

The most places at risk surrounding the COVID-19 treatment hospitals in an urban environment- case study: Tehran city



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ABSTRACT

Investigations on the spatial patterns of COVID-19 spreading indicate the possibility of the virus transmission by moving infected people in an urban area. Hospitals are the most susceptible locations due to the COVID-19 contaminations in metropolises. This paper aims to find the riskiest places surrounding the hospitals using an MLP-ANN. The main contribution is discovering the influence zone of COVID-19 treatment hospitals and the main spatial factors around them that increase the prevalence of COVID-19. The innovation of this paper is to find the most relevant spatial factors regarding the distance from central hospitals modeling the risk level of the study area. Therefore, eight hospitals with two service areas for each of them are computed with [0–500] and [500–1000] meters distance. Besides, five spatial factors have been considered, consist of the location of patients' financial transactions, the distance of streets from hospitals, the distance of highways from hospitals, the distance of the non-residential land use from the hospitals, and the hospital patient number. The implementation results revealed a meaningful relation between the distance from the hospitals and patient density. The RMSE and R measures are 0.00734 and 0.94635 for [0–500 m] while these quantities are 0.054088 and 0.902725 for [500–1000 m] respectively. These values indicate the role of distance to central hospitals for COVID-19 treatment. Moreover, a sensitivity analysis demonstrated that the number of patients' transactions and the distance of the non-residential land use from the hospitals are two dominant factors for virus propagation. The results help urban managers to begin preventative strategies to decrease the community incidence rate in high-risk places.

1. Introduction

COVID-19 is an extraordinary global pandemic that was outbreak in Wuhan, China, in late December formerly dispersal at a very fast rate (WHO, 2019; WHO, 2020). In different geographical areas, the pandemic seems to be scattering at fluctuating rates. COVID-19 spreads more quickly than other breathing diseases (e.g., SARS Severe Acute Respiratory Syndrome) (Coronavirus disease, 2019; Bhagat and Bhimireddy, 2020). According to the number of confirmed cases till 20 January 2021, Iran is the 16th country in the world in terms of COVID-19 infection with 1,3320,000 infected people and 57,057 deaths (Organization, 2020).

Tehran, the Capital of Iran as a hub of different cities, has a high statistical prevalence of COVID-19 due to its large population and high

volume of daily traffic (Rahmatinia et al., 2020). The COVID-19 pandemic, as a community health reserve, has transported to light many tasks in survives and livings in Tehran. Presently, control of the COVID-19 epidemic is a universal concern and has become a crucial challenge in Iran (Asadzadeh et al., 2020). Among different challenges on the COVID-19-episode, detection of involving spatial criteria could help us to prevent form more infection. The first-place people will refer to after the disease is the hospitals. According to the studies, hospitals are the most susceptible places to coronavirus infection. They indicated that the risk of COVID-19 infection would increase with hospitalization or contact with people admitted to hospitals and medical centers (Han et al., 2021; Ertem et al., 2021; Sun et al., 2021; Mohammadi et al., 2021 Arman et al., 2021). Ertem et al. (2021) indicated that keeping social distances from polluted people is the main aid for infection prevention.

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[Arman et al. \(2021\)](#) stated that the low distance to hospitals centered for COVID-19 will increase the possibility of COVID-19 incidence. Based on Tobler's first law of geography ([Tobler, 1970](#)), the nearer locations to the hospitals, the more prone area to the virus infection due to more dense population and movement compared to the distant sites. Therefore, assessing urban infrastructure, people activity (financial transaction as an index of patients' sign), and the number of patients in each hospital could specify the main criteria on COVID-19 propagation in different distances from the hospitals.

The focus of this paper is to find the most places at risk surrounding the hospitals using a multi-layer perceptron artificial neural network. The main contribution is discovering the influence zone of the COVID-19 treatment hospitals and the main spatial factors around them that increase the prevalence of COVID-19 in Tehran. The innovation of this paper is related to finding the most relevant spatial factors regarding the distance from central hospitals and modeling the risk level of the study area due to COVID-19 propagation via MLP-ANN. Thus, eight leading hospitals encountered with COVID-19 with two service areas for each of them have been computed with [0–500] and [500–1000] meters spread. Also, five spatial factors have been considered, including the location of patients' transactions, the distance of streets from hospitals, the distance of highways from hospitals, distance of the non-residential land use from the hospitals, and the number of patients in the hospitals. The involving factors have been considered based on the expertise knowledge (25 experts include 12 urban planners, 7 physicians, and 6 GIS specialists). The proposed method utilized an AI-based approach to detect the association between derived spatial urban factors and predict the risky zones around the hospitals dynamically.

2. Literature review

Different studies evaluated the relationship between environmental and infrastructural factors of COVID-19 outbreak cities using data mining approaches ([Magazzino et al., 2020; Saez et al., 2020; Wu et al., 2021; Velásquez and Lara, 2020](#)). From the knowledge discovery perspective, recent studies present a wide range of research on the COVID-19 infection in urban areas ([Velásquez and Mejía Lara, 2020](#)). [Mele and Magazzino \(2020\)](#) assessed the association between financial evolution, contaminating emanations, and COVID-19 deaths, discovery a fundamental link among PM_{2.5}, CO₂, NO₂ releases, and COVID-19 deaths. They used time series and D2C algorithms and concluded that a specified pollution concentration produced by financial progress could increase COVID-19 contamination via production of the respiratory system more vulnerable to contamination. Their results provide new strategies for controlling COVID-19 prevalence in India. [Wan \(2020\)](#) analyzed the events and travel performance of urban residents as the key for the deterrence and control of epidemic situations due to an improved spatiotemporal trajectory data mining method. Through the applied approach, a lot of valued travel info can be derived and calculated. The regular behavior of separate users and the spatial distribution features of group users' measure can be explored. The consequences of the implemented method revealed the traffic-congested roads as an efficient aid in preventing more infection. [Li et al. \(2020\)](#) used a spatiotemporal design of depressing symptoms produced by COVID-19 by means of the social media and Correlation Explanation (CorEx) learning algorithm. They investigated a robust association amid stress symptoms and the number of enlarged COVID-19 cases for major U.S. cities. The achieved results showed that people's risk insight is sensitive to the release of COVID-19 related media messages and public news. [Pansini and Fornacca \(2020\)](#) studied the spatial appeal of COVID-19 and its association with different ground indexes of air quality in China, Iran, Italy, Spain, France, Germany, the UK, and the USA. The proposed algorithm investigated social media data to compute stress indicators underneath COVID-19 pandemic spatiotemporally. The consequences proved more viral contaminations in the areas distressed by high PM_{2.5} and NO₂ values. [Rajendran and Jayagopal \(2020\)](#) studied the impact of lockdown on

Table 1

The related researches on assessing the relations between spatial factors and COVID-19.

Author/s	Data mining approach	Criteria used	Study area
Mele and Magazzino (2020)	Time series, D2C algorithm	Economic growth, polluting emanations, and COVID-19 deaths	India
Wan (2020)	An improved spatiotemporal trajectory data mining method	Activities and travel behavior of urban residents and COVID-19 outbreak	China
Li et al. (2020)	Correlation Explanation (CorEx) learning algorithm	Stress symptoms, geosocial media and COVID-19 infection	Unites States
Pansini and Fornacca (2020)	Regression	Air quality and COVID-19 deaths	China, Iran, Italy, Spain, France, Germany, U.K. and U.S.A.
Rajendran and Jayagopal (2020)	SIR, SIER	Densely populated districts and COVID-19 outbreak	India
Pourghasemi et al. (2020)	Random forest	Distance from bus stations, some land uses, ATMs, banks, and the minimum temperature	Iran
Sugg et al. (2021)	Spatial cluster analysis	Population density, per-capita income, average household size, and minority configuration	Unites States
Guo et al. (2021)	Lag non-linear model	Daily temperature, relative humidity, and wind	190 countries
Sannigrahi et al. (2020)	GWR	Socio-demographic such as population, income, poverty and etc.	European region
Mansour et al. (2021)	OLS, SLM, SEM, GWR and MGWR	Age structure, long-term illness, population density, nurse practitioners and hospital beds	Oman

densely populated districts using SIR and SIER as regression-based methods. Their achievement demonstrated that three restrictions, including the lockdown, the social distancing, and putting on facemask, could control the wide prevalence. Also, they assessed the age/gender-wise social distancing. The critical findings were to execute lockdowns that defeat the broadcast of the diseases and insulate persons with comorbidity. [Pourghasemi et al. \(2020\)](#) monitored COVID-19 outbreak trend in Iran (from 19 February to 14 June, 2020) using random forest (RF). Alteration discovery of the COVID-19 risk maps with a chance forest model specified that the utmost key urban components were the distance from bus stations, mosques, bakeshops, hospitals, ATMs (automated teller machines), banks, and the least temperature of the coolest month. [Sugg et al. \(2021\)](#) developed a GIS-based multivariate analysis and identified risk issues of COVID-19 cases in the nursing home including population density, per-capita pay, average domestic size, and smaller configuration. [Guo et al. \(2021\)](#) assessed the relationships amid COVID-19 occurrence and diurnal temperature, close humidity, and wind speed using a distributed lag non-linear model. The results showed a stronger relationship with temperature relative to humidity or wind speed. An inverse association was recognized between the COVID-19 frequency and temperature. [Sannigrahi et al. \(2020\)](#) investigated the socio-demographic factors' impacts on the global casualties caused by the COVID-19 using geographically weighted regression (GWR). They applied the global and

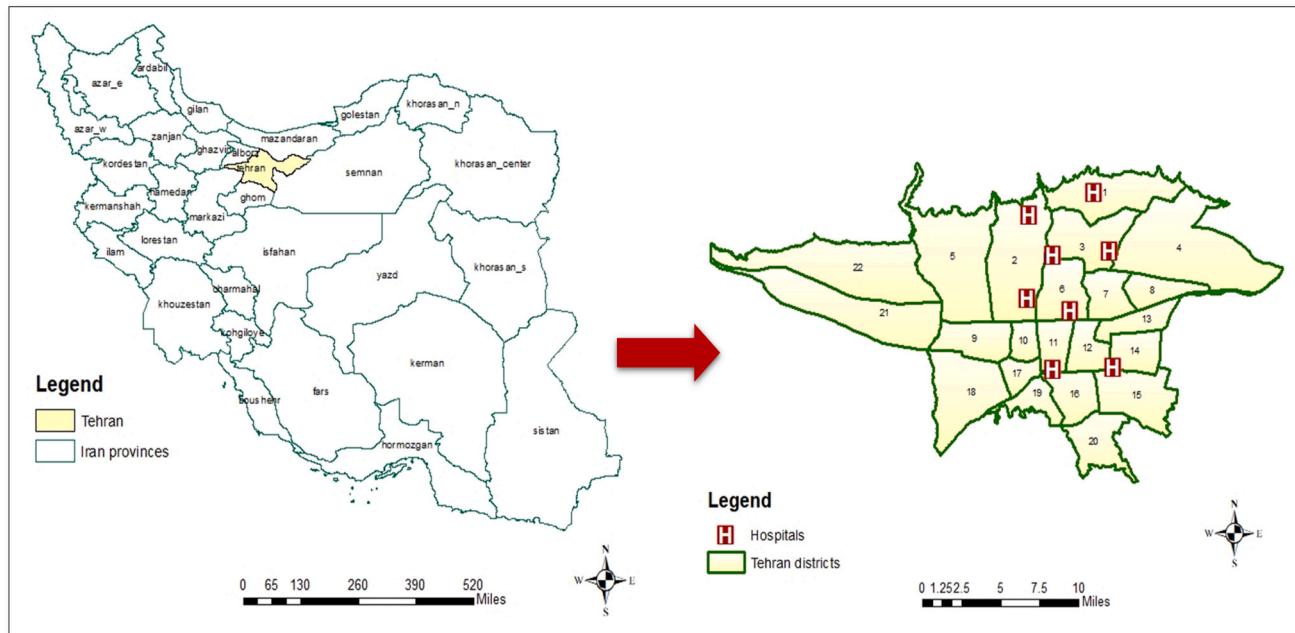


Fig. 1. The study area (Tehran, the Capital of Iran).

local spatial relationships between the main variables and COVID-19 cases and deaths in the European and selected total population, poverty, and income as the most effective criteria for COVID-19 outbreak. Mansour et al. (2021) derived four fundamental factors in increasing the COVID-19 incidence rates geographically. These factors contain global ordinary least squares (OLS), spatial lag, and spatial error regression models (SLM, SEM), also two local regression methods include geographically weighted regression and multiscale geographically weighted regression (MGWR). They concluded that the local models could express the dynamic relationships amongst variables. To

clarify the applied data mining methods, the assessed factors and study area are summarized in Table 1.

The investigation of Table 1 revealed that the role of proximity to the hospital and influential spatial factors around them on the COVID-19 outbreak did not assess until now. However, the primary spatiotemporal maps of COVID-19 outbreaks show that hospitals with COVID-19 infected people are the primary source of virus propagation. This fact could be proved by considering two service areas for the central hospital allocated for COVID-19 treatments and assessing different criteria in the movement of infected people and disease vectors. As a result,

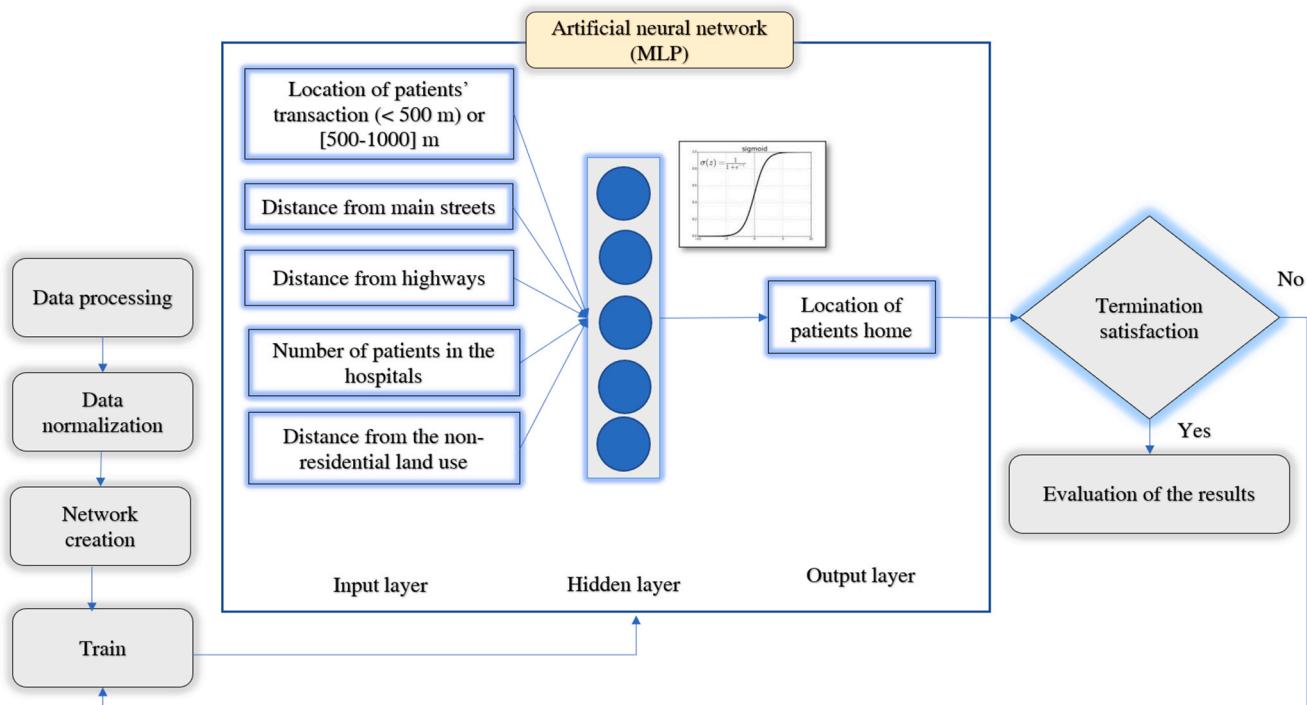


Fig. 2. The flowchart of the proposed method.

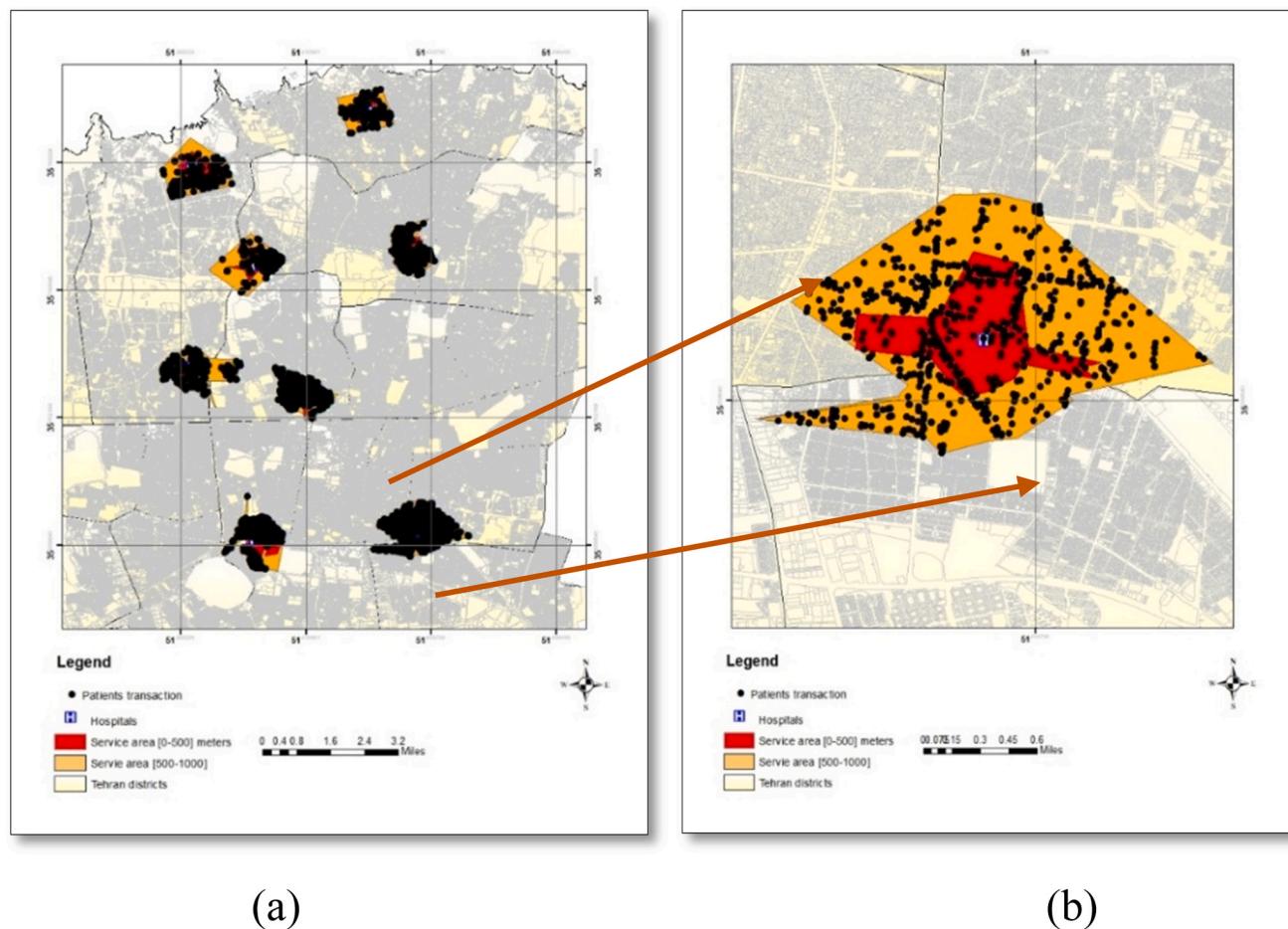


Fig. 3. The selected hospitals and two service areas for each hospital: (a) an overview map of central hospitals for COVID-19 treatment, and (b) financial transactions of the patients for selected hospitals.

introducing an influence zone for hospitals and introducing involving spatial factors leads to a better decision-making process to manage the COVID-19 pandemic. To our knowledge, this is the first research, which applies a GIS-based approach using AI to study spatial patterns of disease incidence. The consequences support the urban managers to initiate some new strategies to decrease the community incidence rate in the high-risk zones.

3. Materials and method

The key idea of this research is a plan of hospitals' influence zones and involving spatial factors of the COVID-19 outbreak. In this regard, Tehran is a high-populated city with central hospitals to treat of COVID-19 infected people. This section describes the study area and the procedure of the proposed method.

3.1. Study area, selected hospitals, and service areas

Tehran, is the Capital of Iran with a population of around 8 million people. It is ranked as the 24th populated metropolitan in the world. The city is separated into 22 urban districts. Most of the city districts are located in Tehran County's central district, while two districts are located in the counties of Shemiranat and Ray ([Tehran, 2021](#)).

More than 200 large clinics and hospitals in Tehran, of which around 140 hospitals accept COVID-19 patients in the study period. Three other medical universities supervise these hospitals in the city and suburbs. Due to many logistics limitations, at the beginning of the pandemic, many people from the different country provinces proceed to these

hospitals. However, after designing and implementing a hospitalization protocol, there is a normal distribution in the cities. Less patient is moving from a town to the Capital, which leads to a more accurate statistic. In this research, the top eight hospitals in COVID-19 treatment, located in the city core and eliminated hospitals in the suburbs, have been considered. The hospitals in the major/minor roads have been selected and instead of using the hospitals with a specific purpose (e.g., maternity), the general hospitals have been assessed. The main reason for choosing these eight hospitals was the highest number of patients. Other hospitals received lower COVID-19 patients significantly in the study period in Tehran. [Fig. 1](#) shows the study area and the considered hospitals for assessing the pattern of the COVID-19 outbreak.

3.2. Proposed method

The chief idea of this paper is to assess the influence zone of the hospitals and involving spatial factors of the COVID-19 outbreak in an urban zone. To attain this goal, an artificial neural network with multi-layer perceptron architecture is developed since they could detect unknown patterns that shares identical distinctive features. Based on this framework, the proposed method is described as depicted in [Fig. 2](#).

The main spatial criteria considered as input are as follows: distance from main streets, distance from highways, distance from the non-residential land use, number of patients in the hospitals and population density, and location of patients' financial transaction within [0–500] and [500–1000] meters. The selected service area distances are based on experts' opinions where the pedestrians travel on foot on an average of 500 m and the drivers travel within 1000 m to get a specific

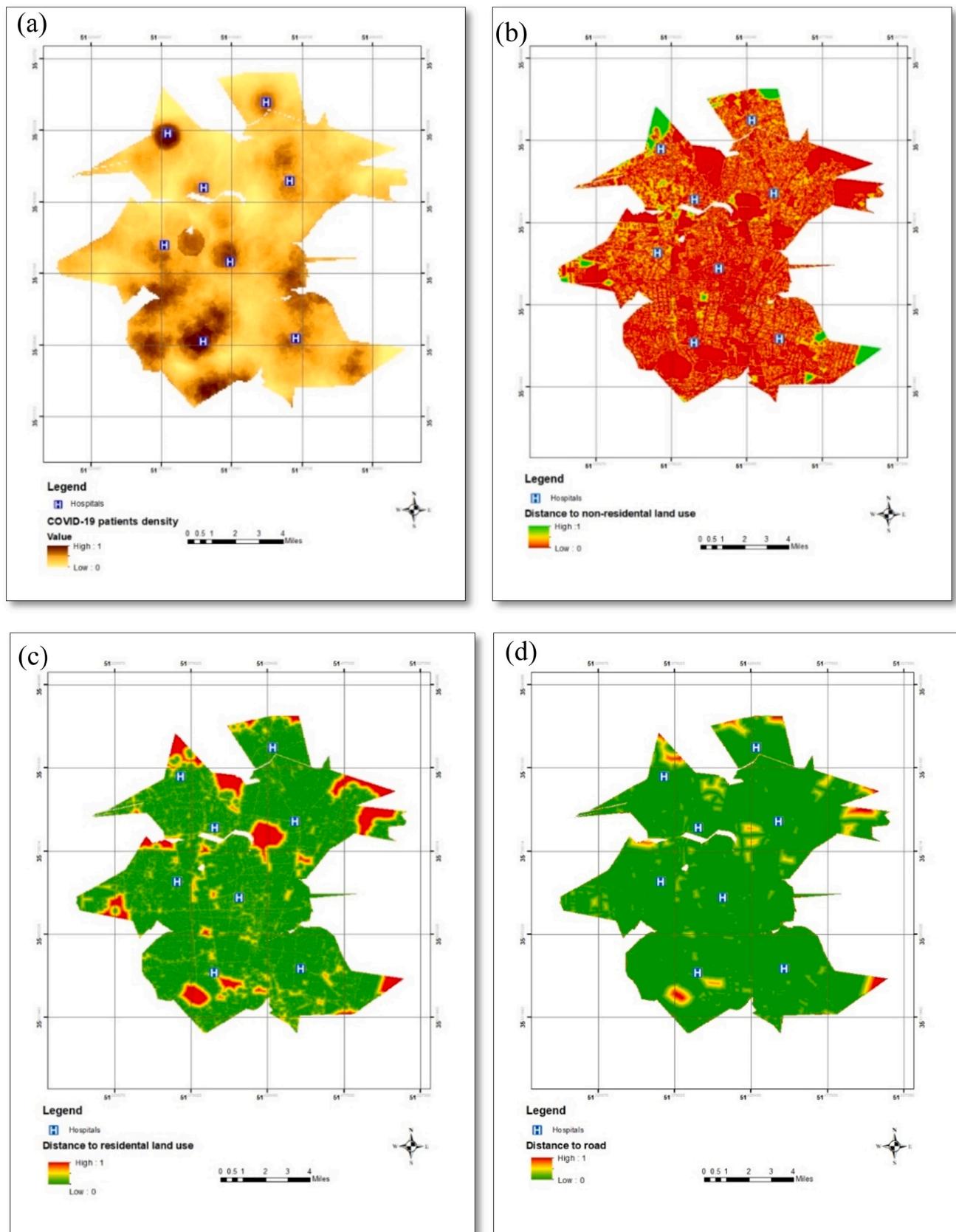


Fig. 4. Data used a) Density map of COVID-19 quarantined patients, b) distance to residential land use, c) distance to non-residential land use, d) distance to the main street, e) distance to highways, f) density map of COVID-19 patients' transaction, and g) population map (all in service area [0–5000]).

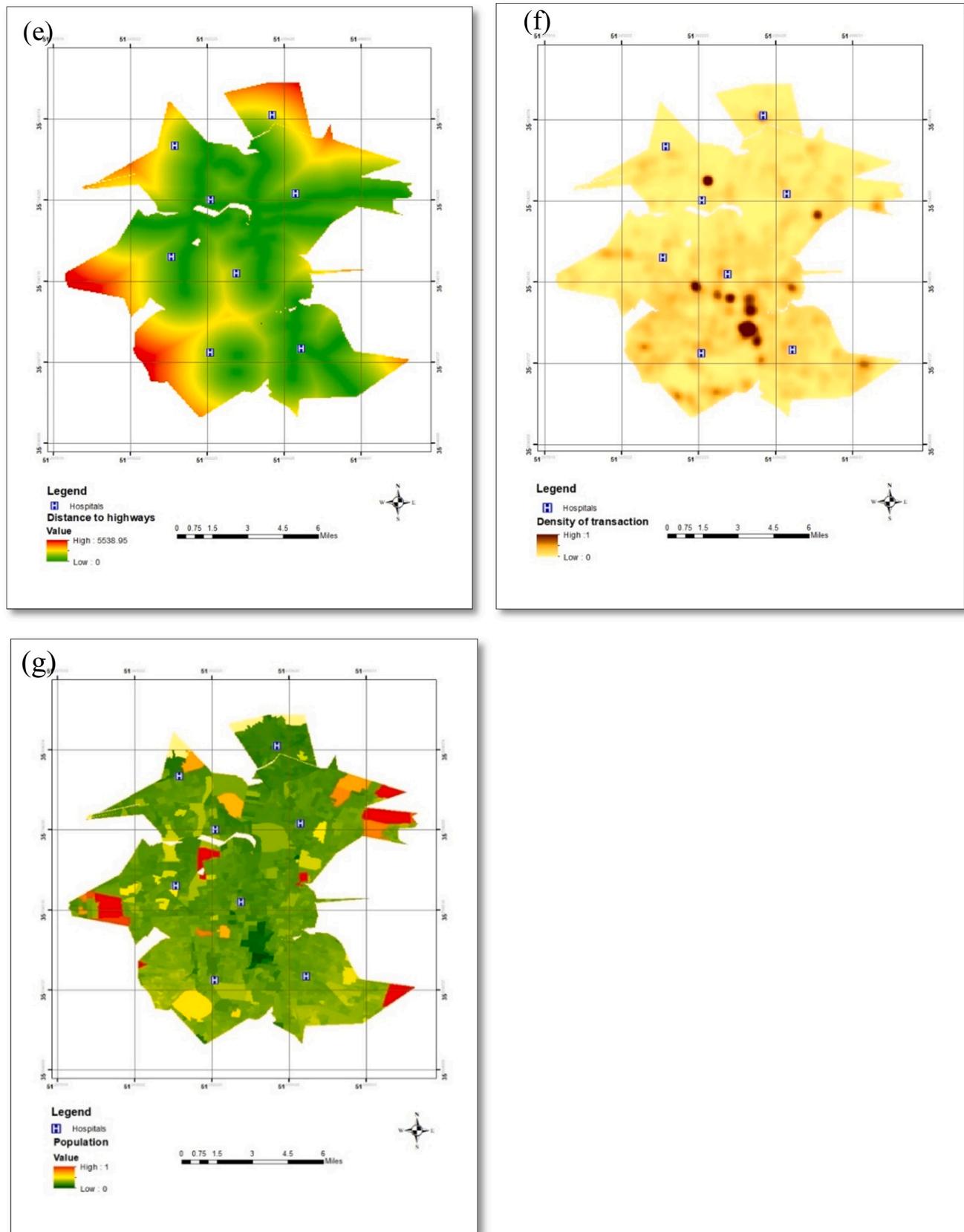


Fig. 4. (continued).

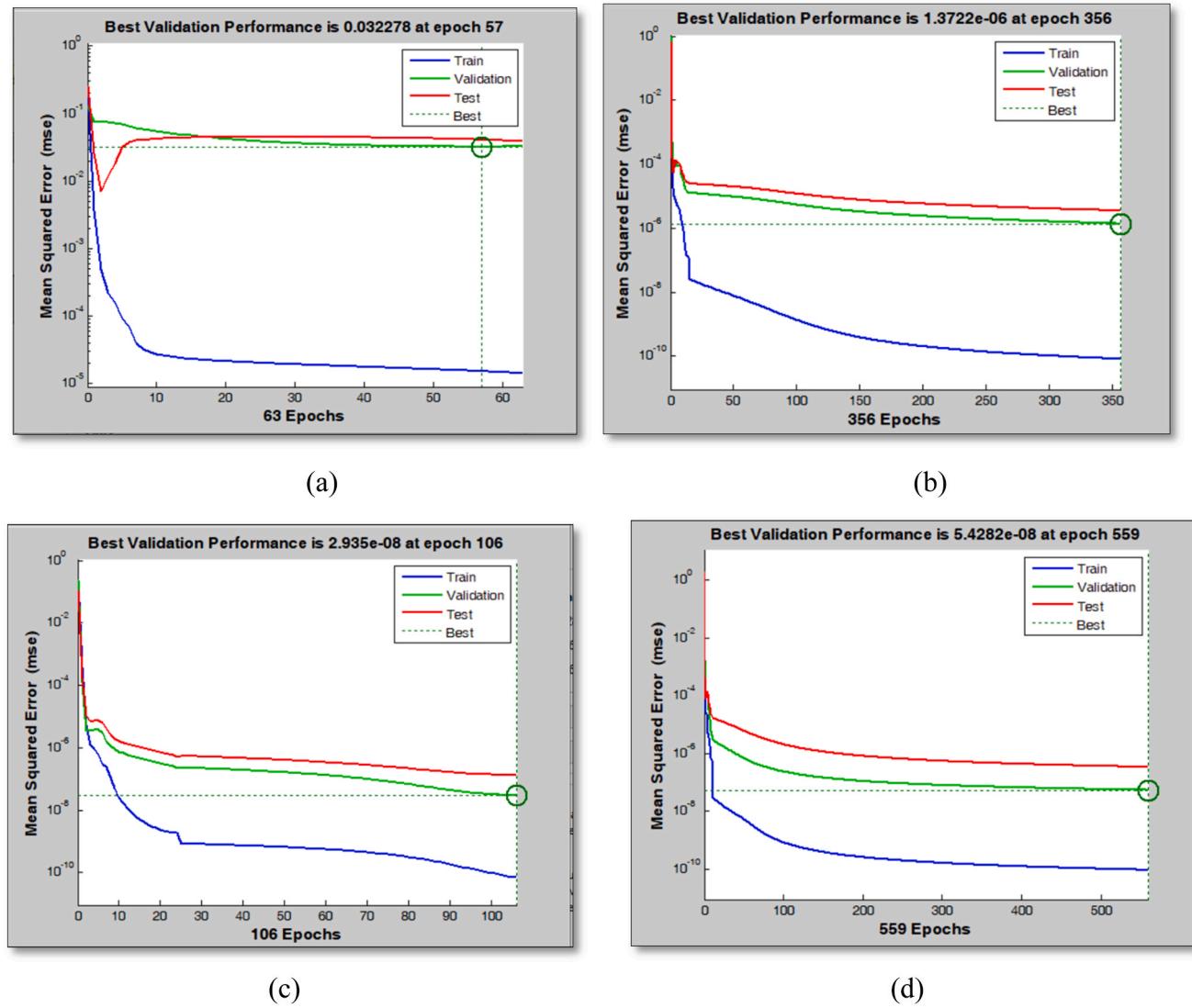


Fig. 5. The convergence curves of the designed MLP within [0–500] meters: (a) Hospital#1, (b) Hospital#2, (c) Hospital#3, (d) Hospital#4, (e) Hospital#5, (f) Hospital#6, (g) Hospital#7, and (h) Hospital#8.

location on purpose (Neysani Samany et al., 2013; Paydar et al., 2020; Omidipoor et al., 2021). The target is regarded as the location of patients in these regions. Then all the criteria maps are obtained using spatial analysis and normalized based on Eq. 1 (Neysani Samany et al., 2014; Boloorani et al., 2021; Naghdizadegan Jahromi et al., 2021; Javanbakht et al., 2021).

The target is regarded as the location of patients in these regions. Then all the criteria maps are obtained using spatial analysis and normalized based on Eq. 1 (Neysani Samany et al., 2014; Boloorani et al., 2021).

$$v_{ij} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Based on the normalized maps, the training data are selected and they are classified into train, validation, and test data considering 70%, 15%, and 15% of all data correspondingly. The multi-layer perceptron is designed to assess the relationships between the input and target values.

3.2.1. Multi-layer perceptron ANN

Multi-layer perceptron network is one of the widespread network architectures, where the weighted summation of the inputs and bias cases are approved to start level over a transfer function to derive the

output, and the units are organized in a layered feed-forward topology called feed forward neural network (Venkatesan and Anitha, 2006; Neysani Samany, 2019; Asadi et al., 2019).

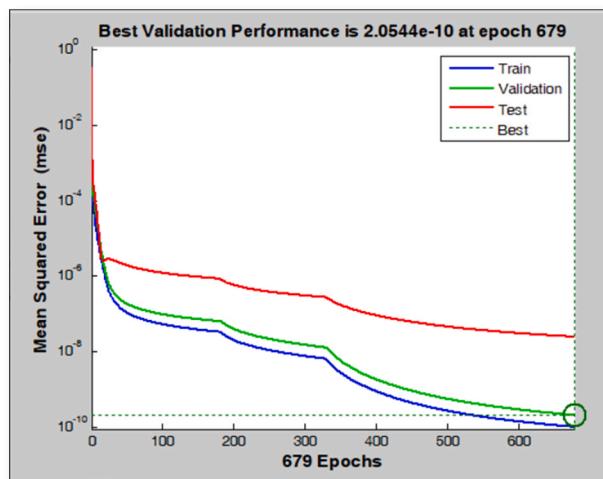
In this paper, two MLP networks consist of an input layer (with five neurons), one hidden layer (with ten neurons), and an output layer (with one neuron) are designed. Where each layer is completely organized with weighted associates to the consequent layer. These networks convert inputs to outputs over a sigmoid function. The output of each network is computed by the activation function as Eq. 2:

$$x_0 = f \sum_h x_h W_{ho} \quad (2)$$

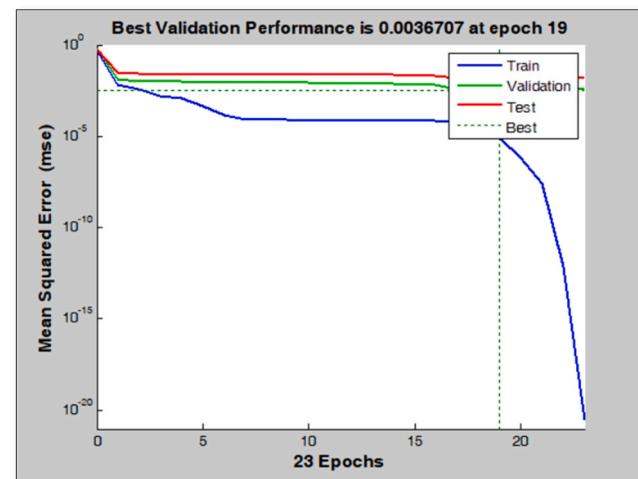
Where f stands for the activation function, x_h is the value of the neurons in layer h and W_{ho} is the interconnection between h^{th} hidden layer node and o^{th} output layer node. The activation function is considered as Eq. 3:

$$x_0 = \frac{1}{1 + \exp[-f_o(-\sum_h x_h W_{ho})]} \quad (3)$$

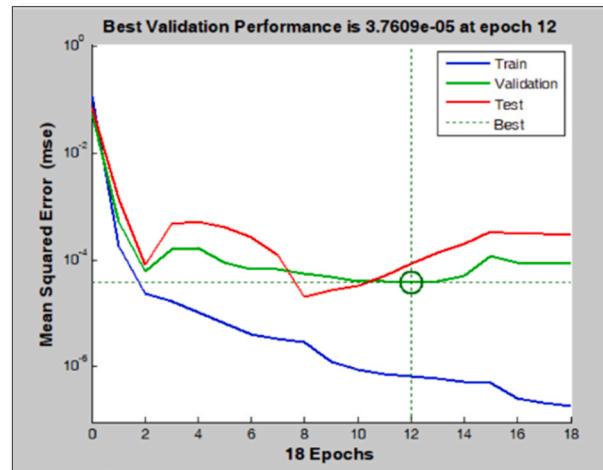
The activation level of the nodes in the hidden layer is calculated similarly. An error is defined According to the differences between the calculated output and the target values Eq. (4):



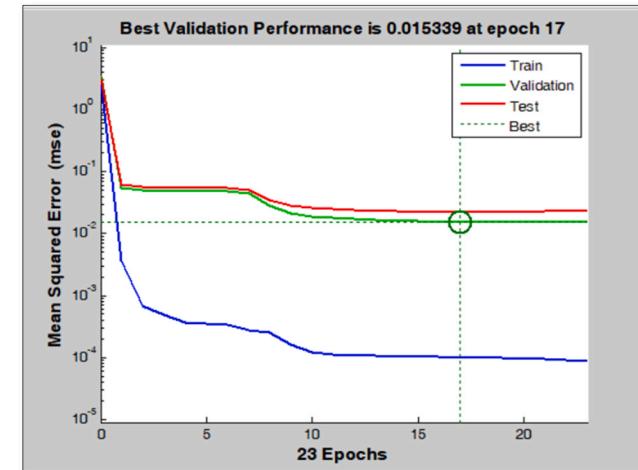
(e)



(f)



(g)



(h)

Fig. 5. (continued).

$$E = \frac{1}{2} \sum_s^n \sum_o^L (t_0^{(s)} - x_0^{(s)})^2 \quad (4)$$

Where n is the number of patterns in the data set and L stays the number of output nodes. The process tries to decrease the error by regulating the interconnections between layers. The weights are tuned using a gradient descent backpropagation (BP) algorithm. During the training process, MLP begins with an accidental set of initial weights, and formerly training continues till the set of W_{ih} and that of W_{ho} is improved to a predefined error threshold is met between x_o and t_o (Altun and Gelen,

Table 2

The R-Values for training, validation and test dataset, for all datasets and the RMSE within [0–500] meters.

Name	Training	Validation	Test	All	RMSE [0–500]
Hospital#1	0.9925	0.9841	0.9895	0.9974	1.372e-05
Hospital#2	0.8924	0.8957	0.8754	0.8960	0.0323
Hospital#3	0.9954	0.9914	0.9924	0.9941	2.935e-8
Hospital#4	0.9964	0.9925	0.9895	0.9952	5.428 e-8
Hospital#5	0.9859	0.91451	0.8548	0.9341	2.054e-10
Hospital#6	0.9741	0.9345	0.7541	0.9167	0.0037
Hospital#7	0.9641	0.9457	0.9214	0.9478	3.761e-05
Hospital#8	0.9142	0.8545	0.8142	0.8895	0.0153

2004). To assess the reliability of the designed networks, the number of hidden neurons is changed and the best design (based on least RMSE, and best performance) will select for valuation.

4. Implementation and results

The proposed algorithm is implemented in the study area to assess the influence zones of the hospitals. The two designed MLPs have been programmed and accomplished in MATLAB 2016 on a computer with an Intel Core i7@3.20 GHz Processor with 4 GB RAM.

4.1. Data used

For each selected hospital, two specific service areas within [0–500] and [500–1000] meters distance derived from the road network. Fig. 3 (a), represents the distribution of the existing and selected hospitals in the study area. As the main factors, the location of transactions around the hospitals is illustrated in Fig. 3(b). Also, the density map of quarantined during June-August 2020, is depicted in Fig. 4. First, the density map of COVID-19 quarantined patients is shown in Fig. 4(a), then 'distance to residential land use', 'distance to non-residential land use', 'distance to the main street', 'distance to highways' are illustrated in Fig. s (b-e). Finally, the density map of COVID-19 patients' transaction and

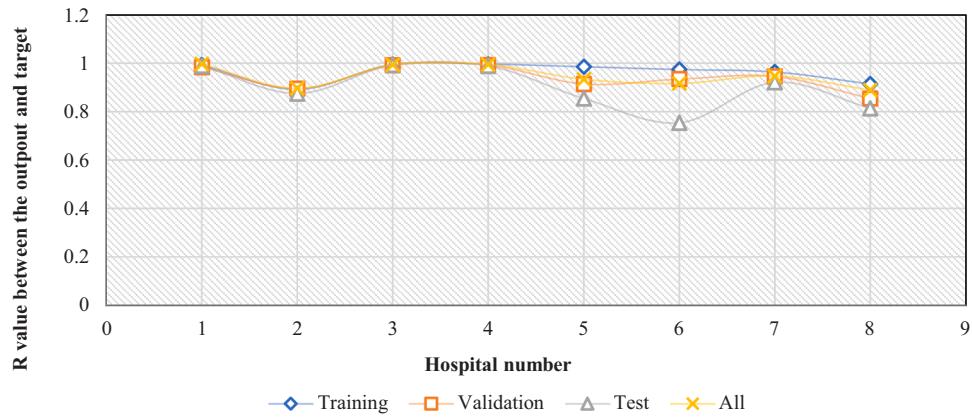


Fig. 6. The R-Values for training, validation, and test dataset in the first within [0–500] meters.

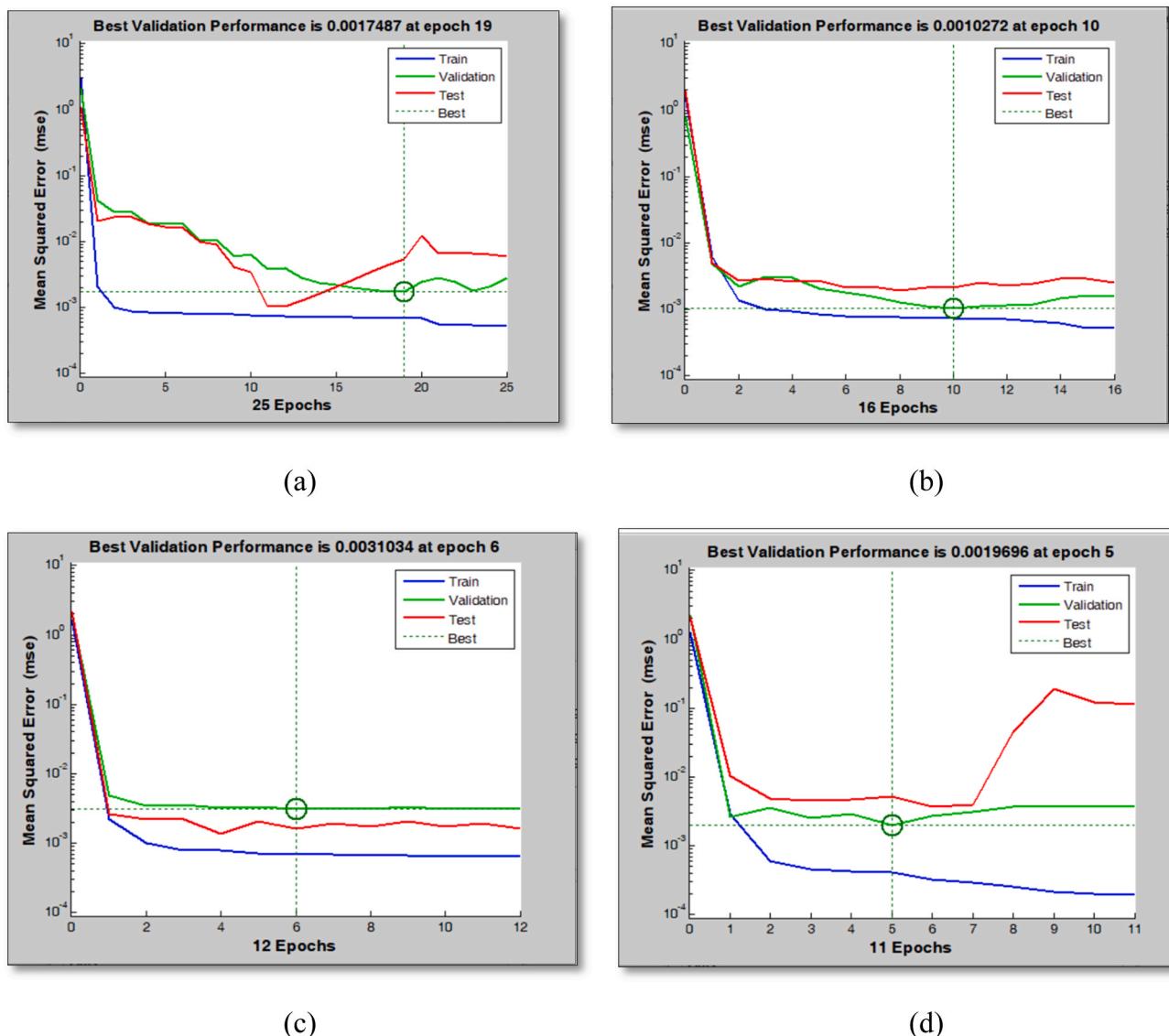


Fig. 7. The convergence curves of the designed MLP within [0–500] meters: (a) Hospital#1, (b) Hospital#2, (c) Hospital#3, (d) Hospital#4, (e) Hospital#5, (f) Hospital#6, (g) Hospital#7, and (h) Hospital#8.

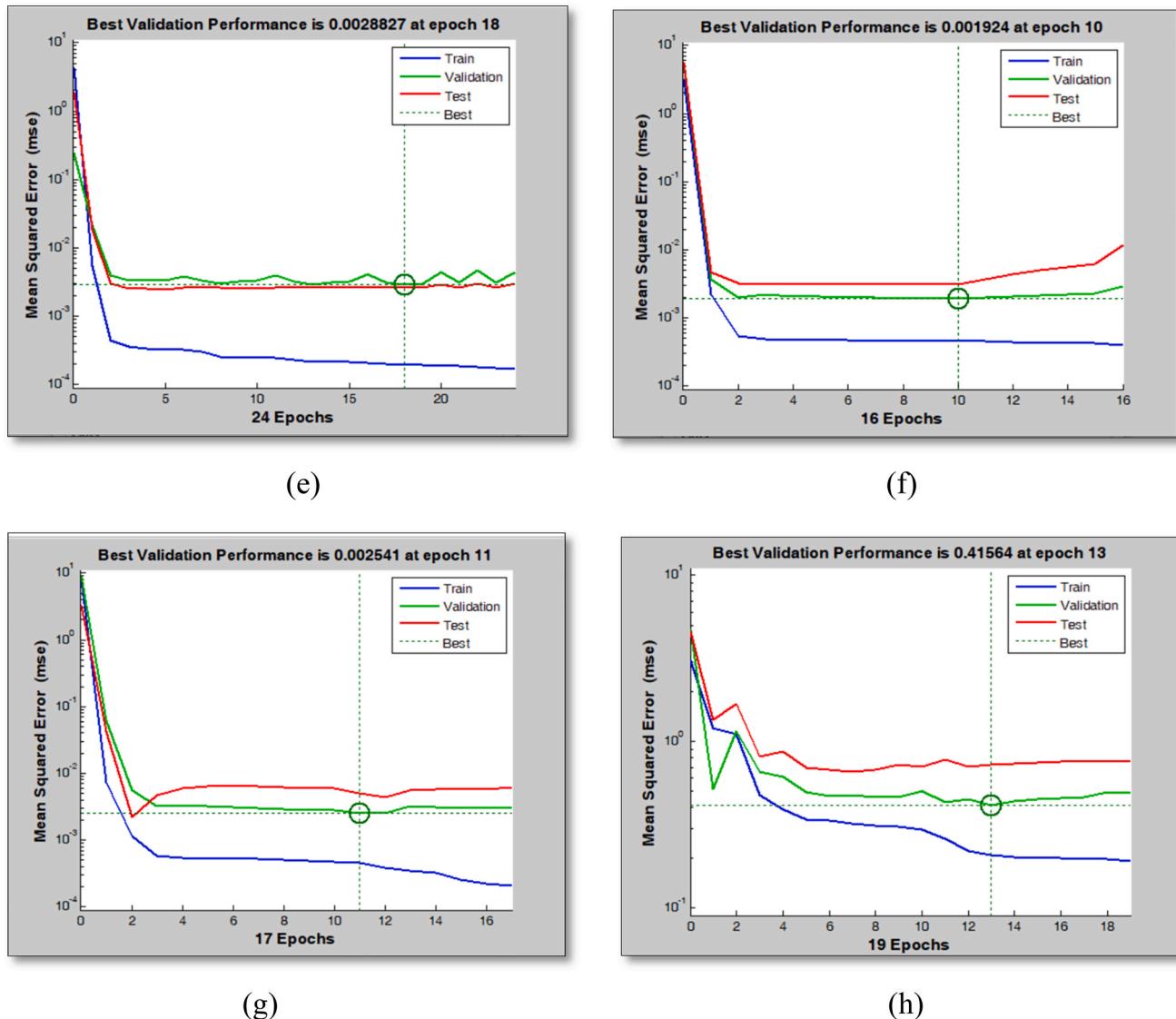


Fig. 7. (continued).

population maps are depicted in Fig.s (f and g). All maps are generated in the service area [0–5000].

4.2. Running MLP

To validate the robustness of the designed MLP, the number of hidden neurons considered as 8,10, and 12, while the best results due to the RMSE, R, and performance curve is related to 10 neurons in the hidden layer. The results of the proposed method in the first scenario (within [0–500] meters distance) are depicted in Fig. 5(a-h) for eight hospitals. The hospital names are omitted due to privacy reasons.

The R-values of training, validation, test dataset, and the RMSE of the implemented ANN within [0–500] meters are considered as described in Table 2.

Fig. 6 shows the relationships between the input and target in the first scenario. According to the R-value, the stronger relations between the input parameters and target are related to the 'Hospital#1', 'Hospital#3', and 'Hospital #4'. The weaker relation is associated with 'Hospital#6'. It means that by decreasing the distance from 'Hospital#1', 'Hospital#3', and 'Hospital #4', the role of non-residential land use and patients' transaction has been intensified.

The results of the proposed method in the second scenario (within

Table 3

The R-Values for training, validation and test datasets, for all dataset and the RMSE within [500–1000] meters.

Name	Training	Validation	Test	All	RMSE [500–1000]
Hospital#1	0.9854	0.9801	0.9884	0.9894	0.0017
Hospital#2	0.8812	0.8801	0.8621	0.8841	0.0010
Hospital#3	0.9898	0.9852	0.9841	0.9874	0.0031
Hospital#4	0.9874	0.9814	0.9745	0.9801	0.0028
Hospital#5	0.9745	0.9245	0.8012	0.8801	0.0019
Hospital#6	0.9540	0.8914	0.7412	0.8741	0.0037
Hospital#7	0.9221	0.8842	0.8254	0.8421	0.0025
Hospital#8	0.8042	0.7524	0.7024	0.7845	0.4160

[500–1000] meters distance) are depicted in Fig. 7 for eight hospitals. In each diagram, the best performance according to the RMSE values for train, validation, and test datasets is depicted.

The R-Values of training, validation and test dataset, also the RMSE of the implemented ANN within [500–1000] meters, are considered as described in Table 3.

Fig. 8 shows the relationships between the input and target in the second scenario. The stronger relations between the input parameters and target are related to the 'Hospital#1', 'Hospital#3' and 'Hospital#4'

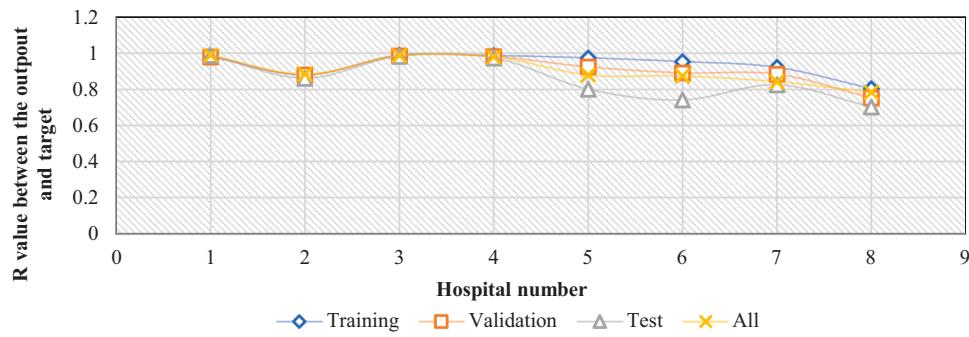


Fig. 8. The R-Values for training, validation and test dataset in the first within [500–1000] meters.

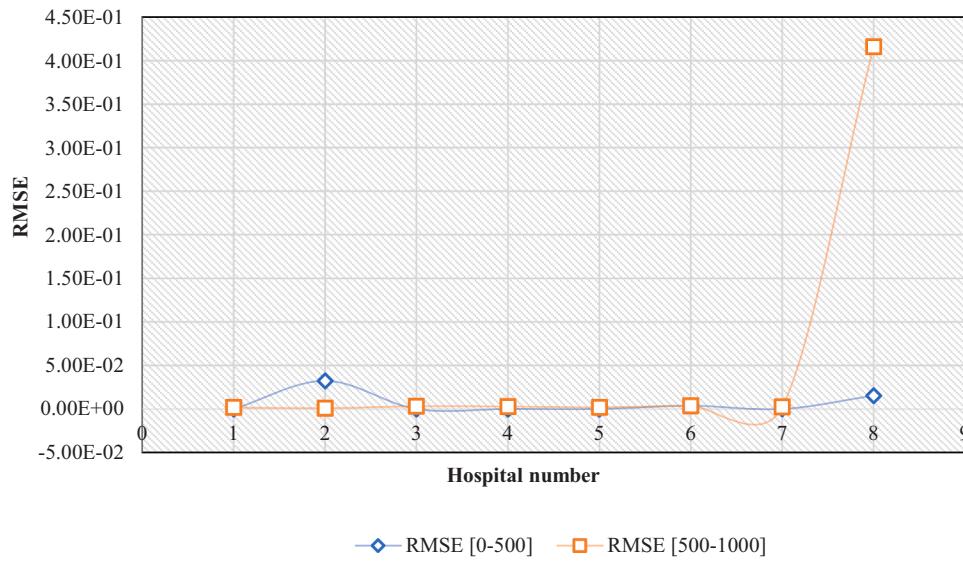


Fig. 9. The RMSE values for training, validation and test dataset in the first within [500–1000] meters.

hospitals and the weaker relations are associated with 'Hospital#5' and 'Hospital#6' hospitals. It means that by decreasing the distance from 'Hospital#1', 'Hospital#3', and 'Hospital #4', the role of non-residential land use and patients' transaction has been intensified which states the same rule as [0–500] service zones.

The results of the proposed method in the second scenario (within [500–1000] meters distance) are depicted in Fig. 9 for eight hospitals.

According to the trained MLP, the output risk map of COVID-19 is generated as depicted in Fig. 10.

4.3. Sensitivity analysis

The purpose of sensitivity analysis is to determine the impact of each of the input parameters on the output. Indeed, the sensitivity analysis indicates the influence of uncertainty sources (input and model) on the output uncertainty (Neysani Samany et al., 2009; Rezaei et al., 2020; Nadizadeh Shorabeh et al., 2020). In each stage, one of the factors is omitted, and the R-value has been computed as it has been depicted in Fig. 11. In other words, by omitting one factor, the designed MLP is iterated and the R-value shows the significance of that factor. The greater the quantity of decline, the more significant factor.

According to R values in Fig. 11, the most important factors are the location of patients' transactions ($R=0.6021$ and $R=0.7014$) and distance from non-residential land use ($R=0.6482$ and $R=0.7524$). It indicates that by increasing the number of patients' transactions and decreasing the distance between non-residential parcels and hospitals, the number of patients who are quarantined in the home will also be

increased. However, there are no significant relations between the number of patients in the hospitals and the distance of the street from the hospitals with the number of patients quarantined in the home.

5. Discussion

In this study, the focus was to determine the influence zones of the central hospital for COVID-19 treatment, and the association between the spatial risk factors and location of home patients have been assessed. The spatial risk factors include the location of patients' transactions, the distance of streets from hospitals, the distance of highways from hospitals, the distance of the non-residential land use from the hospitals, and the number of patients in the hospitals. The proposed approach has some specific characteristics that make it applicable in different provinces in Iran, also in other countries worldwide.

The first key feature of this study is related to defining two service areas for each hospital, which provides a comparative framework for assessing the effect of closeness to the hospitals on COVID-19 incidence. Furthermore, considering more service areas or using gradual distance seems beneficial. It means that by considering 10 different intervals from 100 to 5000 m and assessing the role of each factor, maybe some new results about the spatial pattern of disease infection are achieved. The second property of the proposed method is evaluating the effect of residential and non-residential land uses on COVID-19 outbreak that confirmed the role of non-residential land uses around the hospitals as they resulted in the transaction of the financial transaction of patients. In most developing countries, still physical payment with debit cards is

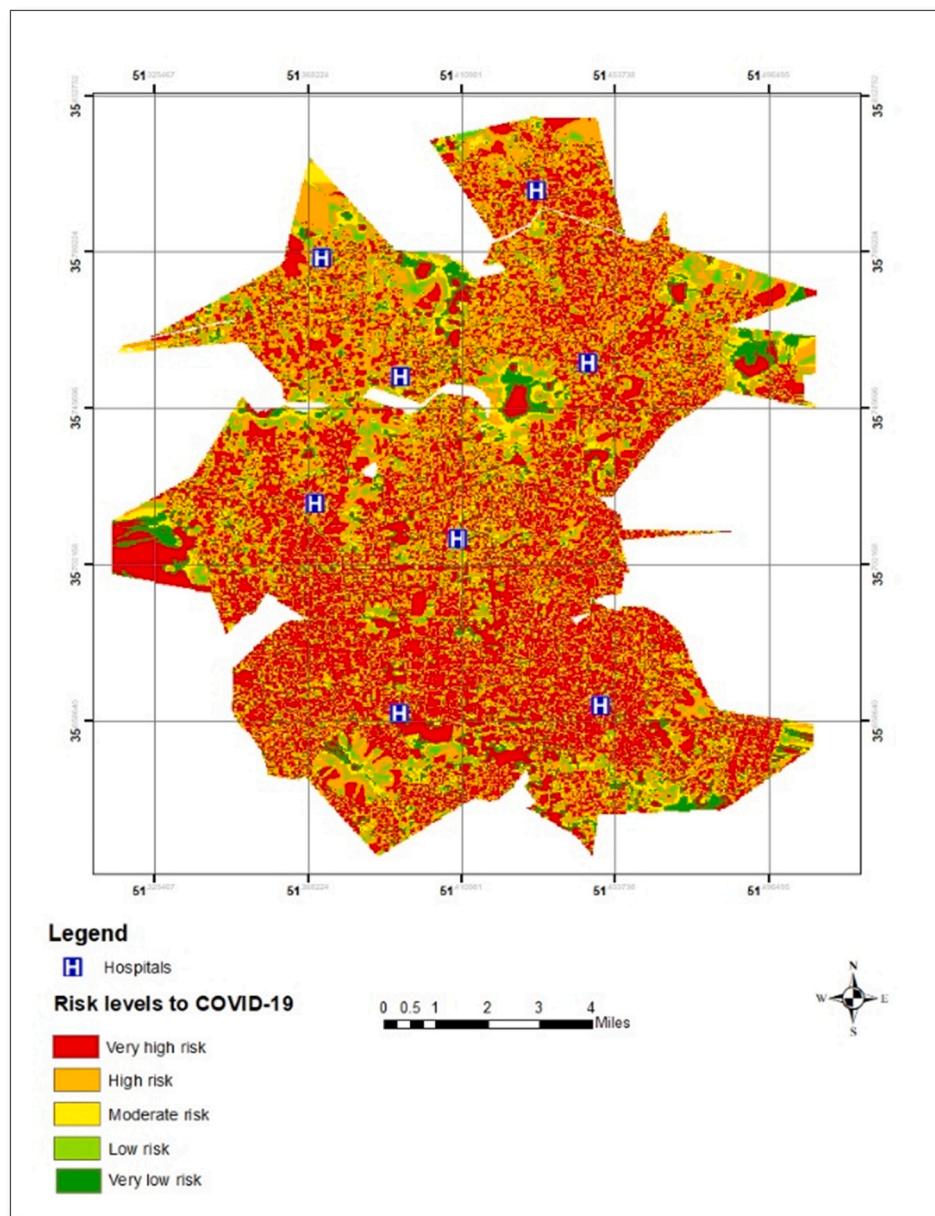


Fig. 10. The risk map of COVID-19.

used besides internet-based transactions. Therefore, the financial transactions of any patient one week before/after hospitalization to explore the influence of the hospital locations on the locomotion of people is obtained meaningful in COVID-19 propagation. More into details, the commercial land uses especially fast foods, supermarkets, and stationery stores, are the high-risk zones within the 1000-meter distance from hospitals. This knowledge may help the decision-makers to control the specific land uses directly and define different protocols for people referring to these locations. Currently, there is a particular district-level monitoring program in Tehran city, in which the authorities directly control the specific sites based on similar knowledge. In other words, the key findings of the present work comparing to the previously published literature is related to the determination of the influence zone surrounded by central hospitals, which is sensitive to land use. By decreasing the amount of non-residential land use, the quantity of COVID-19 patients is increased. This relationship is intensified by decreasing the distance to the hospital and deteriorated by staying away from the hospital.

The other promotion of this study is referred to the method of implementation, which used the MLP-ANN with sigmoid activation function as it can discover the nonlinear relationships between the risk factors and COVID-19 spatial statistics. At the same time, the sensitivity analysis specified the more decisive risk factors of COVID-19 incidence. Another advantage in comparison with other similar studies is network service areas instead of the raster data model. COVID-19 infection spread is a continuous concept and needs an associated data model. However, the style of current research in which people travel through a road to reach a specific location such as land use (e.g., fast food, supermarket), requires a network analysis. In addition, the proposed method can predict the geographical distribution of patients in the study area according to the designed input and trained ANN.

Though the compensations of the proposed method are evident, there are some shortcomings to this research that should be considered in future studies. The use of financial transactions has some challenges. One significant issue is the duration of stay of suspicious people in the financial transaction location. According to medical studies, the

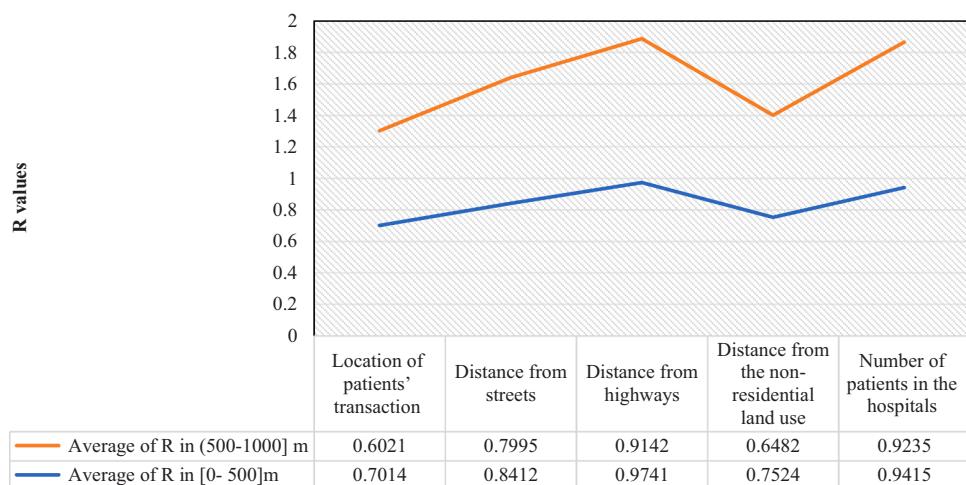


Fig. 11. The sensitivity analysis diagram of the proposed method in both scenario.

duration time of contact has a major effect on the infection spread (Ashcroft et al., 2021). The more transaction in a location, the higher the probability of space. Another challenge of using financial transactions during the hospitalization period is using the Bankcard by accompanying and not the patient. This might be correct in some cases, but in reality, the patient was with the family during the disease incubation period and all of them might be a disease vector. Moreover, a similar weight was given to all location/ land uses to simplify the calculation. However, as an example, a location in a more population-dense area can be at higher risk rather than a site in a less populated place.

Another dimension of limitation in this study is accessing diverse datasets. Although we have had a complete dataset from the headquarters in the study area for COVID-19, still a number of datasets can improve the results. An important dataset is the traffic dataset that can help to determine the dynamic population in the study area. Such datasets can be derived from cellphone tracking datasets but accessing a mobile dataset is almost impossible for the study area due to privacy reasons. More detailed information about the land use datasets can be counted as other important resources to enrich the research. In this study, the focus was the location of land uses. Yet, additional attributes help get better results, such as the number of employees in each workplace showing the spread density in hotspots. As a result, there are other parameters and effecting factors that can be selected as a weight for any of these models and were skipped due to the complexity of the prototype and data access limitations.

6. Conclusion and future directions

This paper aimed to find the most places at risk using the multi-layer perceptron artificial neural network technique in Tehran city. Eight hospitals with two service areas with 500 and 1000 m for each location, and five spatial factors have been considered (location of patients' transactions, distance of streets from hospitals, distance of highways from hospitals, distance of the non-residential land use form the hospitals and number of patients in the hospitals). The implementation results revealed a meaningful relation between the distance from the hospitals and patient's density in the study area. In addition, the sensitivity analysis consequences demonstrated that the number of patients' transactions and the distance of the non-residential land use from the hospitals are two dominant factors for virus propagation. However, the distance of streets from hospitals and the number of patients in the hospitals have the less influence on the COVID-19 outbreak.

The achieved consequences established the ability of the proposed technique to develop for big data as it clusters the vast data into several divisions in different distances. The consequences will support the urban

managers to initiate some new strategies to decrease the community incidence rate, such as: (1) according to the critical role of urban land use, some new restrictive rules for unnecessary land uses due to the closeness to hospitals should be determined. These rules should be intensified based on the number of patients in a hospital, and (2) the spots with a high density of financial transactions of COVID-19 patients should be recognized and restricted.

Finally, the financial transaction location can be used as a measure to track patients' behavior besides personal cellphone location monitoring records. More into details, instead of tracking people's mobile movement, individual payment location records may track suspicious people and monitor the patients during/ after quarantine. This is due to the sensitivity of mobile location records and more restriction to access such datasets. In addition, the land uses where the purchase is located can be investigated more in detail to define different scenarios such as lockdown and/or limitations for each commercial union.

CRediT authorship contribution statement

The authors contributed fully and equally to this work Najmeh Neysani Samany and Ara Toomanian specified the research design and implemented the methodology. Ali Maher and Khateresh Hanani investigated the sources, literature, and the applied policy. Ali Reza Zali analyzed the data and also provided an extensive discussion. All authors supported a detailed revision and inscribed the paper, read, and agreed with the final manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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