra[4]

[1]Department of Basic Sciences, Babu Banarasi Das University, Lucknow, emaiil: g.kant.82@gmail.com

[2]Department of Computer Science, Lucknow University, Lucknow, email: hpandey010@gmail.com

[3]Department of Basic Sciences, Babu Banarasi Das University, Lucknow, email: atulpal892@bbdu.ac.in

[4]Department of Computer Science, BBDEC, Babu Banarasi Das University, Lucknow, email: mishrasumit221@gmail.com

Abstract

Today, the general situation worldwide is that the hospitals, sanatoriums and medical colleges are running out of beds, oxygen, medical staff, ventilators and other required paraphernalia that is mandatory for the treatment of the vicious pandemic [1]. The requirement is for a system that takes in some input parameters like Oxygen level of the patient, pulse rate and respiration rate and in turn predicts the Life Risk Rate of that patient [2]. The model used here is a fuzzy regression model that gives the prediction of Life Risk Rate between 1 and 10 units. The lower the predicted Life Risk Rate, the better the chances of survival of the Covid patient. But if the predicted Life Risk Rate is more than the mean of the observations of the Risk in the dataset, then immediate emergency is needed. The benefit of this system is that the patients requiring immediate admission and treatment can be filtered and medical aid in hospital be thereby provided for critical patients. Rest may be home quarantined and domestic medical aid may be given to them until in some unfortunate situation their Risk Rate is near alarming. This paper aims to provide some help in this crucial situation.

Keywords: Fuzzy, Regression, Covid, Prediction, Oxygen Level, Pulse rate

I. Introduction

I. Literature Review

Fuzzy regression analysis gives a fuzzy functional relationship between dependent and independent variables where vagueness is present in some form. The input data may be crisp or fuzzy. In this chapter the authors consider two types of fuzzy regression. The first is based on possibilistic concepts and the second upon a least squares approach. However, in both the notion of "best fit" incorporates the optimization of a functional associated with the problem. In possibilistic regression, this function takes the form of a measure of the spreads of the estimated output, either as a weighted linear sum involving the estimated coefficients in linear regression, or as quadratic form in the case of exponential possibilistic regression. These optimization problems reduce to linear programming. For the least squares approach, the functional to be minimized is an L_2 distance between the observed and estimated outputs. This reduces to a class of quadratic optimization problems and constrained quadratic optimization. The method can incorporate stochastic fuzzy input and fuzzy kriging uses covariances to obtain BLUE estimators [3].

In this paper, we propose simple but powerful methods for fuzzy regression analysis for Covid affected patients on the basis of oxygen, pulse rate and Respiration rate using R language. Since neural networks have high capability as an approximator of nonlinear mappings, the proposed methods can be applied to more complex systems than the existing LP based methods. First we propose learning algorithms of neural networks for determining a nonlinear interval model from the given input-output patterns. A nonlinear interval model whose outputs approximately include all the given patterns can be determined by two neural networks. In this paper, next is shown two methods for deriving nonlinear fuzzy models from the interval model determined by the proposed algorithms. Nonlinear fuzzy models whose *h*-level sets approximately include all the given patterns can be derived. Last is shown an application of the proposed methods to a real problem[4].

During the ongoing coronavirus disease (COVID-19) pandemic, reports in social media and the lay press indicate that a subset of patients are presenting with severe hypoxemia in the absence of dyspnea, a problem unofficially referred to as “silent hypoxemia.” To decrease the risk of complications in such patients, one proposed solution has been to have those diagnosed with COVID-19 but not sick enough to warrant admission monitor their arterial oxygenation by pulse oximetry at home and present for care when they show evidence of hypoxemia [5]. Though the ease of use and low cost of pulse oximetry makes this an attractive option for identifying problems at an early stage, there are important considerations with pulse oximetry about which patients and providers may not be aware that can interfere with successful implementation of such monitoring programs [6]. Only a few independent studies have examined the performance of pocket oximeters and smart phone–based systems, but the limited available data raise questions about their accuracy, particularly as saturation falls below 90%. There are also multiple sources of error in pulse oximetry that must be accounted for, including rapid fluctuations in measurements when the arterial oxygen pressure/tension falls on the steep portion of the dissociation curve, data acquisition problems when pulsatile blood flow is diminished, accuracy in the setting of severe hypoxemia, dyshemoglobinemias, and other problems. Recognition of these issues and careful counseling of patients about the proper means for measuring their oxygen saturation and when to seek assistance can help ensure successful implementation of needed monitoring programs [7].

The fundamental differences between fuzzy regression and ordinary regression are identified Here [8]. Fuzzy regression can be used to fit fuzzy data and crisp data into a regression model, whereas ordinary regression can only fit crisp data. Through a comprehensive literature review, three approaches of fuzzy regression are summarized. The first approach of fuzzy regression is based on minimizing fuzziness as an optimal criterion. The second approach uses least-squares of errors as a fitting criterion, and two methods are summarized in this paper. The third approach can be described as an interval regression analysis. For each fuzzy regression method, numerical examples and graphical presentations are used to evaluate their characteristic and differences with ordinary least-squares regression.

RT&A, No 3 (63)
Volume 16, September 2021

II. Fuzzy Regression Model for Covid Risk Prediction

The fight to Covid-19 has produced numerous immature remedies, though not quite effective but some being a ray of hope. The major problems in nearly all Covid affected countries are lack of beds or insufficient oxygen and ventilators [9].

The primary deciders for the level of risk associated with a Covid patient are blood oxygen level, pulse rate and respiratory rate. Blood Pressure and Sugar level do play very important part clinically. But when Correlation Analysis of the sample data was done, both of these factors showed minuscule relatedness with Risk shown in table 1[10]. In addition to average levels of systolic and diastolic BP, blood pressure variability (BPV) has also been positively associated with high risks of morbidity and mortality in patients with hypertension. Recent studies also suggested that high BPV could predict a high risk of organ damage, cardiovascular events, and all-cause and cardiovascular mortality independent of mean Blood Pressure in patients with hypertension or cerebrovascular disease [11]. So, though, there is a direct impact of Blood Pressure clinically on Covid patients, the authors have hardcoded the range of Blood Pressure to Risk Factor. Same is also true for Patients with abnormal Sugar levels [12].

Table1: *Correlation between Risk and Oxygen, Pulse Rate and Respiration Rate.*

	Oxygen	*BP(50-120)*	*Sugar (67-210)*	*Pulse Rate(60-120)*	*Rrate(12-25)*	*RISK*
Oxygen	1					
BP(50-120)	0.047024825	1				
Sugar (67-210)	-0.022852292	-0.103454373	1			
Pulse Rate(60-120)	0.841028127	-0.063381361	0.013401908	1		
Rrate(12-25)	0.766020421	-0.127063601	0.048936429	0.896696141	1	
RISK	-0.784911875	0.11131738	-0.062356984	-0.924711669	-0.941593809	1

As is evident from the above table of correlation coefficients, Oxygen, Pulse Rate and Respiration Rate shown in yellow are significant but Blood Pressure and Sugar shown in red do not statistically contribute much as they are very low in correlation coefficientsand so avoided [13].

I. Generation of Input and output variable data values through programming in RLanguage

The authors through a self-developed program in R Language have used the “FuzzyR” library to pass a “fis” file (Fuzzy Inference System) that contains all the details of the fuzzy system including all Member Functions and also the rules that govern the functioning of the system shown in table 2. [14].

Table 2: *Fuzzy Rules*

Rule	IF Oxygen		AND Pulse Rate	AND Respiration Rate	THEN RISC
1	Low		low	low	High
2	medium		Medium	medium	Medium
3	High		low	medium	Low
4	Low		low	low	High
5	Low		Medium	medium	High
6	medium				Medium
7	Low				High
8	Low		Low		High
9	Low		High		High
10	Low		Low	High	High
11				Medium	Medium

The fis file used here is shown in figure 1. The dataset has been programmatically generated by using the “FuzzyR” library of R language where all input variables were created randomly through loops and so does the output variable. The program is shown in snippetas figure 2 [15].

```
% $Revision: 1.1 $

[System]
Name='COVID_fis.fis'
Ninputs=5
Noutputs=1
Nrules=17
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='Oxygen Level'
Range=[70 99]
NumMFs=3
MF1='low':'trimf',[70 75 85]
MF2='medium':'trimf',[75 90 100]
MF3='high':'trimf',[85 95 99]
[Input2]
Active='yes'
Name='Pulse Rate'
Range=[60,120]
NumMFs=3
```

```
MF1='low':'trimf',[60 75 90]
MF2='high':'trimf',[90 105 120]
MF3='Medium':'trimf',[70 90 110]
[Input5]
Active='yes'
Name='Respiration Rate'
Range=[9 16]
NumMFs=3
MF1='low':'trimf',[11 12 13]
MF2='high':'trimf',[12.500 14.500 16]
MF3='medium':'trimf',[12 13 14]
[Output1]
Name='RISC'
Range=[0 10]
NumMFs=3
MF1='Low':'trapmf',[0 2 5]
MF2='Medium':'trimf',[2 5 8]
MF3='High':'trapmf',[6 8 10]
[Rules]
1 0 0 0 0, 3 (1) : 1
2 0 0 0 0, 3 (1) : 1
3 0 0 0 0, 1 (1) : 1
0 1 0 0 0, 3 (1) : 1
0 2 0 0 0, 2 (1) : 1
0 0 1 0 0, 3 (1) : 1
0 0 2 0 0, 3 (1) : 1
0 0 0 1 0, 3 (1) : 1
0 0 0 3 0, 2 (1) : 1
0 0 0 0 1, 3 (1) : 1
0 0 0 0 2, 3 (1) : 1
#In this experiment all the possible input MFs (Oxygen, Blood Pressure, Sugar, Pulse Rate and
#Respiration Rate) values were tried by a loop and evalfis() function to compute the output crisp
#values of all possible range of complexities. These all 1000 value sets were recorded
library(ggplot2)
library(FuzzyR)

#the fis file is read in fisStdr variable that contains the fis file.
fisStdr<-readfis("F:\\COVID_fis.fis")
#IL is a matrix that has 1000 rows and number of columns are 5. The sample size, n is taken to be
1000.
IL<-matrix(, nrow = 1000, ncol = 5)
```

```
#44 different combinations of the 5 input variables were run through this fuzzy program and recorded in IL Matrix.
for(i in 1:45)
{
IL[i,1]<-runif(1, min=70,max=99)#oxygen
IL[i,2]<-runif(1, min=50,max=120)#BP Diastolic
IL[i,3]<-runif(1, min=70,max=180)#sugar level
IL[i,4]<-runif(1, min=60,max=120)#Pulse rate
IL[i,5]<-runif(1, min=9,max=16)#Respiration Rate
}
#inpt variable stores the resultant matrix IL
inpt<-matrix(IL,1000,5)

print(inpt)

#print("Defuzzified Value")
#evalfis function computes the inference of the fuzzy rules and gives the output variable for each set of the input variables
resMATStdr=evalfis(inpt,fisStdr)
print(resMATStdr)
```

Figure 1: *Fuzzy Program to find Risk*

The output of the program with manual alignment and correction is shown in figure 2, discussed later in the paper.

Sl.No	Oxygen	Pulse Rate	RR	RISK
1	92.75268	90	20	1.44063
2	81.29803	55	14	7.475597
3	93.28156	91	22	1.798155
4	94.75914	89	21	1.670695
5	84.28443	57	12	7.578823
6	82.02732	58	12	7.768271
7	92.73445	90	19	1.3326018
8	82.2335	56.5	13	7.838347
9	97.95146	91	16	2.985029
10	86.9621	61	13	5.139235
11	76.94824	60	10	7.693251
12	98.59557	90	19	1.688301
13	79.19153	55	13	6.45691
14	85.87632	58	13	5.189274
15	97.63994	92	22	1.705292
16	90.54865	55	13	5.63892
17	85.19086	59	13	5.25
18	77.85256	57	12	5.459252
19	82.89129	50	10	8.64634
20	73.35761	56	12	6.206666
21	80.25458	50	11	7.36884
22	83.4767	51	12	6.804132

21	80.25458	50	11	7.36884
22	83.4767	51	12	6.804132
23	93.2275	90	21	1.859923
24	79.50032	50	10	8.25
25	87.0218	49	10	7.768378
26	71.38359	47	9	8.080668
27	95.48155	95	18	1.943947
28	93.24146	95	18	1.95
29	96.19863	94	19	1.802394
30	80.56792	60	11.131345	5.186457
31	87.22132	50	10	7.811492
32	88.14657	58	12	6.838689
33	72.17375	48	9	8.476195
34	87.03107	61	10	7.312335
35	85.96788	65	10	7.787564
36	88.32188	65	10	7.8
37	88.29243	68	11	7.058466
38	91.9299	91	20	1.789683
39	82.09052	50	11	7.080497
40	79.15857	45	10	8.638569
41	85.30994	67	10	7.7220664
42	78.05531	49	12	8.398254
43	83.3797	52	11	7.058882

Figure 2: *The output of the program with manual alignment and correction*

The Blood Pressure and Sugar Membership Functions were not included due to the reason that they had very less correlation with Patient's Risk but it is hereby pointed that the blood pressure and sugar levels do have strong impact on Covid Patients [16]. So the authors have taken these two factors differently using hard coding system, discussed later in this chapter [24].

II. Membership Functions in Fuzzy Regression Patient Risk Prediction System (FRPRPS)

FRPRPS shown in figure 3 is a combination of Fuzzy and Regression system. In this system, Fuzzy Input variables like Oxygen level of Covid +ve patient, pulse rate and respiratory rate are identified as being significant factors for calculating the Fuzzy output variable Risk factor or Mortality Rate of that patient. Then through the 'R Language' a series of combinations of 1000 tuples or rows containing crisp values are generated as shown in figure 2.

After this, the crisp values are perused and checked to see if the Oxygen level-Pulse rate-Respiratory rate-Risk Factor row values are correct in actuality, that is, near to Real world values. If there is some correction needed then that correction is made by having proper alignment and resetting the said crisp input variable(s).

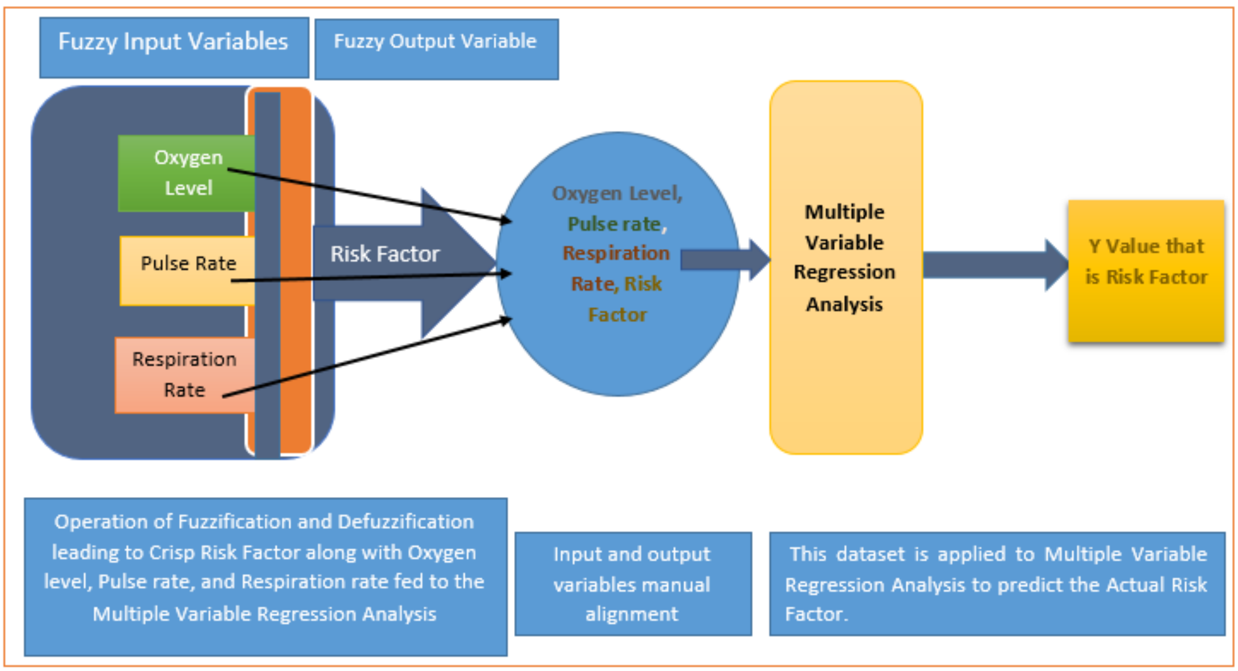

Figure 3: *Membership Functions in Fuzzy Regression Patient Risk Prediction System FRPRPS*

As a final step these crisp values are passed to the regression analysis component of this system where Oxygen level, Pulse rate, Respiratory rate crisp values are fed as independent variables and Risk Factor is predicted (Risk factor / Mortality rate is the dependent variable).The manual correction of seemingly incorrect crisp values of input variables is as in figure 4.The step by step process of FRPRPS is shown in figure 5.

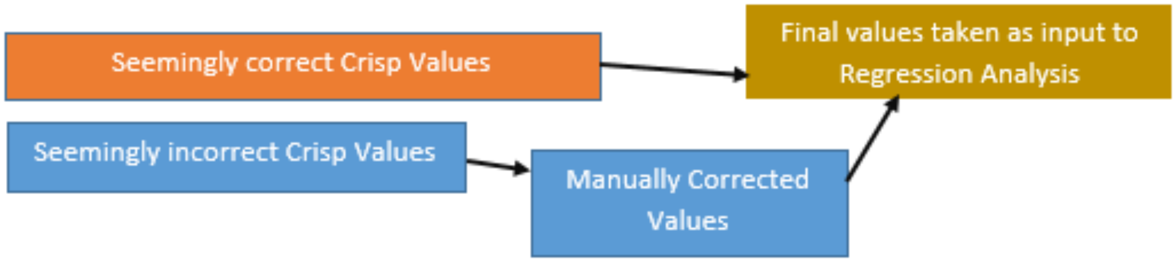

Figure 4: *Manual correction of incorrect Crisp values of SaO_2, Pulse Rate and Respiratory Rate.*

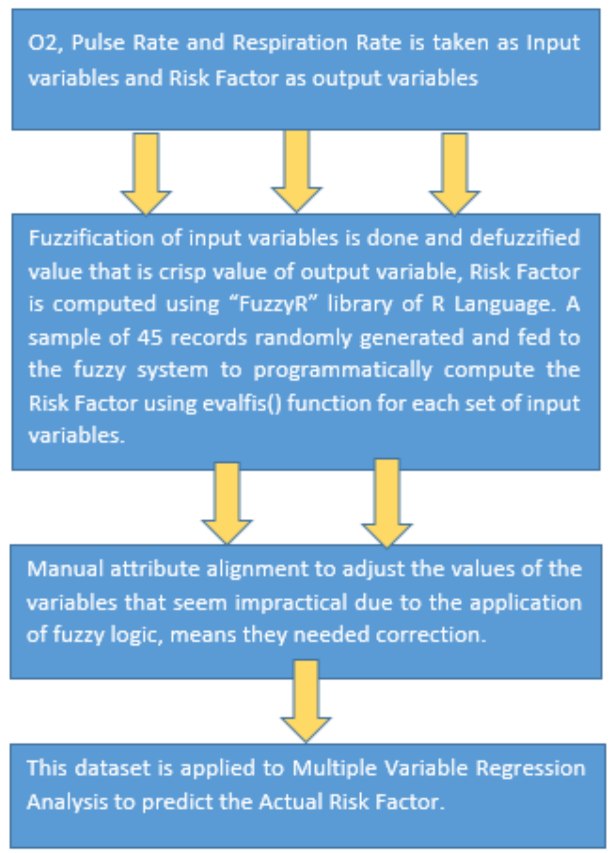

Figure 5. *Step by step process of FRPRPS*

III. Input Membership Functions

The fuzzy system is developed in FISPro software where all membership functions are created, rules written and inference conducted. But it is pertinent to mention over here that after designing the member ship functions and rules, "FuzzyR" library of R Package is utilized to infer 1000 samples of input and output variables iteratively. The FisPro software interface is shown in figure 7[18]

- Oxygen Level (70 to 99)

The Oxygen Level input variable keeps the record of the oxygen level. The second input variable Pulse Rate ranges from 70, which is very low to 99 that is kept on a higher side and in between lies the range of medium. The "Mamdani" inference mechanism is used with conjunction set to "minimum". The shape of the membership functions is decided by trial and error.

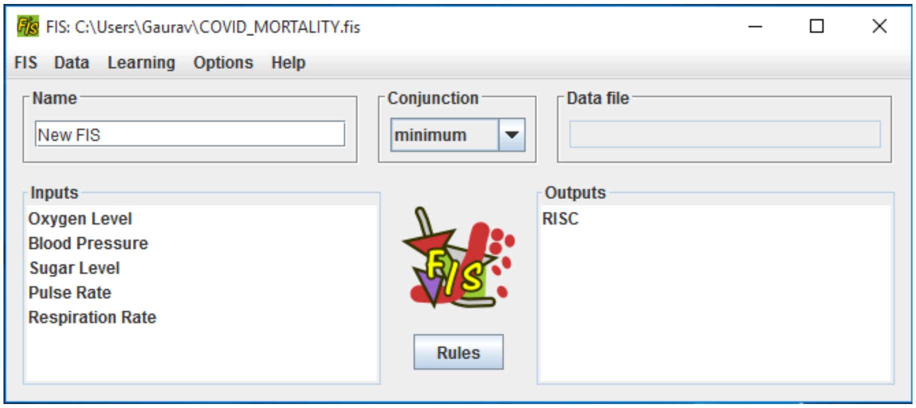

Figure 7: *FisPro Software for Fuzzy Logic implementation*

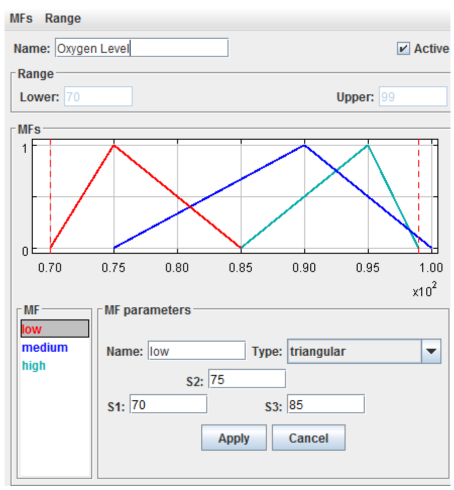

Figure 8a: *Oxygen Level Input Variable*

- Pulse rate (60 to 120)

The second input variable Pulse Rate ranges from 60 to 120. As in case of oxygen input variable membership functions which are low, medium and high are designed using trial and error basis.

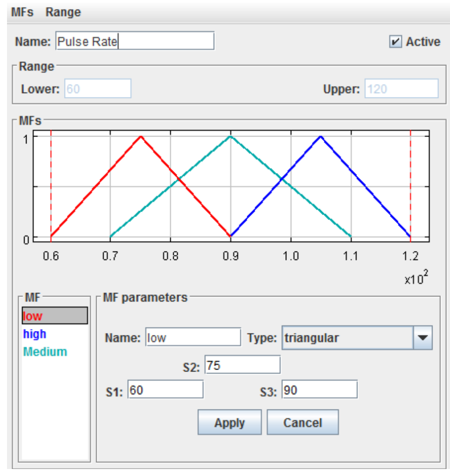

Figure 8b: *Pulse Rate Input Variable*

- Respiration Rate (11 to 20)

The third input variable Pulse Rate ranges from 11 to 20. As in case of before mentioned input variable membership functions of respiration rate are low, medium and high and are designed using trial and error basis.

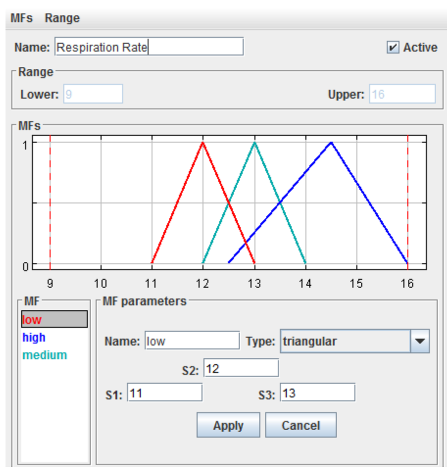

Figure 8c: *Respiration Rate Input Variable*

IV. Output Membership Functions

I. Risk Factor (1 to 10)

The only output variable Risk Factor ranges from 1 to 10. As in case of input variables membership functions of risk factor are low, medium and high and are also designed using trial and error technique.

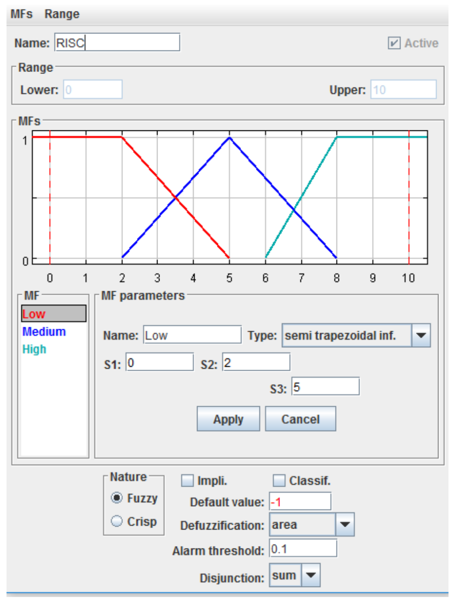

Figure 8d: *Risk Factor Output Variable*

Once the defuzzified values have been generated for Risk Membership Functions, then the full set of the 3 input MFs and 1 output MF is perused to find if any abruption, illogical values of variables, or some discrepancy in the combination of all the variables that look incorrect have been manually aligned and set until all 1000 records look correct [11], [19].

The frequencydistribution graph for Risk factor generated through Ggplot2 in R for Risk Output Variable is shown in figure 9. According to the graph maximum cases are having Risk factor nearly 2 and the next below level is the number of cases having Risk factor of 7.8 [20], [21]. The third maximum cases are having Risk factor of 4.5.

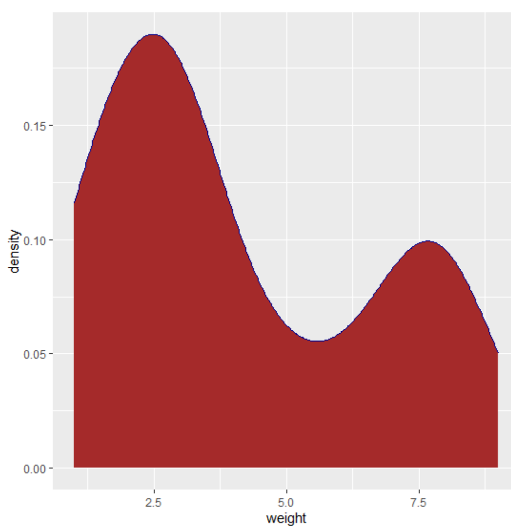

Figure 9: The frequency distribution graph for Risk factor generated through Ggplot2 in R for Risk Output Variable

II. Inference on Fuzzy sets

The data obtained in figure 3 is used as an input to the Regression Analysis. Through the regression analysis conducted over this data, the line of best fit along with coefficients and intercept are established as shown in figure 11a, 11b and 11c [22].

Regression is done in SPSS, Statistical Package for Social Sciences [23]. The Regression details are shown in figure 10[24].

SUMMARY OUTPUT

Regression Statistics	
Multiple F	0.958948
R Square	0.919581
Adjusted I	0.913395
Standard E	0.763177
Observati	43

ANOVA

	df	*SS*	*MS*	*F*	*gnificance F*
Regressio	3	259.7439	86.58129	148.6531	2.2E-21
Residual	39	22.71511	0.582439		
Total	42	282.459			

	Coefficients	*andard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*Upper 95.0%*
Intercept	14.75931	2.002229	7.371441	6.66E-09	10.70942	18.8092	10.70942	18.80920106
Oxygen	-0.00049	0.030823	-0.01595	0.987354	-0.06284	0.061854	-0.06284	0.061854182
Pulse Rate	-0.06193	0.01847	-3.35304	0.001788	-0.09929	-0.02457	-0.09929	-0.024571267
RR	-0.36706	0.065726	-5.58468	1.95E-06	-0.5	-0.23412	-0.5	-0.234116598

Figure 10: *Regression Analysis of Fuzzy Data*

As enclosed in the yellow boundary, the coefficient of X1 that is, Oxygen is -0.00049, the coefficient of X2 that is, Pulse Rate is -0.06193, the coffecient of X3, Respiratory Rate is

-0.36706. The intercept c=14.75931.

The equation of Line of Regression is Y=m1X1+m2X2=m3X3…………………..……(1)

Which turns out to be: Y=-0.00049X1+-0.06193X2+-0.36706X3+14.75931……………(2)

As an example X1 is taken to be 92, X2 as 70 and X3 as 12. The result comes out to be 5.9742…

The Regression Line of fit for Oxygen is shown in figure 11. a

The x axis shows the oxygen level of the Covid patient that ranges from 70 to 99. On the Y axis lies the risk factor dependent variable Risk which is dependent on Oxygen Level. Safe Oxygen level lies above 95[25]. The Risk is interpreted between 1 and 10 where 1 is least risk and 10 denotes highest risk.

Table 3: *Level of attention required on the basis of Risk factor / Mortality Rate*

Risk Factor/ Mortality Rate	Level of Attention Required
1-3	Home Quarantine/Isolation and inhiliation
3-5	Home Quarantine with Oxygen support and inhilation
5-7	Immediate Hospital bed allotment with Oxygen Support, Nebulization and inhilation
7-10	Immergency (Extremely high Mortality rate)

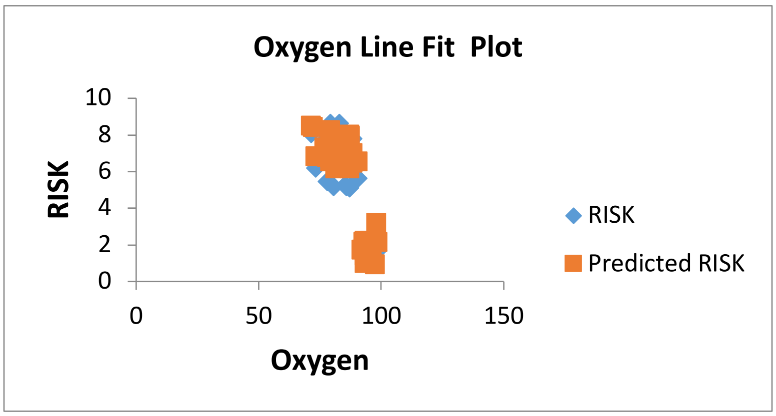

Figure 11.a: Oxygen Line Fit Plot

The Regression Line of fit for Pulse Rate is shown in figure 11.b

The x axis shows the pulse rate of the Covid patient that ranges from 60 to 120.

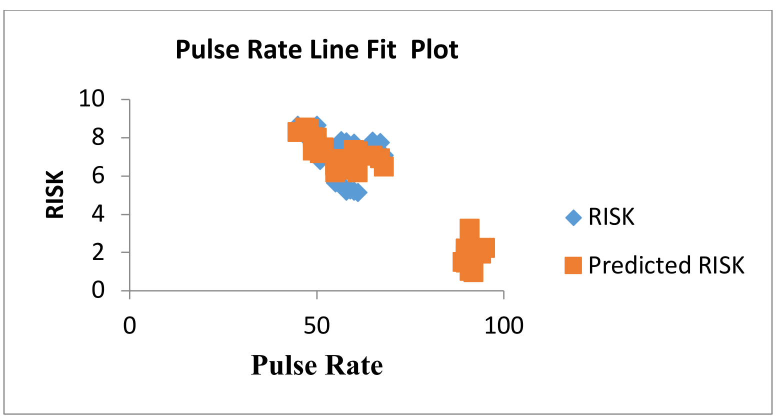

Figure 11b: *Pulse rate Line Fit Plot*

The Regression Line of fit for Respiration Rate is shown in figure 11.c

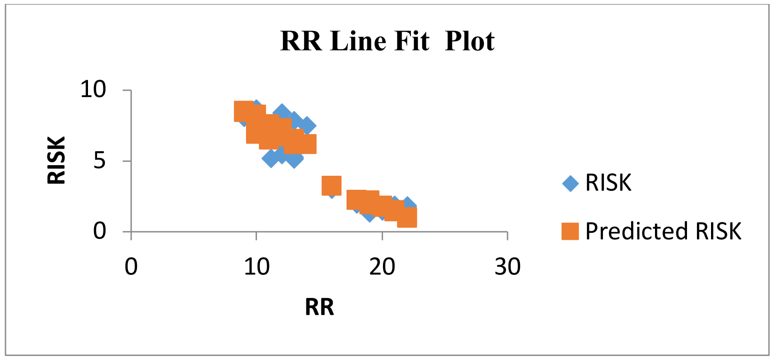

Figure 11 c *Respiration Rate Line Fit Plot*

The x axis shows the respiration rate of the Covid patient that ranges from 11 to 20. The overlapping clearly indicates the level of dependence between RR and Risk.

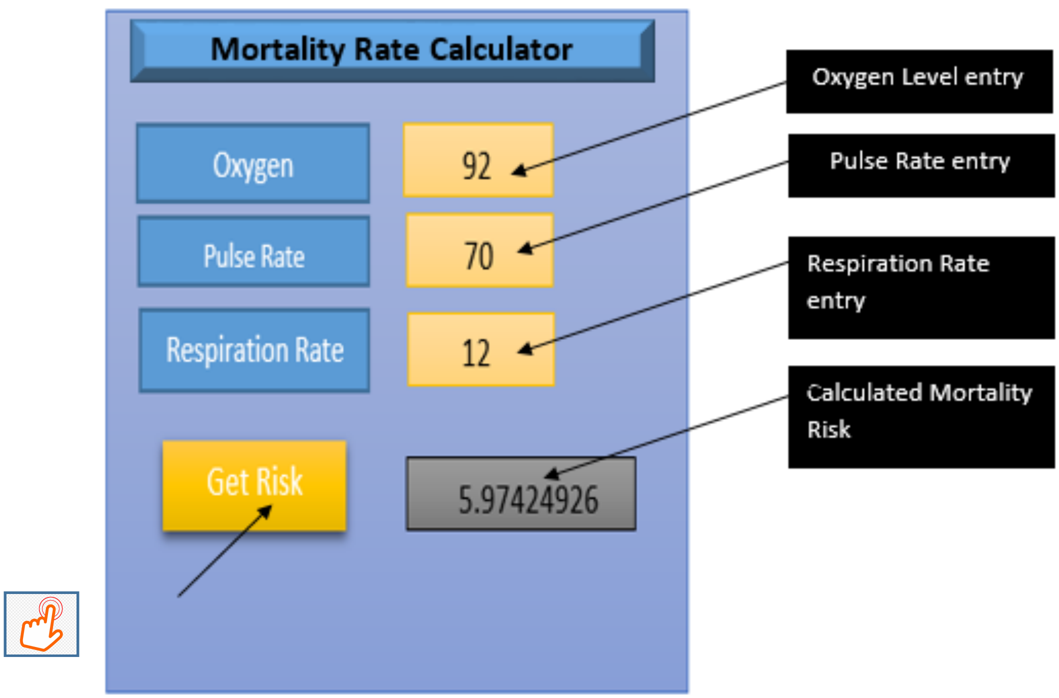

Figure 12.*Implementation of Risk factor Prediction*

The authors have developed a Mortality Rate Calculator which predicts the risk associated to a Covid patient on the basis of his oxygen level, SaO_2 measured in percentage (%), pulse rate in BPM and respiration rate in breaths per minute. The normal reading of Oxygen level is 98. Anything below 95 is alarming. The pulse rate should be between 70 to 100. The normal respiration rate has 12 to 16 breaths per minute.As you can see the three input variables Oxygen level, Pulse rate and Respiration Rate have to be entered to get the Mortality Risk of a Covid patient as in figure 11. Here with the given data, the click on Get Risk button displays the risk associated. [26].

The graph for the data having Oxygen level SaO_2, pulse rate and RR along with Risk factor in % is shown in figure 12.

Normal range of A normal ABG oxygen level for healthy lungs falls between 80 and 100 millimeters of mercury (mm Hg). If a pulse ox measured your blood oxygen level (SpO_2), a normal reading is typically between 95 and 100 percent.[32].

The normal pulse for healthy adults ranges from 60 to 100 beats per minute. The pulse rate may fluctuate and increase with exercise, illness, injury, and emotions. Females ages 12 and older, in general, tend to have faster heart rates than do males. Athletes, such as runners, who do a lot of cardiovascular conditioning, may have heart rates near 40 beats per minute and experience no problems [33]. The mortality rate of a Covid patient is shown as a curved line in figure 13 where SaO_2, PR and RR are depicted as clustered column histogram.

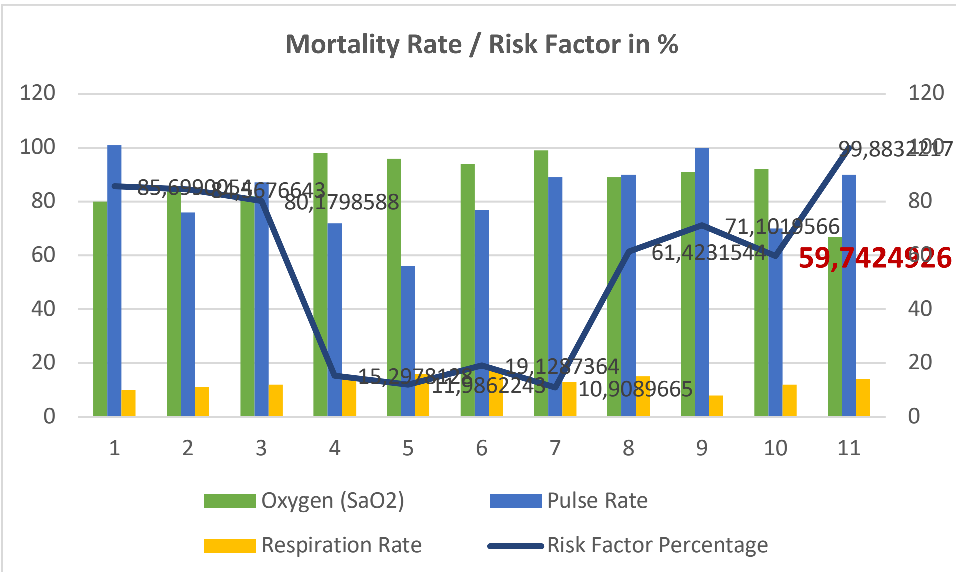

Figure 13. *Clustered column Histogram for Oxygen, pulse rate and Respiration rate with output variable Risk factor measured here in this graph as percentage.*

V. Blood Pressure and Sugar Level

As pointed out earlier that blood pressure and sugar showed very low level of correlation with Risk, but clinically both play a vital role in deciding the risk. The problem with Blood Pressure and sugar level is that these values move in both directions that is Low←--Normal--→High which is not a suitable criteria for fuzzy logic. This was the reason for taking blood pressure and sugar separately as factors for calculating risk [27].

If you have high blood pressure, it's a good idea to take extra care to protect yourself during the coronavirus (COVID-19) outbreak. Early research shows that people with this condition may be more likely to get COVID-19, have worse symptoms or even die from the infection [19].

High Blood Pressure Risks

Growing data shows a higher risk of COVID-19 infections and complications in people with high blood pressure.

Analysis of early data from both China and the U.S. shows that high blood pressure is the most commonly shared pre-existing condition among those hospitalized, affecting between 30% to 50% of the patients. Same also goes for people having moderate to high diabetes.

VI. Conclusion and Future Scope

This paper aims to provide a quick opinion about the degree of Risk involved for a Covid patient on the basis of his Oxygen level, pulse rate and respiration rate. The FRPRPS first applies Fuzzy logic rules on three input variables and a single output variable. This is done iteratively to generate 1000 rows of oxygen level, pulse rate and respiration rate along with the Risk using FuzzyR library. Then, this fuzzy system is manually aligned for correctness if it was needed. The fuzzy system is then passed through a regression model to predict the Risk. Blood Pressure and Sugar were not taken as input variables because they grow in both directions that is normal to low and normal to high. This feature of bidirectional growth cannot be accommodated by fuzzy paradigm [28].

As a future scope, the shape of the membership functions may be altered in order to produce better results [29], [30]. Blood Pressure and Sugar level may be vectored unidirectional in order to be suited as input variables for Fuzzy System to produce results dependent on these two as well [31].

References

[1] Zadeh, Lotfi A. "Fuzzy logic." *Computer* 21.4 (1988): 83-93.
[2] Tanaka, Kazuo. "An introduction to fuzzy logic for practical applications." (1997).
[3] Diamond, Phil, and Hideo Tanaka. "Fuzzy regression analysis." *Fuzzy sets in decision analysis, operations research and statistics*. Springer, Boston, MA, 1998. 349-387.
[4] Ishibuchi, Hisao, and Hideo Tanaka. "Fuzzy regression analysis using neural networks." *Fuzzysets and systems* 50.3 (1992): 257-265.
[5] Schmee, Josef, and Gerald J. Hahn. "A simple method for regression analysis with censored data." *Technometrics* 21.4 (1979): 417-432.
[6] Kaneko, Hiromasa, Masamoto Arakawa, and Kimito Funatsu. "Development of a new regression analysis method using independent component analysis." *Journal of chemical information and modeling* 48.3 (2008): 534-541.
[7] Luks AM, Swenson ER. Pulse Oximetry for Monitoring Patients with COVID-19 at Home. Potential Pitfalls and Practical Guidance. *Ann Am Thorac Soc*. 2020;17(9):1040-1046. doi:10.1513/AnnalsATS.202005-418FR
[8] Usher, Ann Danaiya. "Medical oxygen crisis: a belated COVID-19 response." *The Lancet* 397.10277 (2021): 868-869.
[9] Hayes, Matthew James, and Peter R. Smith. "A new method for pulse oximetry possessing inherent insensitivity to artifact." *IEEE Transactions on Biomedical Engineering* 48.4 (2001): 452-461.
[10] Chang, Yun-Hsi O., and Bilal M. Ayyub. "Fuzzy regression methods–a comparative assessment." *Fuzzy sets and systems* 119.2 (2001): 187-203.
[11] Stein, Felix, et al. "Oxygen provision to fight COVID-19 in sub-Saharan Africa." *BMJ Global Health* 5.6 (2020): e002786.

[12] World Health Organization. *Oxygen sources and distribution for COVID-19 treatment centres: interim guidance, 4 April 2020*. No. WHO/2019-nCoV/Oxygen_sources/2020.1. World Health Organization, 2020.
[13] Daniel, Yvonne, et al. "Haemoglobin oxygen affinity in patients with severe COVID-19 infection." *British Journal of Haematology* 190.3 (2020): e126-e127.
[14] Melin, Patricia, et al. "Multiple ensemble neural network models with fuzzy response aggregation for predicting COVID-19 time series: the case of Mexico." *Healthcare*. Vol. 8. No. 2. Multidisciplinary Digital Publishing Institute, 2020.
[15] Ocampo, Lanndon, and Kafferine Yamagishi. "Modeling the lockdown relaxation protocols of the Philippine government in response to the COVID-19 pandemic: An intuitionistic fuzzy DEMATEL analysis." *Socio-economic planning sciences* 72 (2020): 100911.
[16] Ran, J., Song, Y., Zhuang, Z. *et al.* Blood pressure control and adverse outcomes of COVID-19 infection in patients with concomitant hypertension in Wuhan, China. *Hypertens Res* 43, 1267–1276 (2020). https://doi.org/10.1038/s41440-020-00541-w
[17] Civanlar, M. Reha, and H. Joel Trussell. "Constructing membership functions using statistical data." *Fuzzy sets and systems* 18.1 (1986): 1-13.
[18] Turksen, I. B. "Measurement of membership functions and their acquisition." *Fuzzy sets and systems* 40.1 (1991): 5-38.
[19] Hong, Tzung-Pei, and Chai-Ying Lee. "Induction of fuzzy rules and membership functions from training examples." *Fuzzy sets and Systems* 84.1 (1996): 33-47.
[20] Ali, Omar Adil M., Aous Y. Ali, and Balasem Salem Sumait. "Comparison between the effects of different types of membership functions on fuzzy logic controller performance." *International Journal* 76 (2015): 76-83.
[21] Wang, Hsiao-Fan, and Ruey-Chyn Tsaur. "Insight of a fuzzy regression model." *Fuzzy sets and systems* 112.3 (2000): 355-369.
[22] Bardossy, Andras. "Note on fuzzy regression." *Fuzzy Sets and Systems* 37.1 (1990): 65-75.
[23] Hong, Dug Hun, and Changha Hwang. "Support vector fuzzy regression machines." *Fuzzy sets and systems* 138.2 (2003): 271-281.
[24] Sarvazad, H., et al. "Evaluation of electrolyte status of sodium, potassium and magnesium, and fasting blood sugar at the initial admission of individuals with COVID-19 without underlying disease in Golestan Hospital, Kermanshah." *New Microbes and New Infections* 38 (2020): 100807.
[25] National High Blood Pressure Education Program. *The fourth report on the diagnosis, evaluation, and treatment of high blood pressure in children and adolescents*. No. 5. US Department of Health and Human Services, National Institutes of Health, National Heart, Lung, and Blood Institute, National Hight Blood Pressure Education Program, 2005.
[26] Shankhdhar G.K., Sharma R., Darbari M. (2021) SAGRO-Lite: A Light Weight Agent Based Semantic Model for the Internet of Things for Smart Agriculture in Developing Countries. In: Pandey R., Paprzycki M., Srivastava N., Bhalla S., Wasielewska-Michniewska K. (eds) Semantic IoT: Theory and Applications. Studies in Computational Intelligence, vol 941. Springer, Cham. https://doi.org/10.1007/978-3-030-64619-6_12.
[27] Sumit Kumar Mishra, V.K. Singh, Gaurav Kant Shankhdhar, Ontology Development For Wheat Information System, IJRET-International Journal of Research in Engineering and Technology 2015, V0l4/I05.
[28] G. K. Shankhdhar, M. Darbari, R. Sharma and H. Ahmed, "Fuzzy Approach to Select Most Suitable Conflict Resolution Strategy in Multi-Agent System," 2019 International Conference on Cutting-edge Technologies in Engineering (ICon-CuTE), Uttar Pradesh, India, 2019, pp. 9-15.

[29] Gaurav Kant Shankhdhar, Manuj Darbari (2016), Building Custom, Adaptive and Heterogeneous Multi-Agent Systems for Semantic Information Retrieval Using Organizational-Multi-Agent Systems Engineering, O-MaSE, IEEE Explore, ISBN: 978-1-5090-3480-2.

[30] J. Singh and H. Pandey. , "Moving Video Camera Vigilance Using DBSCAN", Reliability: Theory & Applications, No 2 (53) Volume 14, ISSN: 1932-2321, June 2019.

[31] H. Pandey, and M. Darbari., Coalescence of Evolutionary Multi-Objective Decision making approach and Genetic Programming for Selection of Software Quality Parameter, International Journal of Applied Information System (IJAIS), Foundation of Computer Science, New York, USA, Volume 7, No. 11, PP. ISSN: 2249-0868, Nov. 2014.

[32] S. Bansal and H. Pandey, Develop Framework for selecting best Software Development Methodology, International Journal of Scientific and Engineering Research, Volume 5, Issue 4, PP. 1067-1070, ISSN: 2229-5518, Apr. 2014.

[33] M. Srivastava and H. Pandey,A Literature Review of E- Learning Model Based on Semantic Web Technology, International Journal of Scientific and Engineering Research" Volume 5, Issue 10, PP. 174-178, ISSN: 2229-5518, Oct. 2014.

[34] H. Pandey, A New NFA Reduction Algorithm for State Minimization Problem, International Journal of Applied Information Systems (IJAIS), Foundation of Computer Science FCS, New York, USA, Volume 8, No.3, PP. 27-30, ISSN: 2249-0868, Feb. 2015.

[35] H.Pandey, LR Rotation rule for creating Minimal NFA, International Journal of Applied Information Systems (IJAIS), Foundation of Computer Science FCS, New York, USA, Volume 8, No.6, PP. 1-4, ISSN: 2249-0868, Apr. 2015.