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Research Article

Categorization of Urban Slums Using Fuzzy Logic System: A Theoretical Approach

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Abstract: This article deals with the categorization of urban slums on the basis of infrastructure and basic facilities. An empirical abstract model based on Fuzzy Logic is proposed to categorize the urban slums into three categories named as A, B and C. The modern world. especially developing countries are suffering from several serious problems related to high population growth and rapid urbanization. The most pressing problem includes solid waste management, water supply, pollution, health, population explosion and education. The population explosion is a serious cause of concern and alarming growth rate cannot be supported by the city infrastructure. This has caused the formation of countless slums within and around the urban areas, where living conditions are deplorable. This categorization might help to prioritize the necessary actions to be taken in order to improve the quality of life and basic infrastructure in slum areas.

Keywords: Urban slums, Fuzzy logic system, Empirical model of slums, Categorization of slums.

1. INTRODUCTION

The word "slum" is mostly used to describe illegal and informal settlements within the cities, where, living conditions are inadequate and miserable. People living in these slum areas have to cram into very small living spaces. These slums constitute the most persistent problem of urban life. They are found in almost all metropolitan cities of the world. The migration of the underprivileged from rural areas to urban centers is the main cause of rapid urbanization, which results in acute shortage of housing, infrastructure and basic facilities in the these areas and hence contributes to play a very important role in the formation of slums. The irresistible wish for a shelter, forces the P to encroach on any vacant land. A variety of studies are found in the open literature that have been carried out to analyze the pattern of slums all around the globe. Gulyani and Bassett [1] proposed a 'Living Conditions Diamond', in which the characteristics of slums were refined to 4 dimensions: infrastructure, tenure, neighborhood location and unit quality. The slums of a city were placed in this diamond depending on the particular problems within the 4 domains, thus highlighting the variation in the slums within that particular city or area. Although this model provides an excelent way to differentiate among the slums up to some extent but it lacks an overall indicator of variability that could be utilized in statistical analysis.

In big cities, population has a very rapid growth due to expansion and rural-urban migration. This speedy growth gives birth to a large number of under-serviced and un-serviced areas where the inhabitants are living in very miserable conditions. Shafqaat et al. [2] proposed that the GIS could be used to establish a spatial and temporal pattern of slums in order to examine their distribution in space and time. The study exposed that most of the slums were found along main transport lines.

In order to rehabilitate the urban slums, it is required to invent a technique for categorization of the slum areas so that the situation in W categories might be controlled at the earliest. As the Governments use to have limited resources, this categorization would help to make the best

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use of available resources in order to provide the basic infrastructure and facilities to these deprived areas. The categorization of slums on the basis of infrastructure, housing, health, education and socio-economic conditions is a novel idea. In this work, we have proposed a cogent approach based on fuzzy logic technique for categorization of slums on the basis of aforementioned attributes.

Fuzzy logic is widely used for the classification and categorization purposes. Kim et al. [3] developed a vehicle classification technique using fuzzy logic. The proposed fuzzy logic system used the speed and weight of the vehicle as inputs. The output of this a fuzzy logic system was used to adjust the calculated vehicle length. Ghofrani et al. [4] presented a novel fuzzy scheme for medical X-ray image classification by partitioning each image into 25 overlapping sub-images. The shape-texture features from shape and directional information of each sub-image were then extracted. The accuracy rates of this classification obtained by fuzzy classifier were found higher than those of multilayer perceptron or even SVM classifier. Malik et al. [5] developed a fuzzy inference system for classifying the satellite images of $472\times54\times7$ pixels. In our proposed system a technique for categorization of urban slums using fuzzy logic is presented. The main objective behind this effort is to provide an efficient way for categorization of urban slums which might help to improve the quality of life in these areas.

2. MATERIALS AND METHODS

2.1 Research Design

In this work, an efficient and novel technique is proposed to categorize the urban slums into three categories termed as A, B and C on the basis of education, health, infrastructure, housing and socio-economic conditions. Through the analysis of slum areas, it is found that all the slums have been suffering from a large number of common problems regarding housing ownership, sewerage system, water availability, housing structure, education facility, medical facility and large number of dwellings in a small area etc. However, here we have squeezed twenty-one of these attributes into three conditions:

Table 1. Attributes for categorization of slums

Attributes		Empirical Evaluation		
		0	1	2
H & EC	Literacy Rate (Male)	Below 25%	25%-35%	Above 35%
	Literacy Rate (Female)	Below 25%	25%-35%	Above 35%
	School	None	Private or Govt.	Private and Govt.
	Distance from School	Above 2 Km	1-2 Km	Less than 1 Km
	Privilege of Epidemics	All	Malaria & Gastro	Malaria
	Gynecological Facility	Accoucheuse	LHV/Nurse	Qualified Doctor
	Medical Facility	None	Hakeem/Quack	Qualified Doctor
SEC	Per Capita Income	Rs. 0-1000	Rs. 1000-2000	Above Rs. 2000
	Dependency Rate	Above 10	5-10	1-5
	Room Density	Above 5	2-5	0-2
	Crime Rate	Above 100	50-100	0-50
	Un-employment	Above 15 %	(5-15) %	(0-5) %
	Children per couple	Above 8	3-8	0-3
	Family Income	Below Rs. 10000	Rs. 10000-30000	Above Rs. 30000
I & HC	House Ownership	Un-authorized	Government	Own
	House Structure	Tent	Adobe	Bricked
	Sewerage	None	Open	Underground
	Water Supply	None	Hand Pump	Tap Water
	Bath Room	None	Temporary	Permanent
	Street Size	Less than 10 ft.	(10-20) ft.	More than 20 ft.
	Solid Waste Management	Open	Heap	Carried Out

- Health & Education condition (H & EC)
- Socio-economic condition (SEC)
- Infrastructure & Housing condition (I & HC)

To determine the category of a slum area, its percentage empirical score in all three conditions is evaluated on the basis of seven attributes which are given an empirical number ranging from 0 to 2 as shown in Table 1.

These conditions are used as three input variables in the proposed fuzzy logic system for the categorization of slums. The system has one output variable which determines the category of the slum area.

2.2 Methodology

The proposed system for categorization of slums has three input variables: Health and Education condition (H & EC), Socio-economic condition (SEC) and Infrastructure and Housing condition (I & HC). The design work utilizes four triangular membership functions (MFs) for each variable. For simplicity, the ranges of all the input MFs are kept same. These MFs are equally decided over a range of percentage empirical score (0-99) % for all the input variables. The MFs used here are termed as: W (Worst) (0-33%), P (Poor) (0-66%), F (Fail) (33-66%) and G (Good) (66-99%) as shown in the Table 2.

Table 2. MFs and percentage scores of input variables

MF	Ranges (% age score)			Region occupied
	H & EC	SEC	IHS	
W	0-33	0-33	0-33	1
P	0-66	0-66	0-66	1-2
F	33-99	33-99	33-99	2-3
G	66-99	66-99	66-99	3

As, the percentage score range of each input MF is same, the plot of each input variable defined in the proposed system is also same, as shown in the Fig. 1.

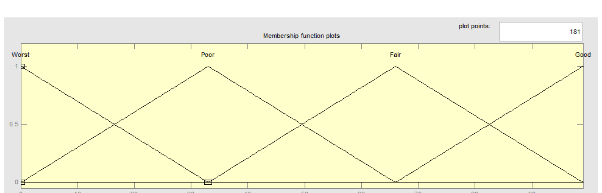

Fig. 1. Plot of input Membership Functions

The proposed system has one output variable i.e. category of slum. The design work utilizes 4 triangular MFs for the output variable. These functions are equally decided over a range of percentage empirical score (0-100) %. The category of a particular slum area is determined on the basis of its percentage empirical score. The four MFs used here are termed as: A (0-25%), B (25-50%), C (50-75%) and Non-Slum (N) (75-100%) as shown in the Table 3. The plot of output membership function is shown in the Fig 2.

Table 3. MFs and ranges of output variable-slum category

MF	Ranges (% age score)	Regions Occupied
A	0-25	1
B	25-50	1
C	50-75	2-3
N	75-100	3

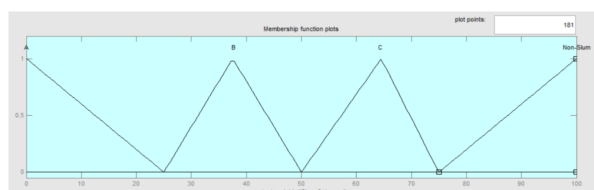

Fig. 2. Output Membership Function plot

The values 3 input variables possibly lie in any one of the 3 regions. The mapped values of fuzzy input variables with the MFs engaged in the three regions are known as the linguistic values. The linguistic values for input variable H & EC are denoted by f_1 and f_2 , the linguistic values of SEC are denoted by f_3 and f_4 and the linguistic values of I & HC are denoted by f_5 and f_6 as shown in the

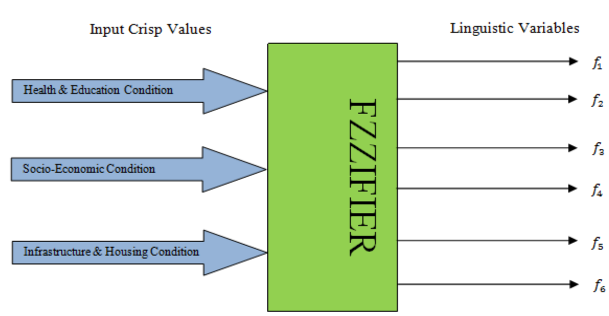

Fig. 3. Fuzzifier with 3 input crisp values and 6 output linguistic values

Fig. 3.

The Fuzzifier takes the input crisp values as input and returns the linguistic fuzzy values as output. For 3 input variables, 3 Fuzzifier are required. The mapped values of the input fuzzy variables with the MFs in 3 regions are written in Table 4. Each region of membership graph has 2 functions. The relations of linguistic fuzzifier outputs are shown in the Table 5. Each one of the 3 regions is considered to be divided into two equal parts for designing discussion.

Table 4. Linguistic values of fuzzifier outputs in 3 regions

Input	Linguistic Fuzzifier Outputs	Region-1	Region-2	Region-3
H & EC	f_1	$f_1[1]$	$f_1[2]$	$f_1[3]$
	f_2	$f_2[2]$	$f_2[3]$	$f_2[4]$
SEC	f_3	$f_3[1]$	$f_3[2]$	$f_3[3]$
	f_4	$f_4[2]$	$f_4[3]$	$f_4[4]$
I&HC	f_5	$f_5[1]$	$f_5[2]$	$f_5[3]$
	f_6	$f_6[2]$	$f_6[3]$	$f_6[4]$

Table 5. Relations of linguistic outputs

Input	Linguistic Fuzzifier Outputs	First Half Region	Second Half Region	Region Mid Point	Staring Region
H & EC	f_1	$f_1 > f_2$	$f_1 < f_2$	$f_1 = f_2$	$f_1 = 1$
	f_2				$f_2 = 0$
SEC	f_3	$f_3 > f_4$	$f_3 < f_4$	$f_3 = f_4$	$f_3 = 1$
	f_4				$f_4 = 0$
I & HC	f_5	$f_5 > f_6$	$f_5 < f_6$	$f_5 = f_6$	$f_5 = 1$
	f_6				$f_6 = 0$

In order to discuss the designed algorithm, we use particular values of input fuzzy variables. We suppose that a particular area acquires the percentage empirical score of H & EC=70, SEC=52 and I & HC=25. The value of H&EC input belongs to the first half of the Region-3, SEC input belongs to the in the second half of the Region-2 and I & HC input belongs to the second half of Region-1. Three

Table 6. Fuzzification results

Input	Values (% age Score) X	Region Selection	Fuzzy Set Calculations
H & EC	70	$66 \le X \le 99$ Region 3	$f_1 = \frac{(99-70)}{33} = 0.8788$ $f_2 = 1 - f_1 = 0.1212$
SEC	52	$33 \le X \le 66$ Region 2	$f_3 = \frac{(66-52)}{33} = 0.4242$ $f_4 = 1 - f_3 = 0.5758$

Fuzzifiers are needed for the Fuzzification of 3 input variables. The working results of 3 Fuzzifiers after processing the above input values are listed in Table 6.

The inference engine is comprised of eight Min-AND operators. These operators choose the minimum input value for the output. This inference engine receives 6 inputs from the Fuzzifier, implements the min-max composition to produce output R values. The number of active rules can be calculated by the formula $\boldsymbol{m^n}$ where m denotes the maximum no. of overlapping fuzzy sets and n denotes the no. of inputs. For the present design, ***m*=4** and ***n*=3**, therefore, total number of possible active rules are 64. The total number of rules may also be calculated by multiplying the number of membership functions associated with the input variables in their range [6]. Each of the 3 input variables used here have 4 MFs. Therefore, **4×4×=64** rules are required, as shown in the Table 7.

As we have three input variables and each variable value in a region represents the mapping of 2 functions, therefore, for the specified values of input variables, we need 8 rules. The corresponding mapped values of $\boldsymbol{f_1}$ **[3]**, $\boldsymbol{f_2}$ **[2]**, $\boldsymbol{f_3}$ **[1]**, $\boldsymbol{f_3}$ **[2]**, $\boldsymbol{f_2}$ **[3]** and $\boldsymbol{f_1}$ **[4]** are used to establish the eight rules. Here $\boldsymbol{f_1}$ **[4]** represents the corresponding mapping value of the fourth MF for the first variable H&EC in its region and similarly the others can also be defined [7]. The min-max inference method utilizes min-AND operation between the 3 inputs.

$$R_1 = f_1 \wedge f_3 \wedge f_5 = f_1[3] \wedge f_2[2] \wedge f_3[1] = 0.8788 \wedge 0.4242 \wedge 0.7576 = 0.4242$$
$$R_2 = f_1 \wedge f_3 \wedge f_6 = f_1[3] \wedge f_2[2] \wedge f_3[2] = 0.8788 \wedge 0.4242 \wedge 0.2424 = 0.2424$$
$$R_3 = f_1 \wedge f_4 \wedge f_5 = f_1[3] \wedge f_2[3] \wedge f_3[1] = 0.8788 \wedge 0.5758 \wedge 0.7576 = 0.5758$$
$$R_4 = f_1 \wedge f_4 \wedge f_6 = f_1[3] \wedge f_2[3] \wedge f_3[2] = 0.8788 \wedge 0.5758 \wedge 0.2424 = 0.2424$$
$$R_5 = f_2 \wedge f_3 \wedge f_5 = f_1[4] \wedge f_2[2] \wedge f_3[1] = 0.1212 \wedge 0.4242 \wedge 0.7576 = 0.1212$$
$$R_6 = f_2 \wedge f_3 \wedge f_6 = f_1[4] \wedge f_2[2] \wedge f_3[2] = 0.1212 \wedge 0.7576 \wedge 0.2424 = 0.1212$$
$$R_7 = f_2 \wedge f_4 \wedge f_5 = f_1[4] \wedge f_2[3] \wedge f_3[1] = 0.1212 \wedge 0.5758 \wedge 0.7576 = 0.1212$$
$$R_8 = f_2 \wedge f_4 \wedge f_6 = f_1[4] \wedge f_2[3] \wedge f_3[2] = 0.1212 \wedge 0.5758 \wedge 0.2424 = 0.1212$$

functions denotes the Min-AND operation. This operation returns the minimum of the function values. The inference engine is shown in the Fig 4. The rule selector for the proposed system takes the crisp values from the three input variables and returns the singleton values of output function under the algorithm rules implemented on the design

Table 2. MFs and percentage scores of input variables

S.N.	Input			Output
	H & EC	**SEC**	**I & HC**	**Slum Category**
1	W	W	W	A
2	W	W	P	A
3	W	W	F	A
4	W	W	G	C
5	W	P	W	A
6	W	P	P	B
7	W	P	F	B
8	W	P	G	C
9	W	F	W	A
10	W	F	P	B
11	W	F	F	C
12	W	F	G	C
13	W	G	W	B
14	W	G	P	C
15	W	G	F	C
16	W	G	G	N
17	P	W	W	A
18	P	W	P	B
19	P	W	F	B
20	P	W	G	C
21	P	P	W	B
22	P	P	P	B
23	P	P	F	B
24	P	P	G	C
25	P	F	W	B
26	P	F	P	B
27	P	F	F	C
28	P	F	G	C
29	P	G	W	B
30	P	G	P	C
31	P	G	F	C
32	P	G	G	N
33	F	W	W	B
34	F	W	P	B
35	F	W	F	B
36	F	W	G	C
37	F	P	W	A
38	F	P	P	B
39	F	P	F	C
40	F	P	G	C
41	F	F	W	B
42	F	F	P	C

43	F	F	F	C
44	F	F	G	C
45	F	G	W	C
46	F	G	P	C
47	F	G	F	C
48	F	G	G	N
49	G	W	W	A
50	G	W	P	B
51	G	W	F	C
52	G	W	G	C
53	G	P	W	B
54	G	P	P	C
55	G	P	F	C
56	G	P	G	N
57	G	F	W	B
58	G	F	P	C
59	G	F	F	C
60	G	F	G	N
61	G	G	W	C
62	G	G	P	N
63	G	G	F	N
64	G	G	G	N

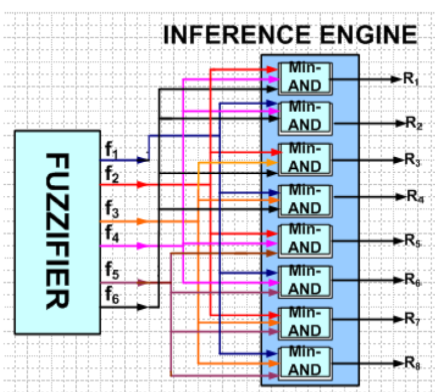

Fig. 4. Block diagram of inference engine

model. In order to find the singleton values S_1, S_2, S_3, S_4, S_5, S_6, S_7 and S_8 of the output variable, eight rules are required as listed in the Table 8. The rule base takes 3 crisp values of inputs, distributes the space of discussion into regions with each region having 3 fuzzy variables, applies the rule and returns the output singleton values corresponding to output variable. The rule base is shown in Fig 5.

The process of defuzzification gives the crisp values outputs after estimating its inputs. In the proposed system 16 inputs are given to the

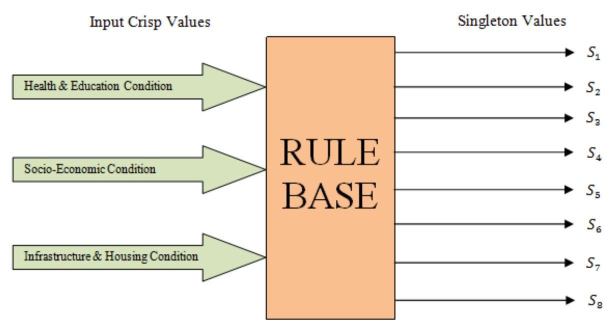

Fig. 5. Block diagram of rule base

Table 8. Illustration of rules applied model

S.N.	Input			Output	
	H&EC	SEC	IHS	Slum Category	Singleton Value
1	F	P	W	A=0.00	S_1
2	F	P	P	B=37.5	S_2
3	F	F	W	B=37.5	S_3
4	F	F	P	C=64.5	S_4
5	G	P	W	B=37.5	S_5
6	G	P	P	C=64.5	S_6
7	G	F	W	B=37.5	S_7
8	G	F	P	C=64.5	S_8

Defuzzifier. Eight values of R_i's received from inference engine and eight values of S_I's received from rule selector, where i=1,2,3,…,8. The crisp output value is calculated by the Centre of Average method by utilizing the mathematical expression $\frac{\sum_{i=1}^{8} S_i \times R_i}{\sum_{i=1}^{8} R_i}$. The Defuzzification block is shown in Fig 6.

3. RESULTS AND DISCUSSIONS

For the proposed system of slum categorization, the results are calculated for a particular arrangements of input variables. The linguistic values from three fuzzifiers are given to the inference engine which utilizes these values and applies 8 inference rules: R_i's : i=1,2,3,…,8. The rule base produces the singleton values S_I's : i=1,2,3,…,8. The R_i and S_I values are used by the Defuzzifier which produces the crisp value output.

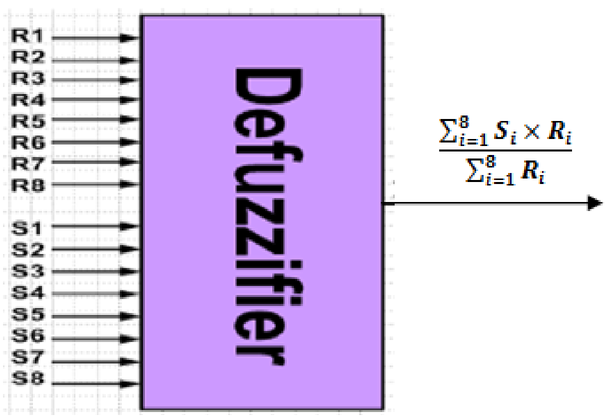

Fig. 6. Defuzzification block

Table 9. Designed value for output

i	S_i	R_i	S_i x R_i
1	0.00	0.4242	0.00000
2	37.5	0.2424	9.09000
3	37.5	0.5758	21.5925
4	64.5	0.2424	15.6348
5	37.5	0.1212	4.54500
6	64.5	0.1212	7.81740
7	37.5	0.1212	4.54500
8	64.5	0.1212	7.81740

Hence

$$\frac{\sum_{i=1}^{8} R_i \times S_i}{\sum_{i=1}^{8} R_i} = \frac{71.0421}{1.9696} = 36.0693$$

Table 10. Comparison of designed and simulated results

Design Value	36.0693 ⇒ The Area is B Category Slum
MATLAB Simulation	42.3 ⇒ The Area is B Category Slum

3.1 Test Example

We suppose that a particular area acquires the percentage empirical score of H & EC=70, SEC=52 and I & HC=25. The designed values for the output, according to the results of inference engine are given in the Table 9.

The output value represents the % age empirical score of a particular area based on its H&EC, SEC and I&HC. The result show that this particular area is B category slum. After calculating the crisp values for output variable, the results were obtained from MATLAB simulation.

Fig 7 shows the output value corresponding to the specified inputs in the MATLAB Rule Viewer. It can be seen that if a particular area is Good in Health & Education, Fair in Socio-Economic and Worst in Infrastructure & Housing, it belongs to B category slum as defined in rule 57 of Table 7.

The designed value and the simulated values are compared in Table 10. It can be observerd that the simulation results are in the line with the design value.

Fig 8 describes the dependency of slum category on Health & Education condition and Socio-Economic condition. The blue colour at the bottom indicates that the slum area of category is more dependent on Health & Education condition as compared to Socio-Economic condition. In three dimensional plot shown in Figure 9 one can see the Health & Education condition and Infrastructure

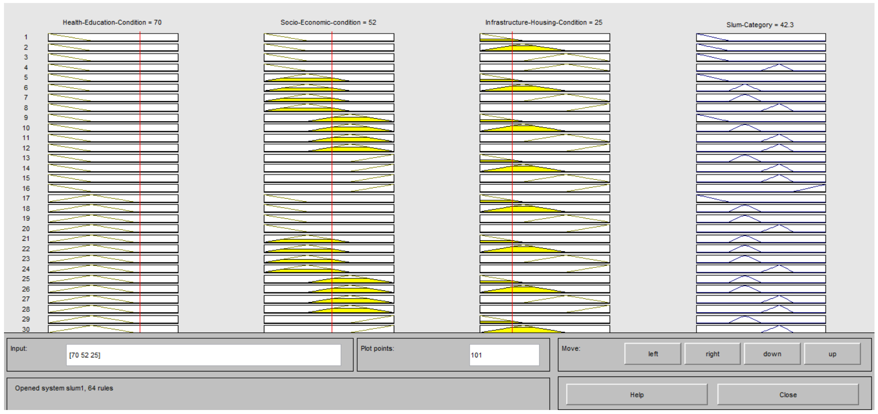

Fig. 7. MATLAB rule Viewer

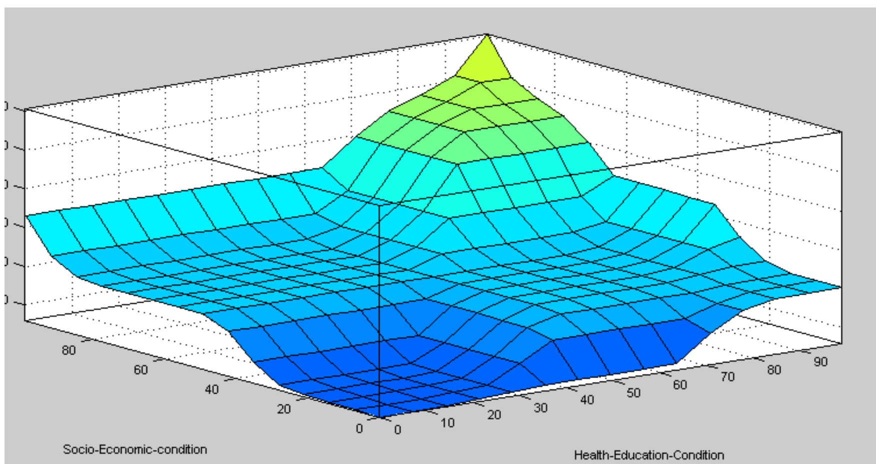

Fig. 8. Plot between slum category, Socio-economic condition and Health and Education condition

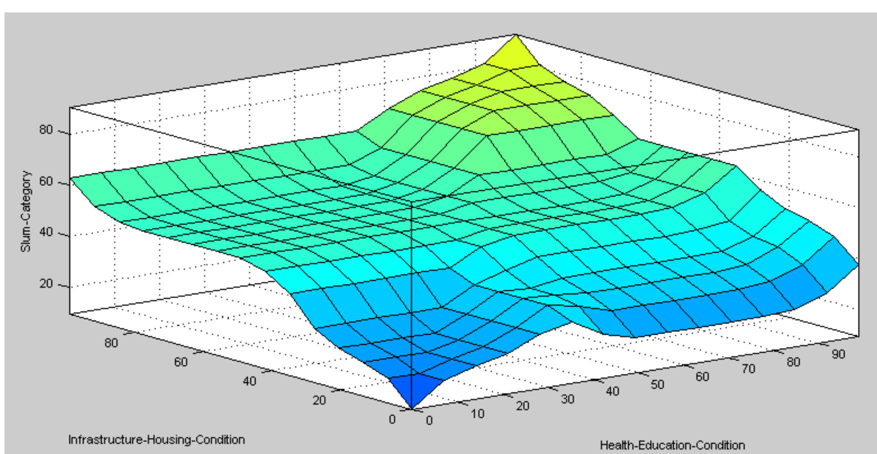

Fig. 9. Plot between slum category, Infrastructure & Housing condition, Health & Education condition

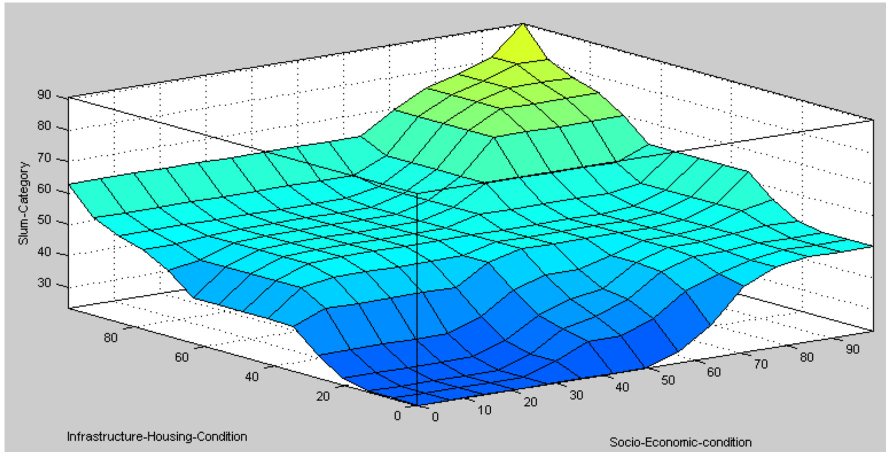

Fig. 10. Plot between slum category, Infrastructure & Housing condition, Socio-Economic condition

& Housing condition playing almost equal role in slum categorization. Similarly, Figure 10 exhibits the contribution of Infrastructure & Housing condition and Socio-Economic condition in slum category.

4. CONCLUSIONS

In this work, a novel approach for categorization of urban slums has been presented. The authors conclude the outcomes of this work as:

- A purely abstract theoretical model has been presented for categorization of urban slums.
- The proposed technique is based on a pre-defined set of rules and fuzzy logic.
- The presented algorithm is novel for categorization of urban slums.
- The designed model can efficiently categorize the slum area on the basis of its Health & Education condition, Socio-Economic condition and Infrastructure & Housing condition.
- In order to corroborate this work, the simulation results for an assumptive test example has been obtained. The results have close agreement with theoretical estimation.
- The fuzzy logic technique can efficiently be used for classification and categorization of slums.

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