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Healthcare Vulnerability Mapping Using K-means ++ Algorithm and Entropy Method: A Case Study of Ratnanagar Municipality

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Abstract: Healthcare is a fundamental human right. Vulnerable populations in healthcare refer to those who are at greater risk of suffering from health hazards due to various socio-economic factors, geographical barriers, and medical conditions. Mapping of this vulnerable population is a vital part of healthcare planning for any region. Very few such research regarding the distribution of healthcare service providers was carried out in the Nepali context previously. Thus, the results of vulnerability mapping can help with meaningful interventions for healthcare demands. This study focused on combining geo-analytics, unsupervised machine learning algorithms, and entropy methods for performing vulnerability mapping. K-means++ clustering algorithm was applied to household data of Ratnanagar municipality for the purpose of creating multiple clusters of households. An open-source routing machine was used to compute the distance to the nearest health service provider from each household in Ratnanagar municipality. The entropy method was used to evaluate the vulnerability measure of each cluster. Later, based on the population of different clusters in each ward and their respective vulnerability measures, each ward's vulnerability measure was quantified. It can be observed that wards that are farther away from the east-west highway have higher vulnerability indices. This study found that machine learning algorithms can be effectively used in combination with the weighting method for vulnerability mapping. Using an unsupervised machine learning algorithm made sure that dimensions of vulnerability are visible.

Index Terms: Healthcare, Vulnerability Mapping, K-Means++ Clustering, Elbow Method, Entropy Method, Openstreetmap, Open-source Routing Machine.

1. Introduction

Vulnerability is a state of being exposed to any potential harm. Vulnerability in healthcare is a measure of damage due to potential health issues. Various factors contribute to this vulnerability. These factors could be divided into the following three categories:

- Social-economic factors such as per capita income and age
- Geographic factors such as distance to the nearest health service provider
- Medical conditions such as illness and disability

Some of the factors have a negative relationship with vulnerability while some have positive relationships. Out of the above-mentioned factors, per capita income has a negative relationship whereas the rest of the factors have a positive relationship with vulnerability. Disability and illness also contribute to vulnerability. Due to disabilities, people have issues getting access to proper healthcare. Their disabilities make interaction with the healthcare system even more difficult. Likewise, people with the illness are already at risk of further deterioration of health. Alongside the above-mentioned factors, age is also an important indicator of vulnerability in healthcare. Children and the elderly are considered more vulnerable. Children are considered vulnerable because of their inability to protect themselves from any potential harm. Likewise, senior citizens are also considered vulnerable because of their decreased immune systems and physical capacity. In line with the above arguments, [1,2] mention that vulnerable populations in healthcare include children, the elderly, the ill, the disabled, and the socioeconomically underprivileged.

Healthcare vulnerability mapping is the process of creating a map that highlights parts of an area and their respective healthcare vulnerabilities.

Nepal has entered into a new federal structure and elected officials are on board after a long time. Its Constitution of 2015 addresses healthcare as a fundamental right, stating that every citizen has the right to basic health services free of cost [3]. According to the prevalent constitution, primary education, and basic health services along with others are responsibilities of local government in Nepal now.

However, Nepal faces frightening challenges such as unequal distribution of healthcare services, poor infrastructure, inadequate supply of essential drugs, poorly regulated private service providers, inadequate budget allocation for healthcare, and poor retention of human resources in rural areas. Nepal has only 0.67 doctors and nurses per 1,000 population, which is significantly less than the World Health Organization's recommendation of 2.3 doctors, nurses, and midwives per 1,000 population [4]. There had not been any assessment regarding healthcare planning in Nepal. Thus, the objective of this research is to use socio-economic data for short-term and long-term planning and decision-making. Based on the results of this research, local governments will be able to perform rationale-based healthcare planning. Besides that, the results will also serve as baseline data for future comparisons.

2. Related Works

Various studies have been done on vulnerability mapping previously. These studies have studied different kinds of vulnerabilities.

Social vulnerability to natural hazards in Nepal was analyzed using a modified social vulnerability index. Using principal component analysis (PCA), 7 components Renters and Occupation, Poverty and Poor Infrastructure, Favorable Social Conditions, Migration and Gender, Ethnicity, Medical Services, and Education out of 39 original indicators were identified as vulnerable indexes for Nepal based on loaded factors and their cardinality. The factors maintained 63.02% of the total variance. Kaiser normalization and Varimax rotation methods were used for selecting factors. Using the Kaiser criterion, factors with eigenvalues greater than 1 were only selected [5]. The authors concluded various vulnerable geographic areas of Nepal for various indicators. However, the authors focused on social vulnerability to natural hazards rather than healthcare vulnerability.

Similar researches are common in other countries. Social vulnerability to natural hazards in Brazil [6] Tha was studied using the social vulnerability index. 45 indicators were selected from 58 variables after testing for multicollinearity using Pearson’s R calculation. After that, factor analysis of PCA using Kaiser normalization and Varimax rotation methods was performed to reduce the 45 indicators to 10 factors which represented about 67% of the variance in data. Indicators that had more than 0.5 correlation or less than -0.5 correlation with the factors were considered as the drivers for the respective factors. Based on the drivers, the cardinality of the components was set. Finally, the factors were summed using equal weights to the product vulnerability index [6]. The method adopted was also followed in [7] in Zimbabwe. In this study, 17 variables were selected first which were then reduced to 4 factors using PCA. Factors were then merged into the vulnerability index using the equal weight method.

Similar Vulnerability to climate change in rural municipalities of Bosnia and Herzegovina was assessed in [8]. In this study, 20 indicators have been prepared for quantitative assessment of vulnerability to climate change. The indicators have been grouped into three components: exposure, sensitivity, and adaptive capacity. The study used an integrated approach that combined both the potential impact of a hazard and the adaptive capacity of a system. This approach considered vulnerability as having both exogenous and socio-economic dimensions. The paper compared two weighting methods of equal weights and principal component analysis. In the equal weight method, the arithmetic mean of indicators for each component was calculated first. Next, the arithmetic mean of indicators for exposure and sensitivity were summed to form a sub-index for potential impact. Likewise, the arithmetic means of indicators belonging to the adaptive capacity component was calculated to form a sub-index for adaptive capacity. Finally, these two sub-indices were summed to form a vulnerability index. Using the equal weight method indicated that each indicator had an equal contribution to overall vulnerability.

In the second approach, the study used principal component analysis to create 6 factors from 20 indicators explaining 71.1% of the variance in the data. Using the Kaiser criterion only those factors were selected whose eigenvalues were greater than 1. Factor loadings were used as a weight for the indicators. Based on these weights, the vulnerability index was calculated as a weighted sum.

The paper suggested that using the equal weight method is arbitrary and the results might be misleading. Using the equal weight method implied that all the indicators had an equal contribution to the overall vulnerability which might not be the case. The paper also suggested that using PCA for assigning weights based on loading factors might not be a guaranteed method as the loading factors were based on correlation and correlation did not necessarily represent the causal relationship between indicators and vulnerability.

Vulnerability mapping was done in regard to chemical hazards in the industrialized city of Shanghai [9]. In this paper, the genetic k-means algorithm was used for clustering civilian populations based on specific attributes which represented exposure, sensitivity, and coping capacity. In this study, min-max normalization was used. After cluster centroids were found, information entropy analysis was done to assign weight to various attributes for finding the most vulnerable cluster of the population. This method has shown the significance of the machine learning method in vulnerability mapping.

With this literature, it is known that very few researches in vulnerability mapping were carried out regarding Nepal and very few machine-learning approaches were explored.

3. Methodology

3.1. Study Area

For this study, the case of Ratnanagar municipality was chosen. A Map of Ratnanagar municipality is shown in figure 1. Ratnanagar municipality lies in the center of Nepal, in the Chitwan district of Bagmati province, Nepal. As per the 2011 census [10], its estimated population is 46,607. Its total area is 35.62 square kilometers. Currently, there are 16 wards in Ratnanagar municipality. The numbers in the map in figure 1 show the wards in Ratnanagar Municipality.

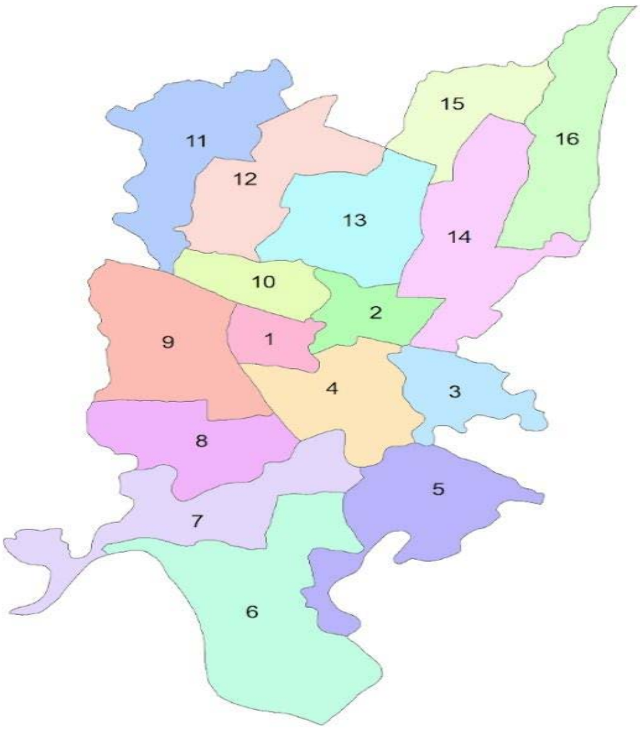

Fig.1. Map of Ratnanagar Municipality.

3.2. Data Used

For this study, household survey data was chosen which included details regarding 17,501 households. Some of the important household information available in this data were: ward number, annual income, family size, age of individual family members, disability status of individual family members, the health status of individual family members, and geolocation. This household data of Ratnanagar municipality was made available by the municipality on request to access the data for research purposes.

3.3. Vulnerability Indicators

For the purpose of vulnerability assessment, the following attributes were defined as vulnerability indicators:

A. Per Capita Income

Per capita income is calculated as follows:

$$per\ capita\ income = \frac{annual\ income}{family\ size} \tag{1}$$

Households with low per capita income are more vulnerable as the impact of adverse health conditions is higher for these households.

B. Disability Ratio

Disability ratio is calculated as follows:

$$disability\ ratio = \frac{number\ of\ family\ members\ with\ disability}{family\ size} \tag{2}$$

Healthcare vulnerability increases with an increase in disability ratio.

C. Illness Ratio

Illness ratio is calculated as follows:

$$illness\ ratio = \frac{number\ of\ family\ members\ with\ some\ form\ of\ illness}{family\ size} \tag{3}$$

People with illness are at higher risk of further aggravation in health. One form of illness can lead to other forms of illness as well.

D. Vulnerable Age Ratio

Vulnerable age ratio is calculated as follows:

$$vulnerable\ age\ ratio = \frac{number\ of\ vulnerable\ age\ group\ members}{family\ size} \tag{4}$$

The vulnerable age group refers to family members who are more vulnerable in terms of their age. Children of age equal to and under 5 years and, elderly of age equal to and above 60 years are considered vulnerable family members. The reason behind choosing these age limits is that globally, the child mortality rate refers to the mortality of children under the age of five [11]. Regarding the elderly age limit, in Nepal, citizens above the age of 60 are considered senior citizens [12]. Here ratio has been used rather than counting for illness, disability, and vulnerable age because, in a household, an individual can be ill and disabled, or can be ill and elderly at the same time.

E. Distance to the Nearest Health Service Provider

An open street routing machine (OSRM) was used to calculate the distance to the nearest health service provider for each household based on the geolocation of the household and health service provider.

3.4. Proposed Model

A proposed model has combined geo-analytics, machine learning, and information theory in order to evaluate the vulnerability index of wards of the municipality.

The model can be divided broadly into 3 parts:

- data preprocessing and feature engineering,
- clustering using K means ++ and Elbow method
- vulnerability index calculation for each ward of Ratnanagar Municipality

Following figure 2 shows the detailed steps involved in the proposed model.

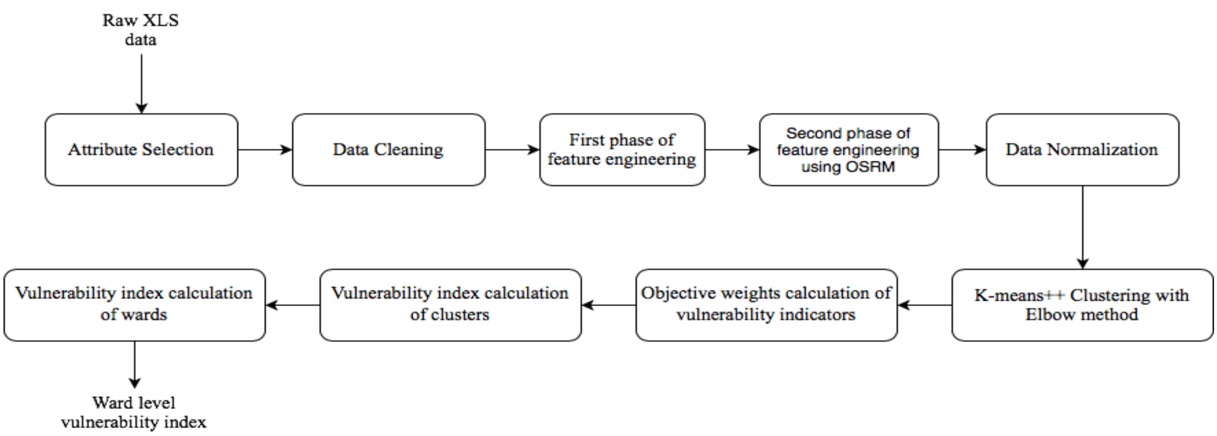

Fig.2. Proposed model.

Attribute selection, data cleaning, and normalization are parts of data preprocessing.

A. Data Preprocessing and Feature Engineering

The first step of this part was attribute selection. While selecting attributes ward, family_size, annual_income, latitude, longitude, and _id was selected from household attributes Similarly, r_age, r_age_unit, r_disability, and r_ill information was selected from respondent attributes. Likewise, m_age, m_age_unit, m_disability, m_ill, and _submission_id was selected for individual family members.

The second step was to clean data where some noisy data were removed and missing data were filled. Finally, the number of household instances was 17,489. Multiple missing data in the annual_income attribute of household data were replaced by the arithmetic mean of known values. The average value was found to be 354621.3504.

After cleaning data, the next step was featuring engineering. Here new features {m_disability_numeric, m_ill_numeric, m_vulnerable_age_numeric, m_disability_total, m_ill_total, m_vulnerable_age_total, per_capita_income, r_disability_numeric, r_ill_numeric, r_vulnerable_age_numeric, disability_total, ill_total, vulnerable_age_total, disability_ratio, ill_ratio, vulnerable_age_ratio, nearest_distance} were created from existing ones.

To make sure that no attributes became dominating in cluster analysis, normalization was applied as the fourth step of preprocessing. Min-max normalization was chosen as the standardization method in this method as it assured that no values were transformed into negative values.

In min-max normalization, values are transformed as follows:

$$Minmax(x) = \frac{\mathrm{x-min}}{\mathrm{max-min}} \tag{5}$$

where, min = minimum value in dataset and, max = maximum value in the dataset

Due to this, the maximum value in the dataset is transformed into 1 whereas the smallest value is transformed to 0. Thus, the whole dataset is transformed to values in the range (0,1).

In case of per capita income, the formula for min-max normalization was modified as follows as it had negative relationship with healthcare vulnerability:

$$Minmax(x) = 1 - \frac{\mathrm{x-min}}{\mathrm{max-min}} \tag{6}$$

B. Clustering

After performing data preprocessing and feature engineering, the k-means++ clustering algorithm using the elbow method was applied to the data.

C. Entropy Method and vulnerability Index Calculation

Clustering led to a set of clusters with different values for centroids of respective attributes. Now, in order to compare the clusters with each other, weightage had to be assigned to all the attributes.

The entropy method was used to assign objective weights to the attributes of clustering. The steps followed in the entropy method were as follows:

1. Create a normalized decision matrix

A decision matrix is prepared where rows correspond to clusters and columns to vulnerability indicators. First, the decision matrix is normalized.

For an attribute j, normalized values are calculated as,

$$n_{ij} = \frac{x_{ij}}{\sum_{i=1}^{k} x_{ij}} \tag{7}$$

where x_{ij} is the centroid value of i^{th} cluster and j^{th} vulnerability indicator and k is the number of clusters.

2. Calculate the entropy of attributes

As per Shannon's Information theory [13], for attribute j, entropy is given by:

$$e_j = -\frac{1}{\ln(k)} \sum_{i=1}^{k} n_{ij}\, ln(n_{ij}) \tag{8}$$

where k is the number of clusters and $0 \leq e_j \leq 1$

3. Calculate the degree of diversification

It can be calculated from entropy as follows:

$$d_j = 1 - e_j \tag{9}$$

4. Calculate the objective weight

For vulnerability indicator j, objective weight is calculated as the normalized degree of diversification as follows:

$$w_j = \frac{d_j}{\sum_{j=1}^{k} d_j} \tag{10}$$

where k is the number of clusters

Vulnerability index of clusters and wards

After obtaining objective weights of the vulnerability indicators, the vulnerability index of a cluster was calculated as follows:

$$v_i = \sum_{j=1}^{k} w_j * c_j \tag{11}$$

where v_i is the vulnerability measure of cluster i, w_j and c_j are the weight and centroid value for cluster i, and vulnerability indicator j.

Finally, the vulnerability index of a ward can be calculated from the vulnerability indices of clusters as follows:

$$x_i = \frac{\sum_{j=1}^{k} v_j * p_j}{p_i} \tag{12}$$

where, x_i is the vulnerability index of ward i, k is the number of clusters, v_j is the vulnerability index of cluster j, p_j is the number of cluster j households in ward i and p_i is the total number of households in ward i.

4. Results, Analysis and Discussion

4.1. Determining Clusters

In order to perform vulnerability mapping, the K-means++ algorithm was applied. To apply the algorithm to the dataset, the optimum value of K had to be provided to the algorithm. For that purpose, the elbow method was used.

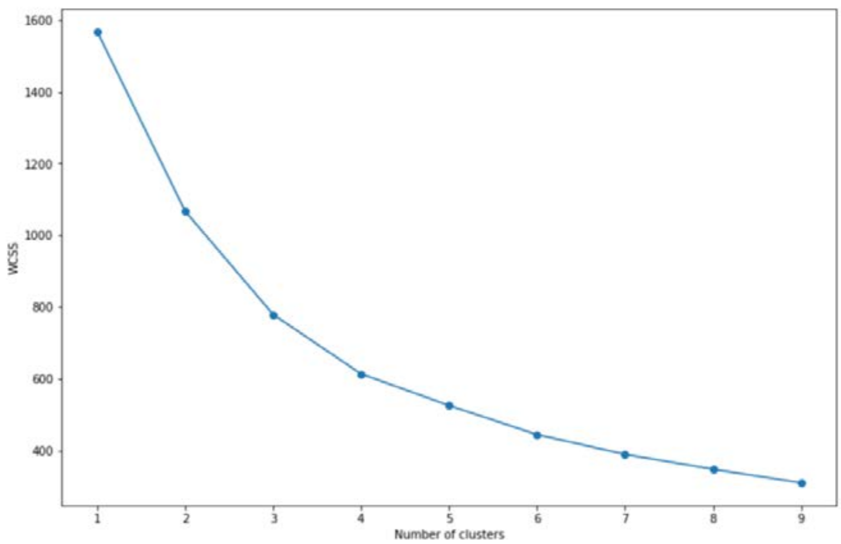

Fig.3. Optimum value of K from elbow method.

As seen in figure 3 above, 4 seemed like a good candidate for the elbow point of the line. Thus, 4 was chosen as the number of clusters to be formed with the K-means++ algorithm.

After performing clustering, the number of households in respective clusters is shown below in figure 4.

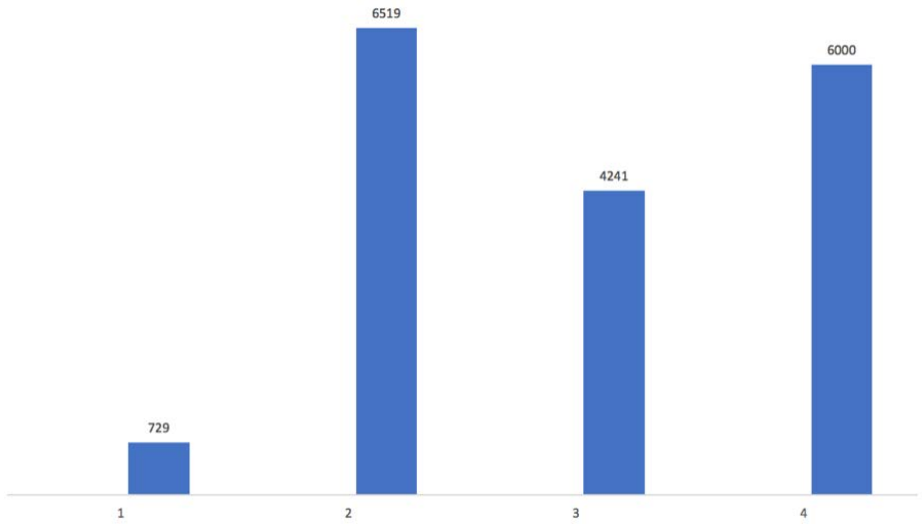

Fig.4. Clusters and respective households' count.

Centroid values for the 4 clusters are as follows:

Table 1. Centroid values of 4 clusters.

Cluster	per_capita_income	disability_ratio	ill_ratio	vulnerable_age_ratio	nearest_distance
1	0.99216206	0.00902153	0.08902153	0.85854479	0.30874419
2	0.99072689	0.00450545	0.02586313	0.01013786	0.19886775
3	0.99313922	0.00455403	0.01181048	0.12195675	0.52110595
4	0.99255159	0.00639147	0.03757455	0.30450913	0.20918066

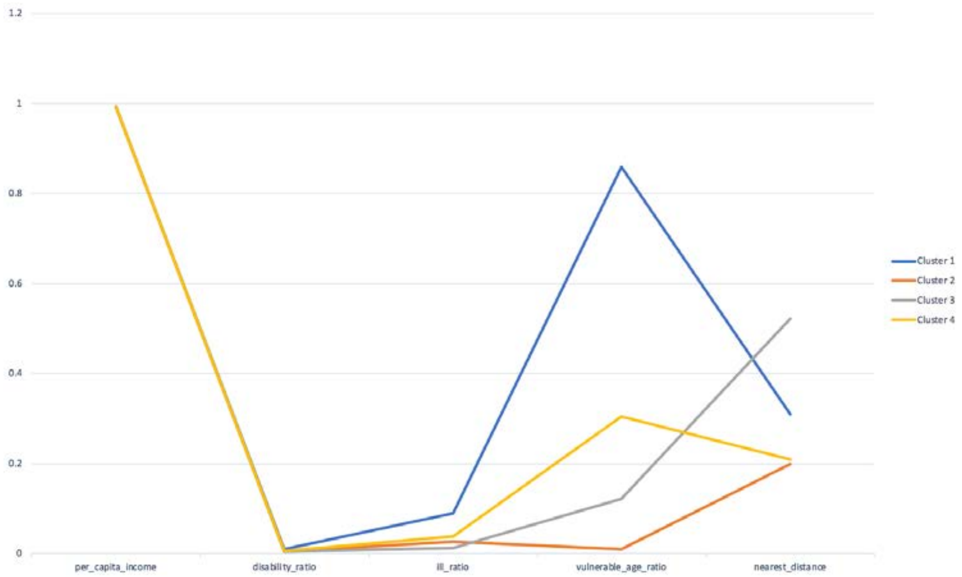

Fig.5. Vulnerability indicators and their centroid values for respective clusters.

In the figure 5 above, the centroid values of vulnerability indicators for the four clusters have been shown. Each color line represents a particular cluster.

It can be observed that centroid values of per_capita_income for the four clusters are very close. Likewise, centroid values of vulnerable_age_ratio for the four clusters are very different.

4.2. Objective Weights of Vulnerability Indicators

By using the entropy method, attribute weights were calculated as follows:

A. Decision Matrix Normalization

In the first step, the decision matrix was normalized using Eq. (7) and results are shown in table 2 below:

Table 2. Decision matrix after normalization.

per_capita_income	disability_ratio	ill_ratio	vulnerable_age_ratio	nearest_distance
0.250004314	0.368639732	0.54192304	0.66289292	0.249409927
0.24964268	0.184102846	0.157443114	0.007827565	0.160649475
0.250250538	0.186087797	0.07189688	0.094164298	0.420960144
0.250102469	0.261169625	0.228736966	0.235115217	0.168980453

B. Entropy Calculation of Vulnerability Indicators

In the second step, the entropy of all the attributes was calculated using Eq. (8) and the results are shown in table 3 below:

Table 3. Entropy of vulnerability indicators.

per_capita_income	disability_ratio	ill_ratio	vulnerable_age_ratio	nearest_distance
0.99999971	0.96875861	0.829377689	0.629997746	0.941186752

C. Calculation of Degree of Diversification of Vulnerability Indicators

In the third step, the degree of diversification of all the attributes was calculated using Eq. (11). Results are shown in table 4 below:

Table 4. Degree of diversification of vulnerability indicators.

per_capita_income	disability_ratio	ill_ratio	vulnerable_age_ratio	nearest_distance
2.89987E-07	0.03124139	0.170622311	0.370002254	0.058813248

D. Calculation of Objective Weights of Attributes

In the fourth and final step of the entropy method, objective weights of the attributes were calculated as the normalized degree of diversification using Eq. (10). Results are shown in table 5 below:

Table 5. Objective weights of vulnerability indicators.

per_capita_income	disability_ratio	ill_ratio	vulnerable_age_ratio	nearest_distance
4.59801E-07	0.04953608	0.270537274	0.586672404	0.093253782

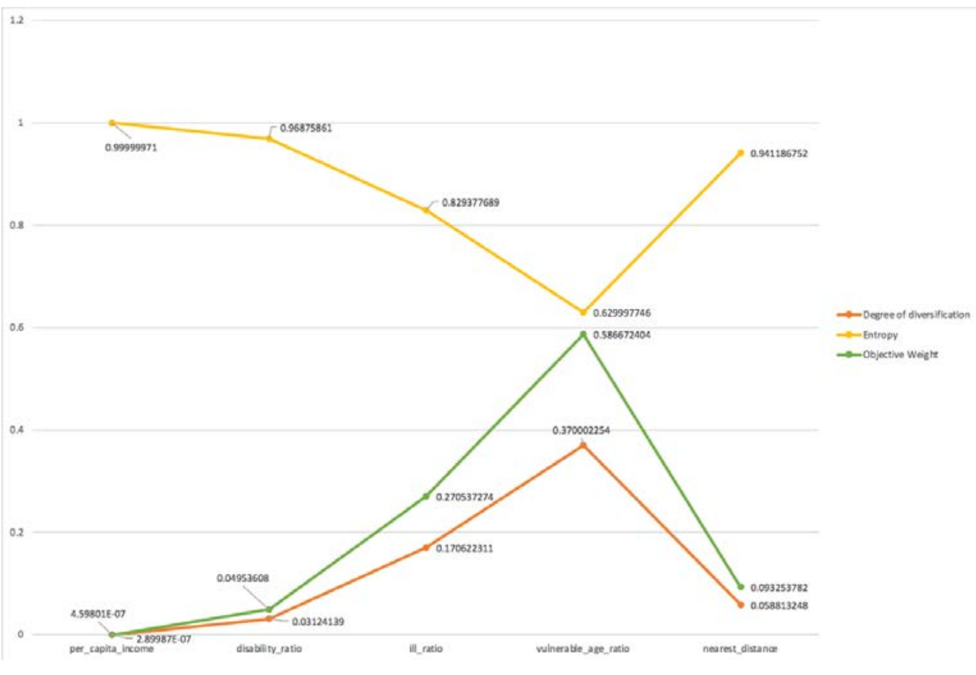

Fig.6. Entropy, degree of diversification and objective weights of vulnerability indicators.

From figure 6 above, it can be observed that per_capita_income has the highest entropy and thus the least degree of diversification. Due to this factor, it has the lowest objective weight. Likewise, vulnerable_age_ratio has the lowest entropy and thus the highest degree of diversification. Due to this, it has the highest objective weight.

4.3. Cluster Vulnerability Index

After computing the objective weights of all the attributes, Eq. (12) was used to calculate the vulnerability index of all the clusters.Results are mentioned in table 6 below:

Table 6. Clusters and their respective vulnerability indices.

Cluster	vulnerability index
1	0.557007089
2	0.031713351
3	0.123564982
4	0.208636371

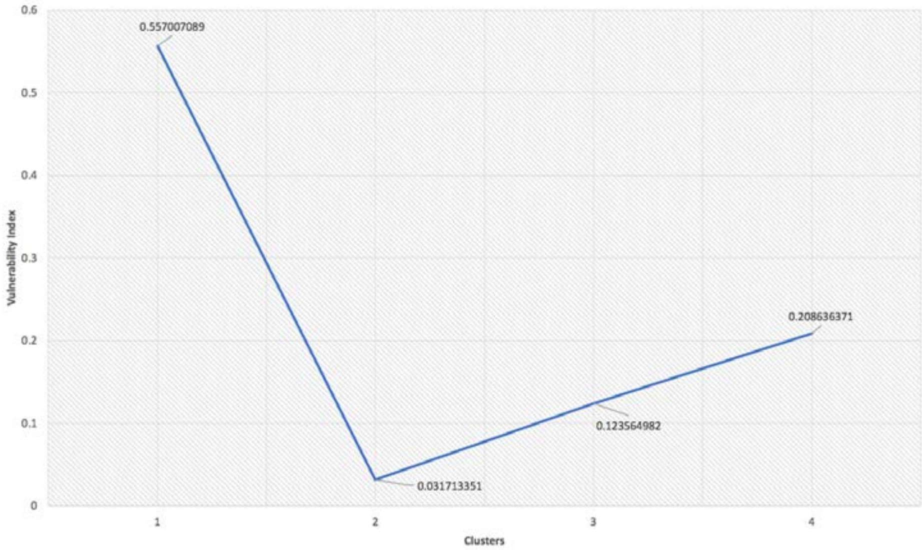

Fig.7. Clusters and their respective vulnerability indices.

From the above figure7, it can be observed that cluster 1 is the most vulnerable cluster and cluster 2 is the least vulnerable cluster. The reason for it is that cluster 1 has the highest centroid value for the vulnerable_age_ratio attribute. And since this attribute has the highest objective weight, it contributed to the cluster being the most vulnerable cluster.

Likewise, cluster 2 has the lowest value of the vulnerable_age_ratio attribute. Due to this, it was the least vulnerable cluster.

4.4. Ward Vulnerability Index

Vulnerability indices of the clusters were combined with household counts of individual clusters for a given ward as per Eq. (12) to obtain the vulnerability index of that particular ward as shown in table 7 below:

4.5. Discussion

As seen from the vulnerability map of the municipality in figure 8, ward 6 has the lowest vulnerability index whereas ward 16 has the highest vulnerability index. It can be observed that wards that are farther away from the east-west highway have higher vulnerability indices. The exception to this is ward 6. The most vulnerable wards are all located near the periphery of the municipality such as wards 16, 8, 9, 15, 5, 11, and 12. Likewise, wards that are close to the east-west highway have lower vulnerability indices such as wards 10, 2, and 4.

Ward 6 was found to be the least vulnerable ward of Ratnanagar municipality. Earlier, ward 6 is found to be the 4th in the list of having maximum average per capita income. The famous tourist destination Sauraha lies in ward 6. Sauraha lies next to Chitwan National Park, which is visited by a lot of domestic and foreign tourists throughout the year for wildlife exploration. Due to this, there are a lot of hotels, resorts, restaurants, cafes, and gift shops in this ward. The higher per capita income of this ward can thus be credited to tourism.

Besides that, it was also found to be the least vulnerable ward in terms of the average vulnerable age ratio in provided data. In terms of the average distance to the nearest health service provider, it was found to be the second least vulnerable ward of the municipality. Due to the adequate number of health service providers in the ward, distance to the health service provider was found to be low for this ward.

Table 7. Wards and their respective vulnerability indices.

	Number of households belonging to particular cluster				
Ward	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Vulnerability Index**
6	20	452	7	326	0.117211166
10	35	726	45	612	0.123952767
2	23	422	1	347	0.12448245
13	74	868	211	709	0.130365796
14	53	619	86	547	0.133258715
4	50	435	143	345	0.134938338
3	35	343	231	325	0.135678007
1	30	431	0	445	0.136006459
7	25	224	259	233	0.137172163
12	70	699	138	669	0.138190246
11	55	416	67	383	0.143338467
5	47	331	147	313	0.143369557
15	56	363	359	414	0.145503045
9	55	97	930	152	0.14614242
8	47	38	836	81	0.147289732
16	54	55	781	99	0.150638896

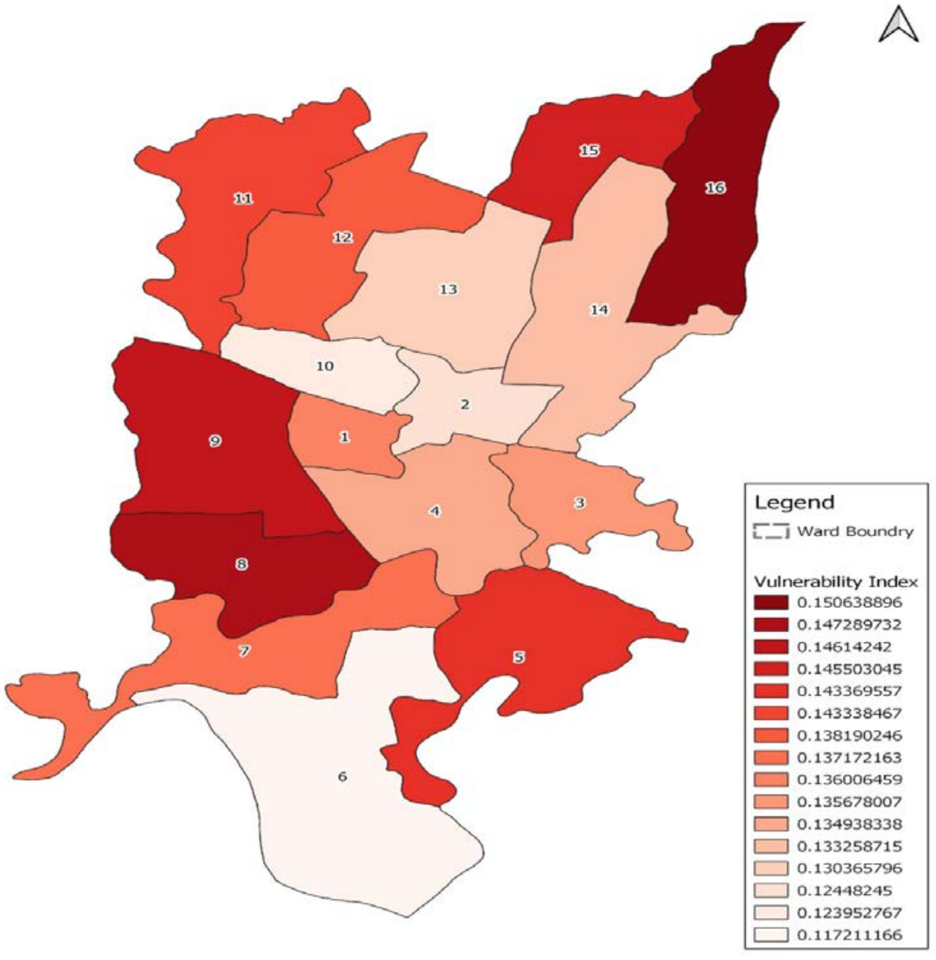

Fig.8. Healthcare vulnerability map of Ratnanagar municipality.

Despite being at the edge of the municipality, the ward 6 was found least vulnerable, unlike other wards at the periphery, due to sound economic activities, lower average vulnerable age group density and abundance of health service providers.

It should be noted that, vulnerable_age_ratio was the vulnerability indicator with the highest objective weight. Due to the highest degree of diversification of this vulnerability indicator it was assigned the highest objective weight as per entropy method.

Likewise, ward 16 was found to be the most vulnerable ward of the municipality. The pre-clustering analysis revealed that ward 16 was the third most vulnerable ward in terms of average vulnerable_age_ratio and distance to the nearest health service provider. Thus, this contributed to the ward being the most vulnerable ward overall. Despite being one of the least vulnerable wards in terms of average per capita income, disability ratio, and ill ratio, ward 16 was found to be the most vulnerable ward of the municipality.

5. Conclusions

An approach to healthcare vulnerability mapping was presented in this study. Real but raw socio-economic data from Ratnanagar municipality was collected for research purposes. It was cleaned, preprocessed, and feature extracted. Machine learning, geo-analytics, and entropy methods were combinedly and implemented on refined data to evaluate the healthcare vulnerability index on the ward level.

This study showed that machine learning algorithms can be effectively used with the combination of a weighting method for vulnerability mapping. The application of an unsupervised machine learning algorithm made sure that dimensions of vulnerability are visible. Besides showing levels of healthcare vulnerability, the machine learning approach also helped in understanding the composition of the vulnerability.

Reference

[1] D. B. Waisel, “Vulnerable populations in healthcare,” *Curr. Opin. Anaesthesiol.*, vol. 26, no. 2, pp. 186–192, 2013, doi: 10.1097/ACO.0b013e32835e8c17.

[2] M. Marmot, J. Allen, R. Bell, E. Bloomer, and P. Goldblatt, “WHO European review of social determinants of health and the health divide,” *Lancet*, vol. 380, no. 9846, pp. 1011–1029, 2012, doi: 10.1016/S0140-6736(12)61228-8.

[3] GoN, “The Constitution of Nepal 2015,” *Nepal Gaz.*, vol. 2015, no. February, p. Art. 58., 2015, [Online]. Available: http://www.lawcommission.gov.np.

[4] P. Neupane, D. Bhandari, M. Tsubokura, Y. Shimazu, T. Zhao, and K. Kono, “The Nepalese health care system and challenges during COVID-19,” *Journal of Global Health*, vol. 11, 2021.

[5] S. K. Aksha, L. Juran, L. M. Resler, and Y. Zhang, “An Analysis of Social Vulnerability to Natural Hazards in Nepal Using a Modified Social Vulnerability Index,” *Int. J. Disaster Risk Sci.*, vol. 10, no. 1, pp. 103–116, 2019, doi: 10.1007/s13753-018-0192-7.

[6] B. M. de Loyola Hummell, S. L. Cutter, and C. T. Emrich, “Social Vulnerability to Natural Hazards in Brazil,” *Int. J. Disaster Risk Sci.*, vol. 7, no. 2, pp. 111–122, 2016, doi: 10.1007/s13753-016-0090-9.

[7] E. Mavhura, B. Manyena, and A. E. Collins, “An approach for measuring social vulnerability in context: The case of flood hazards in Muzarabani district, Zimbabwe,” *Geoforum*, vol. 86, no. December 2016, pp. 103–117, 2017, doi: 10.1016/j.geoforum.2017.09.008.

[8] O. Žurovec, S. Čadro, and B. K. Sitaula, “Quantitative assessment of vulnerability to climate change in rural municipalities of Bosnia and Herzegovina,” *Sustain.*, vol. 9, no. 7, pp. 1–18, 2017, doi: 10.3390/su9071208.

[9] W. Shi and W. Zeng, “Genetic k-means clustering approach for mapping human vulnerability to chemical hazards in the industrialized city: A case study of Shanghai, China,” *Int. J. Environ. Res. Public Health*, vol. 10, no. 6, pp. 2578–2595, 2013, doi: 10.3390/ijerph10062578.

[10] Central Bureau of statistics, “Professionalism in action,” 2015.

[11] The World Health Organization (WHO), “Under-five mortality rate (probability of dying by age 5 per 1000 live births),” *The Global Health Observatory*, 2020. https://www.who.int/data/gho/indicator-metadata-registry/imr-details/7.

[12] GoN, *Senior citizens*, vol. 87, No. 1–2. 2006, pp. 1–4.

[13] R. Seising, “Bell System Technical Journal.,” *American Scientist*. p. 60, 2001.

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