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An Intelligent Method for Detecting the Rate of Poverty Level with Reference to Tuberculosis

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Abstract*: This paper represents the factors, which is important for the prediction of the population living below the poverty level as defined by world health organization through reverse engineering. The objective of this research work is to analyze how the tuberculosis detection rate can help us to predict the people living below the poverty line. The feed-forward artificial neural network and Support vector machines used for comparison. The Authors provide physical reasons behind the startling results that we obtained. This work used data collected by the World Health Organization. The data collected consisted of 202 observations of 358 variables and out of these vast numbers of variables; we selected only six variables of interest to build the model. After removing the not available rows, we get only 75 observations out of which we use only 57 observations to build our model. Although the error was a bit high, still with only these few observations both artificial neural networks and support vector machines yielded similar results, confirming our hypothesis. This paper also compares two well-known algorithms for variable importance and finally provides a solution to the problem of poverty by fuzzy cognitive maps. Various concepts related to the economy have been used to develop this model and results are astounding, based on the results solution to the present-day problems has been proposed.

Keywords: Fuzzy Cognitive Maps, Support Vector Machines, Artificial Neural Network, Fuzzy Weight, Tuberculosis.

I. INTRODUCTION

This article describes the various works that many researchers have done prior to this and discuss some of the shortcomings and problems that we face regarding this issue. Then in the methodology section, we describe what some of the variables involved in our work are and we describe their significance. Then apart from the conventional variables that are there in the dataset. result was calculated and we describe their interpretation.

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We use another derived variable whose significance we describe in that section. Then we present our results along with the analysis and interpretation of their meaning. We also describe here how significance of variables for the prediction of

In this section, we show how both Support Vector Machines as well as Artificial Neural Networks confirms the same result. Finally, we conclude our study with a further analysis of their meanings. Then before conclusion, we also try to implement a fuzzy cognitive map and provide solution to the problem of poverty.

II. LITERATURE SURVEY

In a study by Doshi et al [1], it was found that using AI techniques could revolutionize the management of TB. They described various techniques that can be combined to achieve the desired results in a cost effective manner, Suitable even for poor people. Today's scenario tells us that we have huge amount of growing T.B cases in the world. In a study by Barter et al [2] they have shown how a patients has to incur additional cost for the management of the T.B. In the papers by Das et al [3] [4] particularly focused on diagnosis of disease by certain advanced techniques. Their domain of interest was tuberculosis. However, in this study, it was not considered how socio-economic conditions could affect the spread of this disease. In the counterpart, intuitively if we know the rate of spread of tuberculosis, how can we predict the population lying below the poverty line? In another paper by Bhunu et al [5] their results were illustrating that heterogeneous mixing of the rich and poor will make the epidemic worse, but homogenous mixing will slightly improve the outcome. Our paper mainly focuses on this part and we use artificial neural networks for this purpose. We also review and use certain techniques for predicting te importance of variables in neural networks. Now before considering the techniques we would like to point out that it is usually very unlikely for a homogeneous mix of rich and poor. It is an idealization as poor are usually trapped in a vicious cycle of debts if they are below poverty line and for availing necessities including education they need money. Now as for government, schemes there are corruptions at various stages not allowing the transition of poor. The study showed that the patients could acquire the prediction of diseases in advance by using Soft Computing (SC) and AI techniques[6]–[8].

III. METHODOLOGY

A neural network has several input, hidden, and output nodes. Each node applies a function some data (could be softmax, linear, logistic), and returns an output. Every node in the proceeding layer takes a weighted average of the outputs of the previous layer, until an output is reached.

The reasoning is that multiple nodes can collectively gain insight about solving a problem (like classification) that an individual node cannot.

The cost function differs for this type of model -- the weights between nodes adjust to minimize error.
Support Vector Machine (SVM) fits a hyper-plane/function between 2 different classes given a maximum margin parameter. This hyper-plane attempts to separate the classes so that each falls on either side of the plane, and by a specified margin. There is a specific cost function for this kind of model which adjusts the plane until error is minimized.

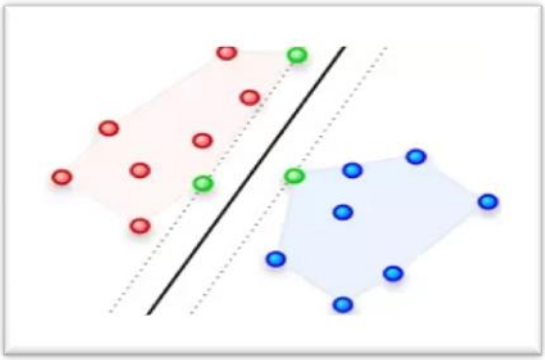


Fig .1 Methodology of working of SVM

Tuberculosis is growing all over the world but thanks to the DOTS treatment that they do not possess a serious threat. Now, let us analyze a bit on certain causes of tuberculosis and the people are more prone to it. Studies have shown that diabetic person is more prone to this disease. There is a conception among the people that it is more prevalent among the poor. Because they do not get enough nutrition, their body is weak to defend from the disease .Here we imported the dataset [9] and using the values of the tuberculosis detection rate and certain other significant variables we try to predict the population below the poverty line. Now we describe certain parameters we used to build our feed forward back propagation artificial neural network. Tuberculosis case detection rate (all forms) is the number of new and relapse tuberculosis cases notified to WHO in a given year, divided by WHO's estimate of the number of incident tuberculosis cases for the same year, expressed as a percentage. Then we have the number of physicians in a population, then population living below poverty line which World Health Organization defines living on less than us 1 $ per day. Then we have gross national income (GNI) per capita, GNI is gross national income converted to international dollars using purchasing power parity rates. An international dollar has the same purchasing power over GNI as a U.S. dollar has in the United States. Then we have the population in thousands total. Then we have also devised a new variable called α.

$$T = \alpha(B(p) - p) \qquad (1)$$

Where, $B(p)$ is the bell number computed for the population-fraction. T is tuberculosis detection rate of the population. The p is the total number of people per 1000 people; we do this to compute bell numbers efficiently as if p is 4.5 that mean we have 4500 people .We define the philosophy behind the new variable α but before that we provide the significance of bell's number. The Bell numbers count the possible partitions of a set. These numbers have been studied by mathematicians since the 19th century, and their roots go back to medieval Japan, but they are named after Eric Temple Bell, who wrote about them in the 1930s [10].
Let us take an example, suppose you have the set S={1,2,3}. What are the number of possible partitions that you can draw: {{1}, {2}, {3}}; {{1, 2}, {3}}; {{1, 3}, {2}}; {{1}, {2, 3}}; {{1, 2, 3}}, i.e. 5 partitions can be drawn excluding the main set itself. Thus, bells-number can give you the number of possible subpopulation you can draw from a population. Nevertheless, there are partitions with single elements, which is unwanted here. Therefore, we subtract the number of people p in a population from the bell number to get our desired results. Now α can be defined as the tuberculosis detection rate per unit number of subpopulation drawn. Using this relation you can find that if we draw a random sample of population from a given number then what would be the tuberculosis detection rate. After removing not applicable rows, we found only 75 observations, as many data could not be collected regarding population living below poverty line from various countries [9].

IV. EXPERIMENTATION

We compare the performance of SVM (Support Vector Machines) against artificial neural network for predicting the outcome variable, which in our case is gross national income. We partitioned the dataset into 80%-20% where 80% is used for training and 20% used for testing the data.
We have also used support vector machines to develop and test the results obtained by artificial neural network.

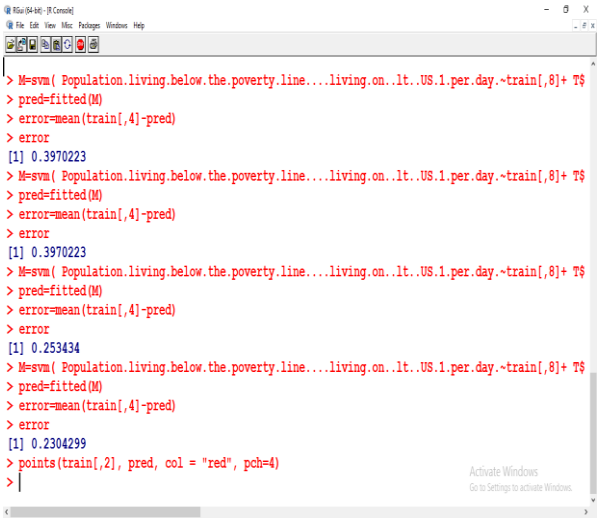


Fig .2 Error estimate of S.V.M for various kernel functions

We used an S.V.M with gamma value=0.005 and cost=5. Different kernel functions were used including polynomial, radial basis and sigmoid. We got the best performance as you can see with sigmoid type kernel, the minimum value of the figure 2.
The two same values that you see are actually polynomial kernels with degree 14 and higher. It was not better than this.

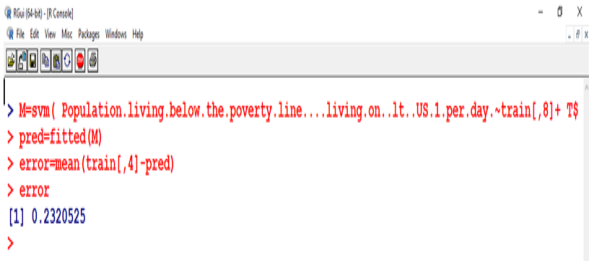


Fig .3 Error estimate when kernel is radial basis function

This Fig.3 is S.V.M for radial basis kernel, which was better than polynomial type but less than sigmoid type. This shows an error of 23% as only 57 observations were available.

Fig .4 Calculations of parameters of hyper-plane

Computation of parameters of S.V.M model, showing that gross national income is the most important variable, and then followed by tuberculosis detection rate for computing the hyper planes.

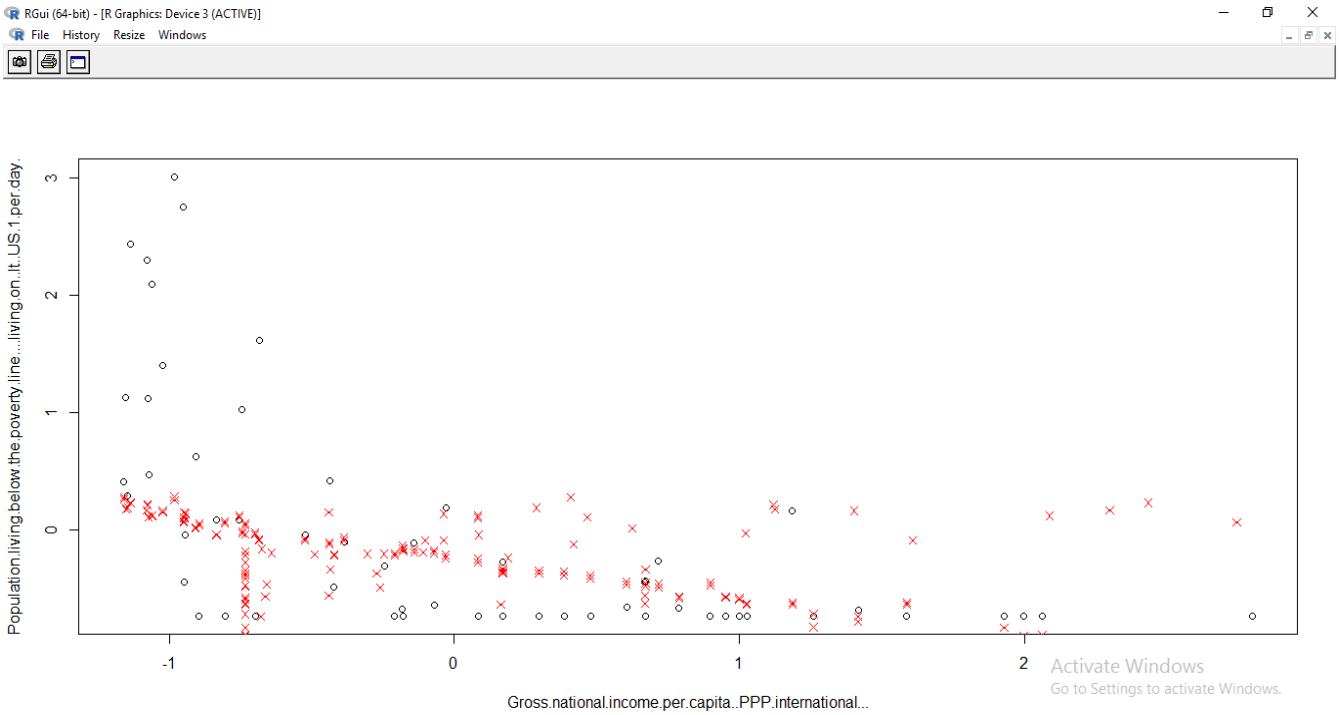


Fig .5 Plot of population below poverty line grosses national income for original data, and predicted values shown as circles and red crosses respectively.

Plot of the data in two dimensions where a circle represents original data and red crosses indicates the predicted value. Now a hyper-plane represented as:

$$Y = W * K(X) + b \qquad (2)$$

From figure 4, we get the parameters of W and b for hyper-plane represented in the figure 2.Where Y is the predicted values, K is the kernel function W is weight vector and b is bias vector. As you can see from the fig.4, gross national income per capita as well as tuberculosis, detection rate is important for the prediction of outputs in our support vector machine. Now comparing this result with fig.11, we get the same results the gross national income is most important followed by tuberculosis detection rate then followed by our new variable log(α) then followed by the measure of population.

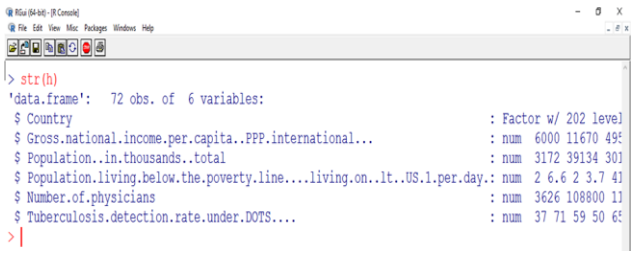


Fig .6 showing the structure of data that we partitioned

The structure of the data frame that has been used in building our model.

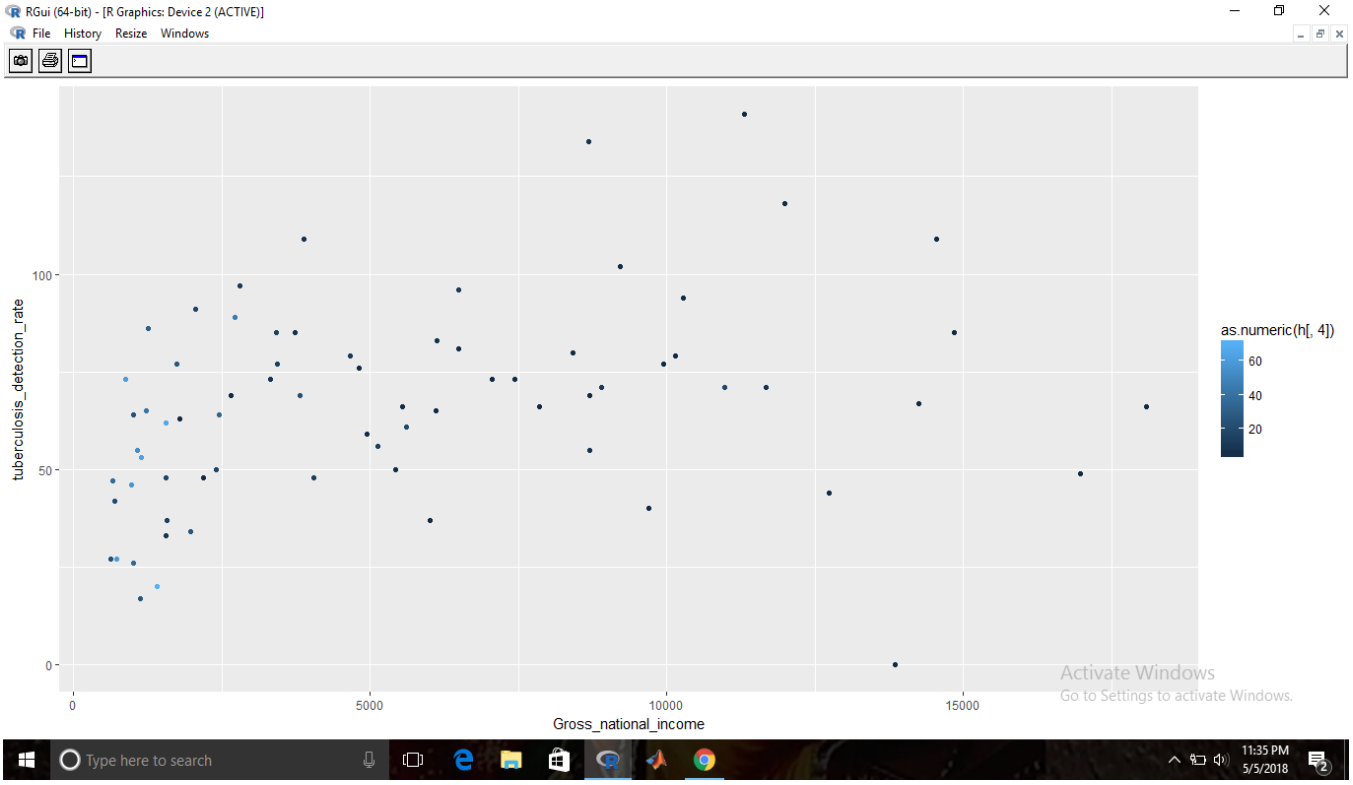
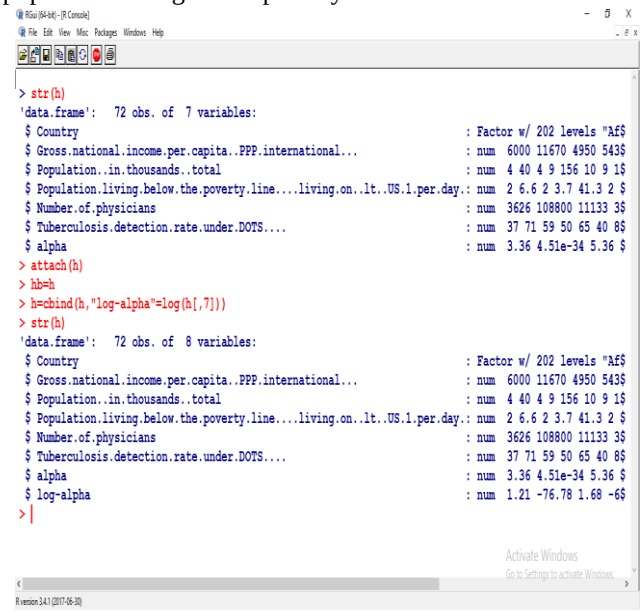


Fig .7 plot of tuberculosis detection rate along y axis versus gross national income

Figure 7 shows the plot of tuberculosis detection rate as gross national income increases. The legend describes the population living below poverty line.

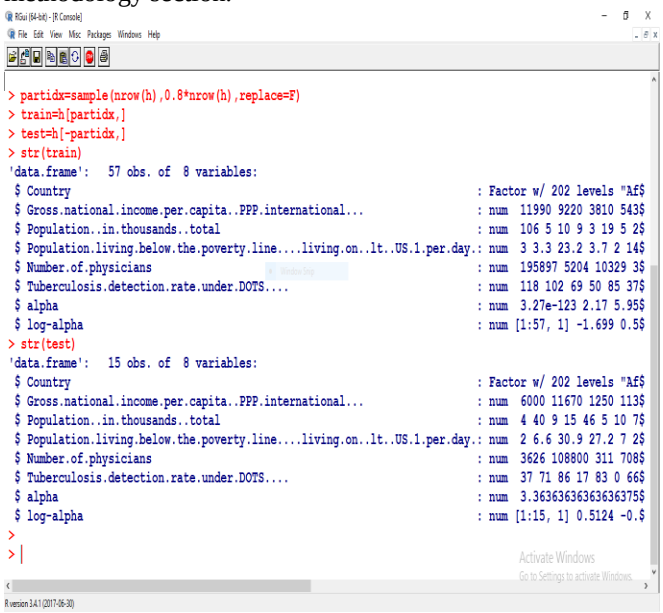


```
> str(h)
'data.frame':   72 obs. of  7 variables:
 $ Country                                                    : Factor w/ 202 levels "Af$
 $ Gross.national.income.per.capita..PPP.international...     : num  6000 11670 4950 543$
 $ Population..in.thousands..total                            : num  4 40 4 9 156 10 9 1$
 $ Population.living.below.the.poverty.line....living.on..lt..US.1.per.day.: num  2 6.6 2 3.7 41.3 2 $
 $ Number.of.physicians                                       : num  3626 108800 11133 3$
 $ Tuberculosis.detection.rate.under.DOTS....                 : num  37 71 59 50 65 40 8$
 $ alpha                                                      : num  3.36 4.51e-34 5.36 $
> attach(h)
> hb=h
> h=cbind(h,"log-alpha"=log(h[,7]))
> str(h)
'data.frame':   72 obs. of  8 variables:
 $ Country                                                    : Factor w/ 202 levels "Af$
 $ Gross.national.income.per.capita..PPP.international...     : num  6000 11670 4950 543$
 $ Population..in.thousands..total                            : num  4 40 4 9 156 10 9 1$
 $ Population.living.below.the.poverty.line....living.on..lt..US.1.per.day.: num  2 6.6 2 3.7 41.3 2 $
 $ Number.of.physicians                                       : num  3626 108800 11133 3$
 $ Tuberculosis.detection.rate.under.DOTS....                 : num  37 71 59 50 65 40 8$
 $ alpha                                                      : num  3.36 4.51e-34 5.36 $
 $ log-alpha                                                  : num  1.21 -76.78 1.68 -6$
>
```

Fig .8 Addition of new derived variable to the data-frame.

Figure 9 shows the partitioning of data-frame h of figure 6 into training and test dataset.

Figure 8 shows the addition of α and log(α) into our data frame. Whose significance, we have described in the methodology section.



```
> partidx=sample(nrow(h),0.8*nrow(h),replace=F)
> train=h[partidx,]
> test=h[-partidx,]
> str(train)
'data.frame':   57 obs. of  8 variables:
 $ Country                                                    : Factor w/ 202 levels "Af$
 $ Gross.national.income.per.capita..PPP.international...     : num  11990 9220 3810 543$
 $ Population..in.thousands..total                            : num  106 5 10 9 3 19 5 2$
 $ Population.living.below.the.poverty.line....living.on..lt..US.1.per.day.: num  3 3.3 23.2 3.7 2 14$
 $ Number.of.physicians                                       : num  195897 5204 10329 3$
 $ Tuberculosis.detection.rate.under.DOTS....                 : num  118 102 69 50 85 37$
 $ alpha                                                      : num  3.27e-123 2.17 5.95$
 $ log-alpha                                                  : num [1:57, 1] -1.699 0.5$
> str(test)
'data.frame':   15 obs. of  8 variables:
 $ Country                                                    : Factor w/ 202 levels "Af$
 $ Gross.national.income.per.capita..PPP.international...     : num  6000 11670 1250 113$
 $ Population..in.thousands..total                            : num  4 40 9 15 46 5 10 7$
 $ Population.living.below.the.poverty.line....living.on..lt..US.1.per.day.: num  2 6.6 30.9 27.2 7 2$
 $ Number.of.physicians                                       : num  3626 108800 311 708$
 $ Tuberculosis.detection.rate.under.DOTS....                 : num  37 71 86 17 83 0 66$
 $ alpha                                                      : num  3.36363636363636375$
 $ log-alpha                                                  : num [1:15, 1] 0.5124 -0.$
>
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Fig .9 Partitioning of the data frame

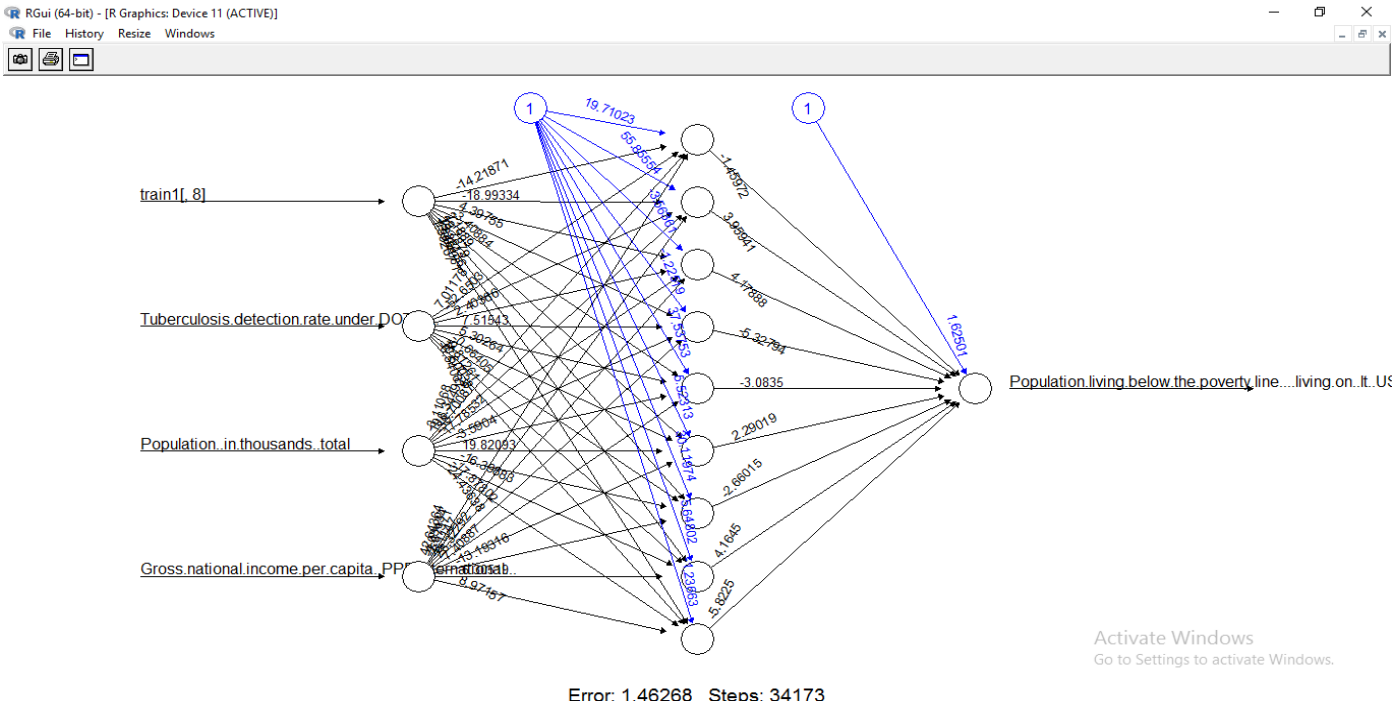


Fig .10 Resultant neural networks generated

Here in figure 10 we show our neural network model that we generated we built the model after normalizing both inputs as well as outputs [11].

Since we have used less number of data for training this network, we are getting this error but if we use more data and if it is available, then our results would be very accurate. We also computed the relative importance of variables using Garson's algorithm [12].Garson proposed an algorithm, later modified by Goh et al [13] for determining the relative importance of an input node to a network. In the case of a single layer of hidden units, the equation is:

$$Q_{ik} = \frac{\frac{\sum_{j=1}^{L}|w_{ij}v_{jk}|}{\sum_{r=1}^{N}|w_{rj}|}}{\sum_{i=1}^{N}\sum_{j=1}^{L}\left(\frac{|w_{ij}v_{jk}|}{\sum_{r=1}^{N}|w_{rj}|}\right)} \quad (3)$$

Where, w_{ij} is the weight between the ith input and the jth hidden unit, and v_{jk} is the weight between the jth hidden unit and the kth output.

V. RESULT AND DISCUSSION

The percentages of the influence of input variable on the output value, Q_{ik} (%), indicating the importance of input variables were determined by the above equation by Garson [12].We computed the importance of variables when only a single hidden layer was used as this algorithm applies for a single hidden layer.

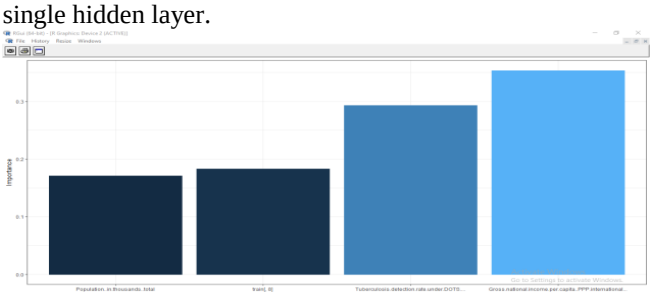


Fig .11 Pictorial representation of importance of variables using Garsons algorithm

Figure 11 shows the relative importance of variables for prediction in neural network. The least is population in thousands .Then second is log alpha, then you have tuberculosis detection rate and finally you have gross national income[14].

Here, this analysis is used for predicting the population below poverty line. It is obvious that gross national income would be the most important variable as also shown in the fig.11. Then as we expected the tuberculosis detection rate under D.O.T.S is important, we here explain the reasons behind this. Poor people are more prone to malnutrition as a result their immunity power decreases and so you can that they are more prone to tuberculosis. Thus if there are more tuberculosis cases reported then you can say that indirectly more poor people live in that country. Thus, this is second most important. Then comes the log(α) value whose significance we have already discussed. Then comes the amount of population, if you have more number of people then you can naively say that number of poor people would increase if you assume other conditions as constant.

Now as we can see from the equation (3). Absolute value of weights is taken in Garson's algorithm. This is a disadvantage also which can sometimes lead to inaccurate results, although this algorithm is used extensively but we have another better alternative Olden's algorithm [15].

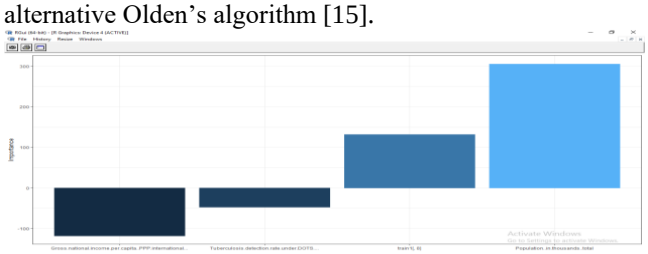


Fig 12. Pictorial representation of importance of variables using olden's algorithm.

We interpret the results. Gross national income and population in thousand are the most important variables. Interestingly log (α) is more significant than the tuberculosis detection rate. Thus, the variable that we derived for our work is better than the raw variable tuberculosis detection rate under DOTS. log (α) is represented in the figure 12 as train1[,8] meaning it was the 8th column of the training data.

Analysis of government schemes and black money on poverty level:

Cognitive maps were introduced as a formal means of modelling decision making in social and political systems. Cognitive maps can also be used for strategic planning, prediction, explanation and engineering concept development[16]. A fuzzy cognitive map extends the idea of conventional cognitive maps by allowing the concepts to be expressed linguistically with an associated fuzzy set. We use a fuzzy cognitive map for finding the effect when poverty increases very much and simultaneously population also increases very much then what happens. Based upon this analysis we can say apart from TB how other factors contribute. FCMs are fuzzy signed directed graphs permitting feedback, where the weighted edge w_{ij} from causal concept C_i to affected concept C_j, describes the amount by which the first concept influences the latter. We now describe how fuzzy cognitive maps work,

$$Ai(k+1) = f\left(\sum_{j=1, j\neq i}^{N} w_{ji} A_j(k)\right) \quad (4)$$

$$Ai(k+1) = f\left(A_i(k) + \sum_{j=1, j\neq i}^{N} w_{ji} A_j(k)\right) \quad (5)$$

Every concept in the FCM graph has a value A_i that expresses the quantity of its corresponding physical value and it is derived by the transformation of the fuzzy values assigned by the experts to numerical values. The value A_i of each concept C_i is calculated during each simulation step, computing the influence of other concepts to the specific concept by selecting one of the equations from (4) and (5). where $Ai(k+1)$ is the value of concept Ci at simulation step (k+1), $Aj(k)$ is the value of concept Cj at the simulation step k, wij is the weight of the interconnection between concept Cj and concept Ci, k is the interaction index an every simulation step and f(·) is the threshold (activation) function. The FCM model of the system takes the initial values of concepts and weights based on expert's knowledge and experience for the real system and then it is free to interact. At each step, the value Ai of a concept is influenced by the values of concepts connected to it and it is updated according to the inference rule. For our case, we used:

$$f(x) = \tanh(\lambda x) \quad (7)$$

The equation 7 as our threshold functions as negative weights were also involved. Where λ is a real positive number, which determines the steepness of this function. The equation (4) is Koskos method. Equation (5) is modified koskos method.

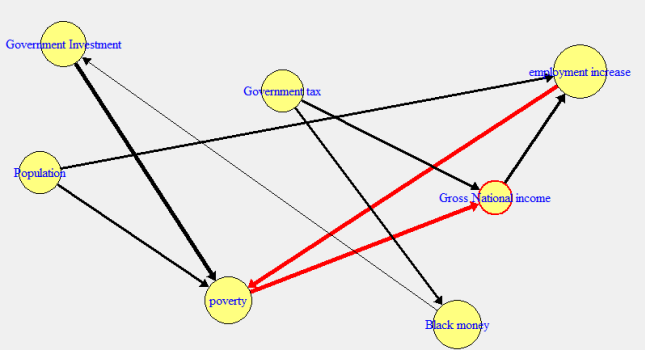


Fig.13. showing the structure of cognitive maps

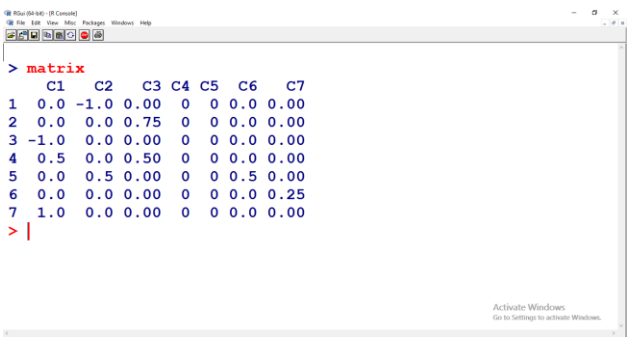
Red arrows in the figure 13 symbolize the negative of the concept and black arrows indicates positive of the concept. Like if, you have more government investment then black money also increases or we can equivalently say that when black money increases then government investment indirectly increases. The thickness of lines indicates the amount of fuzzy weights. As population increases then more production of goods needs to be there which indirectly increases employment.

Table1. Concept representation

Concept	
Notation	Proposition
C1	poverty
C2	Gross National income
C3	employment increase
C4	Population
C5	Government tax
C6	Black money
C7	Government Investment

Table2. Linguistic representation

Fuzzy Representation	
Linguistic Variable	Weights
Very much causes	1
A lot causes	0.75
Moderately causes	0.50
Somewhat causes	0.25
Does not causes	0
Very much causes negative of the concept	-1
A lot causes negative of the concept	-0.75
Moderately causes negative of the concept	-0.50
Somewhat causes negative of the concept	-0.25



```
> matrix
   C1   C2   C3 C4 C5  C6   C7
1  0.0 -1.0 0.00  0  0 0.0 0.00
2  0.0  0.0 0.75  0  0 0.0 0.00
3 -1.0  0.0 0.00  0  0 0.0 0.00
4  0.5  0.0 0.50  0  0 0.0 0.00
5  0.0  0.5 0.00  0  0 0.5 0.00
6  0.0  0.0 0.00  0  0 0.0 0.25
7  1.0  0.0 0.00  0  0 0.0 0.00
>
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Fig.14. Representation of adjacency matrix for our fuzzy cognitive map.

We activated the concept c1 and c4 and finally after 334 iterations the solution converged.

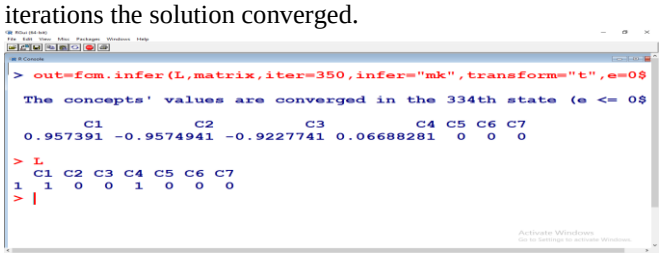

Fig.15 Results of gross National.

As the above figure 15 shows, the result was
C1 =0.96, C2=-0.96, C3=-0.92 and C4=0.07

That means gross national income represented by c2 and employment represented by c3 decreases severely. Whereas you see initially c4 i.e. population was high but now after these changes the population has decreased. This can be justified because as employment and gross national income decreases the poverty will increase. This is justified by the fact that C1 remains close to 1. As poverty increases poor people are not able to survive and die due to either malnutrition or diseases and so population decreases.

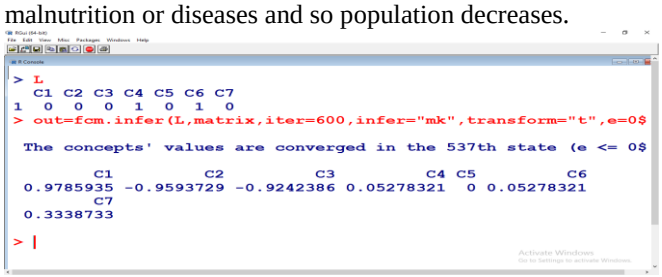

Fig 16. Population vs. Black money

As the above figure 16 shows, we activated the concepts c4 and c6.That means population increases as well as black money also increases. Then the result was as shown in the figure 16.

C1=0.98, C2=-0.96, C3=-0.92, C4=0.05, C5=0, C6=0.05 and C7=0.33

We can interpret the result as when black money and population increases then obviously poverty should increase, Gross national income and employment should decrease. We can justify this fact because if your gross national income decreases then money for funding various government projects would decrease and as a result, black money consumption at various level of government services would decrease. Then we see that under such situation to keep the development stable, government investment would increase somewhat. Thus, the only thing we can do is to check the black money by noticing the minor fluctuations in government investments in various projects.

VI. CONCLUSION

Thus using the results obtained by us, we can absolutely say that Tuberculosis detection rate functionally related to the number of people below poverty line. Although many studies have focused on the fact how poverty can lead to increase in tuberculosis cases, we here consider what if the reverse is true. That is given a tuberculosis detection rate what can you say about the poverty in the population. It is obvious that gross national income is the most important factor but what is not so obvious by common sense is that how can other factors lead to the prediction of this particular variable. More importantly we defined another variable log(α) and saw how it was better than the variable population itself. We also saw why population is also a factor in determining the outcome. Moreover, we see here the power of artificial neural network and support vector machines that they were able to provide us these vital information using only 57 observations.

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