

AN INTELLIGENT FLOOD EVACUATION MODEL BASED ON DEEP LEARNING OF VARIOUS FLOOD SCENARIOS

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ABSTRACT

Efficient evacuation is quite important for decreasing the casualties in flood disasters. Flood hazard map is helpful for residents to recognize the necessity of evacuation but not sufficient for making the criteria to determine when to evacuate, where to go and which path to select dynamically according to the situations during flooding. Learning from experience is important to make evacuation action criteria such as critical water levels in nearby rivers to start evacuation, accumulated rainfall amount to start evacuation, pathway to the shelters according to the flooding condition and so on. Human lifespan, however, is not so long compared to the return period of extreme floods that people have not so many chances to experience flood events.

In order to overcome the lack of experience of residents and to make an effective evacuation framework, an Intelligent Flood Evacuation (IFE) model is developed in this study. Based on the evacuation simulations for various scales of flood events (simulated flood scenarios), the scoring function is derived to give how appropriate the time is to start evacuation. The time is judged most appropriate when the agent encounters flooding in the moving process to shelters if it starts evacuation just after this time. The function gives low scores if the agent starts after or much earlier than this timing. Then IFE model learns the timing to start evacuation with reference to the timing scoring and flood scenarios: it builds the artificial neural network to derive the appropriate timing to start evacuation based on the water levels of neighboring rivers, accumulated rainfall and so on. The IFE employs simple back propagation network and deep learning network according to the size of inputs and outputs. Besides the timing of evacuation, the possibility to learn the selection of the destination shelter and pathway will be also discussed.

Keywords: flood disasters, Intelligent Flood Evacuation (IFE), deep learning, scoring function

1. INTRODUCTION

In present, as a main type of natural hazards all over the world, floods cause a huge amount of damages and losses to economic and wild-effect human lifeline. Especially, Japan is suffered by floods more and more seriously. According to the historical records, there were several serious floods such as, the flood happened at Niigata Prefecture on July 13 and at Fukui Prefecture on July 18, separately (Takeuchi, 2006), which caused 16 people died and 20,655 buildings were damaged, including 70 buildings that were completely destroyed and 5,354 buildings that were partially destroyed. In 2009, Hyogo Prefecture suffered serious flooding due to the Typhoon No.9 (Sumi, 2010), where twenty-eight people were killed by the storm and 7.1 billion (US\$87.5 million) in damage occurred throughout the affected region. Furthermore, as a result of urbanization and industrialization, population and assets are concentrated in low-lying areas, the flooding risk has increased. Just in 2016, the flooding caused around 390 billion-yen losses in Japan. In 2018, the flooding happened at Kinugawa which was caused by typhoon No. 18 submerged 8991 houses (Statistics, 2019).

To deal with flooding, disaster prevention and policy-making are mainly determined to reduce losses in two aspects: on the one hand we should decrease the loss of social assets, on the other hand we should reduce loss of life. The former requires river course modification and storage of flood flow while the latter needs building-up of an efficient evacuation system. Moreover, because plenty of human factors bring about serious uncertainty in evacuation behavior, it is a significant challenge to make evacuation decisions scientifically and reasonably. Although flood hazard maps can assist decision makers and urban residents to understand high risk areas of urban flooding (Bathrellos et al., 2011; Lim et al., 2019), in the actual flooding evacuation, due to the individual

differences of residents such as flood risk recognition and knowledge of evacuation, it is quite difficult to provide more effective evacuation information. Namely, whether to start evacuate? When to evacuate? How to choose evacuation path? Which shelter should be selected? Therefore, it is important for residents in flood-prone areas to study how to behave in evacuation processes. Many researchers have studied this problem. For example, Ohkami et al. (2014) use a multi-agent model to simulate evacuees' behavior in flooding, based on the results water depth status and information transmission. Morita and Ohgushi (2013) develop a model which takes the awareness of disaster prevention as one of the parameters, and simulates the evacuation. Hanajima et al. (2011) developed a flood evacuation model that takes into account congestion on the path road. However, the above studies do not consider the psychological processes and different response by different evacuees, which has prompted the simulation results still having the gap between the result of simulation and the reality.

Since 1970s, some studies adopt action science, sociology and psychology methods to analyze and predict the evacuation behavior of urban residents (Sugima, 1983). Because flood hazards have various scales and associated danger levels, and so residents' evacuation behaviors cannot be repeated, it is impossible to restore and simulate flooding in the laboratory environment. Kugihara et al (1980; 1982) promote the use of action science methods and the computer technology to simulate the human action process when natural hazards occurred. After the 1980s, with the development of computer technology, it is possible to simulate complex evacuation behaviors. Residents behavior in the flooding under various evacuation scenarios can be analyzed through simulation studies. Based on the above theory, Hori (2008) proposed a flood micro evacuation model including flooding psychological factors. Alaeddine et al. (2015) proposed a spatiotemporal optimization model which can provide better rescue to property and evacuation process for relevant technical departments. San Jose and California as object of study, Yu et al. (2014) established a traffic network model and evaluated the efficiency of evacuation. Liu et al. (2008) developed a multi-agent simulation (MAS) system according to the flood situation in the mayor of Kobe.

Previous studies were mainly focusing on the moving process, but the human behaviors before starting evacuation were less involved. Because of the uncertainty of human behavior and also the uncertainty of natural hazards, it is still difficult to predict accurately the evacuation behaviors of people. In order to simulate the people's behavior related to flood evacuation, it is necessary to know how the people interpret the associated information and make decision. With the development and improvement of artificial intelligence, extensive simulations can be completed by deep learning, which brings new methods for human behavior research. For example, in accordance with sensor information and SNS information, a system which gives instructions of evacuation routes and shelters in real time was developed (MIC, 2014).

In order to provide an effective evacuation strategy, this paper develops an intelligent flood evacuation (IFE) model based on deep learning. This model can better decide whether to evacuate or not and when to evacuate. IFE model uses deep learning to calculate the most appropriate evacuation time based on the information of rainfall, elevation, water depth, shelter location, and shelter personnel location. As the model may consider local natural conditions and behavior factors fully, it could give better accuracy and portability

2. DATA AND METHODOLOGY

This paper advances a model (IFE) based on deep learning. Deep learning is a neural network which simulates analysis and learning process in human brain. The concept of deep learning comes from the neural network whose structure includes input layer, hidden layer and output layer. The difference between deep learning and neural network is that deep learning emphasizes the complexity of model structure. Usually, there are 5, 6 or even 10 hidden layers in deep learning. Its characteristic is that the features (weights and parameters) of each layer are not set by man-made, but they are learned from the data. As input data, rainfall, location coordinates and elevation of evacuation points (home positions of evacuees), location coordinates and of shelters, and road length are included in the IFE model, and the most appropriate evacuation time as output data. In this paper, the most appropriate evacuation time is obtained by using the point function. The point function is as in Eq. (1).

$$S(t_s) = \min\left(\frac{T_0}{T(t_s)}, \frac{t_s}{t_c}\right) \quad (1)$$

where,

$S(t_s)$ is evaluation score at time t_s , T_0 is the time of evacuation (sec) from the initial position to the shelter in normal time (when there is no flooding). $T(t_s)$ is the time required for actual evacuation (sec) to the shelter. t_c is the latest evacuation timing. t_s is the most appropriate evacuation time. If the evacuation has failed (when $t_s > t_c$), it is assumed that $T(t_s) = \infty$ and the score $S(t_s) = 0$. Walking speed of evacuators is as in Eq. (2)

$$v_t = 1.1 \times \left(1 - \frac{d_t}{0.7}\right) \quad (2)$$

where,

v_t is the walking speed at time t (m / sec), d_t is the inundation at time t . According to the formula, when the depth of water exceeds 0.7 m, the speed becomes 0 (m / sec), it means that it is impossible to walk, and the evacuation fails at that time. From this formula, it can also be found that the walking speed is affected by the depth of water. Therefore, RRI model (Sayama and Iwami, 2016) is used to simulate the real-time depth of water in this paper. According to the depth of water and the walking speed, the shortest time to get the shelter be calculated. In this paper, path of the shortest evacuation time is chosen as the route to the shelter. The DEM data used are the 10m resolution provided by the Ministry of Land, Infrastructure, Transport and Tourism. Meteorological stations data from the Japan Meteorological Agency are used for hourly rainfall data for simulation. RRI computes water depth data every minute. The road data are obtained from the numerical map 2500 (CD-ROM) issued by the National Land Research Institute.

In this study, firstly, we use the score function to determine the most appropriate evacuation time, and show the distribution results with the spatial visualization technology, and then verify the rationality of the score function. Two hundreds sample points were randomly selected as the evacuation point. At the same time, based on the score function, the most appropriate evacuation time is calculated. Secondly, 200 samples are used as input data to train the deep network model. The study area is Mabi-cho (Fig.1), Kurashiki, Okayama, Japan. Kurashiki city area is located in the central southern part of Okayama prefecture, and Takahashi River flows from the north to the south in the western part of the city and flows into the Seto Inland Sea. Most of the plains are occupied by polder and alluvial plains. Mabi-cho is the northern part of the Kurashiki area. The Oda River, a tributary of the Takahashi River, flows east through the central part of Mabi-cho, and joins the Takahashi River at the southeast end of the district. In Mabi-cho, the embankment of Oda River and Takama River are broken down and flooded a wide area.

3. RESULT AND DISCUSSTION

3.1 Scoring function

In this paper, the result of scoring function is used as the training data for deep learning. Therefore, it is necessary to evaluate the reasonableness of the result of score function. In the score function, the output values are between 0 and 1, it close to 0, indicating that evacuation is not required (or at home), and close to 1, indicating that evacuation is required.

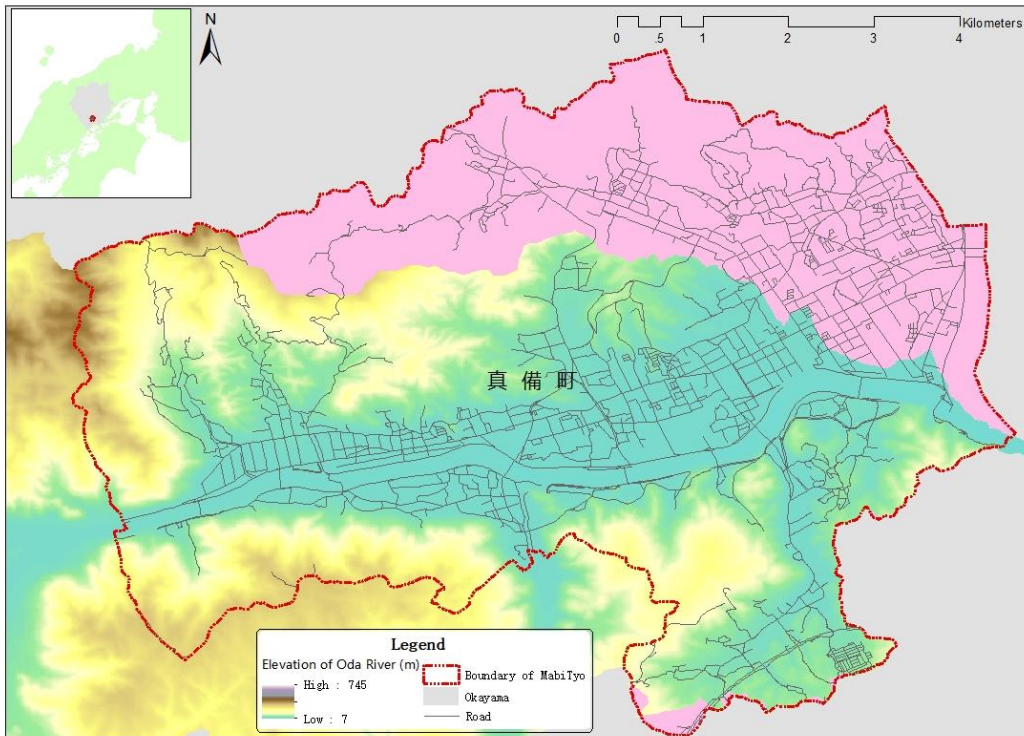


Figure 1. The study area

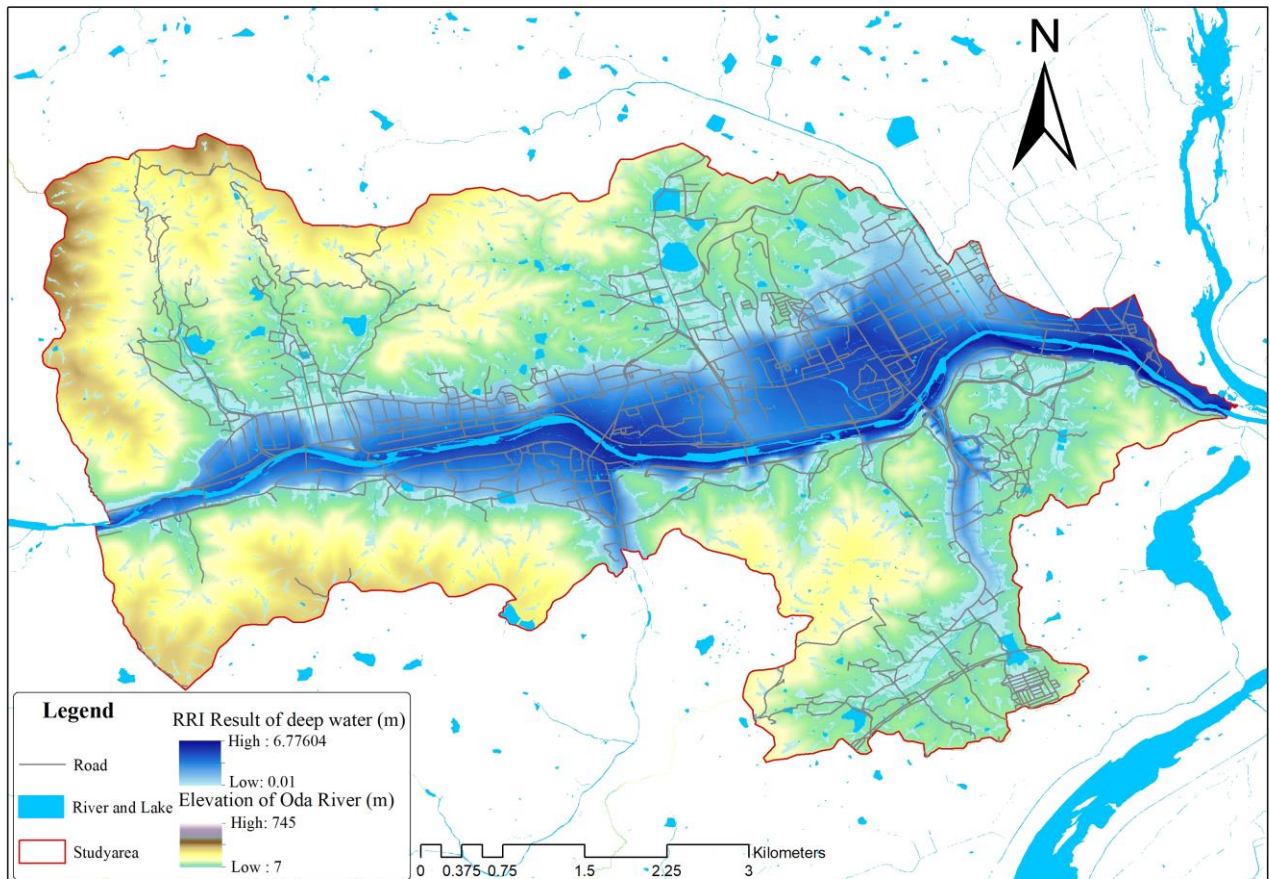


Figure 2. The result of RRI model

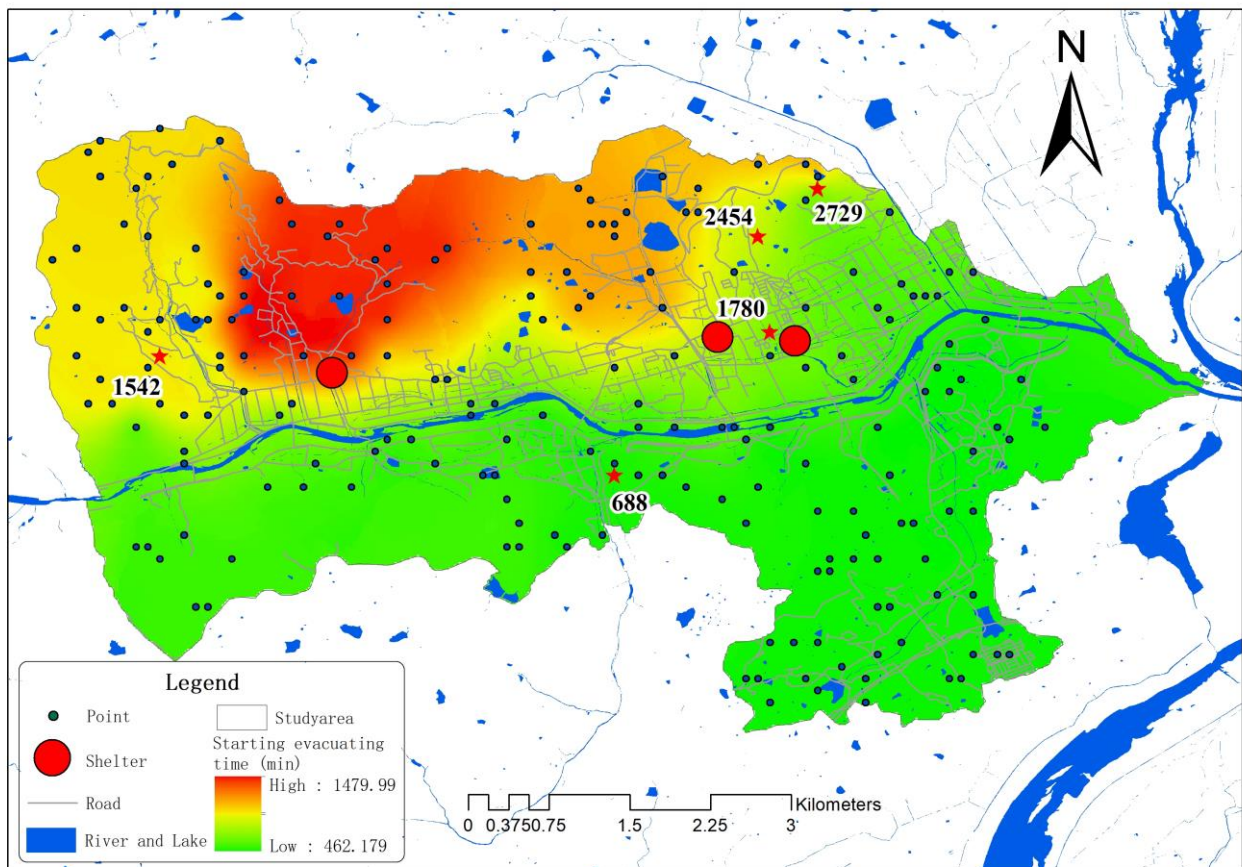


Figure 3. The appropriate evacuation time

A Rainfall-Runoff-Inundation(RRI) Model was applied to simulate the inundation area, the result change with time. For example, Figure 2 shows the result of RRI model at 24:00 July 6. In Figure2, the dark blue area is covered by flooding. According to the DEM data, it can be seen that the low-lying places on both sides of the river are the first places to be submerged by flooding. Combined with Figure 3, we can also understand that

these places are also the first places to evacuate. Figure 3 shows the spatial distribution of the most appropriate evacuation time. From Figure 3 it can be seen that the latest possible evacuation time is 1479 minutes, and the earliest appropriate evacuation time is 462 minutes among the 200 randomly selected evacuation points. As a group, the evacuation time in the north is later than the evacuation time in the south. There may be two reasons for this result. 1. Figure 3 shows that the three shelters in the study area are all distributed in the north, and the density of the road network in the north is higher than that in the south significantly, that is to say, it is easier to reach the shelter in the north, but it is more difficult to reach the shelter in the south. Therefore, for the residents in the south, it is necessary to prepare for evacuation earlier than residents in the north. Combined with the DEM data of study area, it is concurrent with the distribution of the evacuation start time generally. Beginning evacuation time is late in areas with high elevation and dense road network (such as northwest area), while it is early in low areas with sparse road network (such as southeast area). It can also be shown from the figure that the south is closer to the Takahashi River (one of the three main drainage rivers in Okayama Prefecture). When flood is coming, people in the area closer to the river (such as the southeast area) should evacuate as soon as possible. Based on the above two points, we think that the result of score function is reasonable and appropriate.

Figure 4 shows the scoring function of five randomly selected evacuees (the red star in Fig3). When the time exceeds the latest evacuation times t_c , the score will drop rapidly. The time with the highest score is the most appropriate evacuation start time. As shown in Figure 4, the most appropriate evacuation time for ID688 is the 475 minutes. Similarly, the most appropriate evacuation time for each evacuation point can be obtained. But the computation of the scoring function takes a lot of time. Only 200 points in this paper need to be calculated for one week.

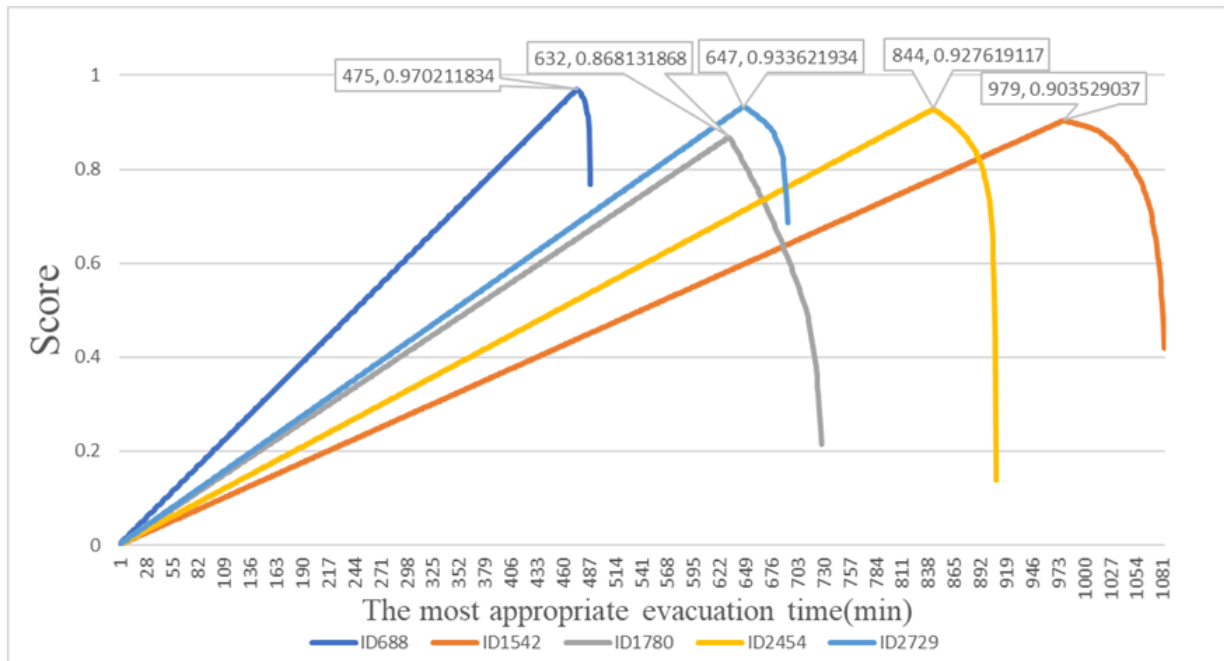


Figure 4. Scoring function

3.2 Deep learning

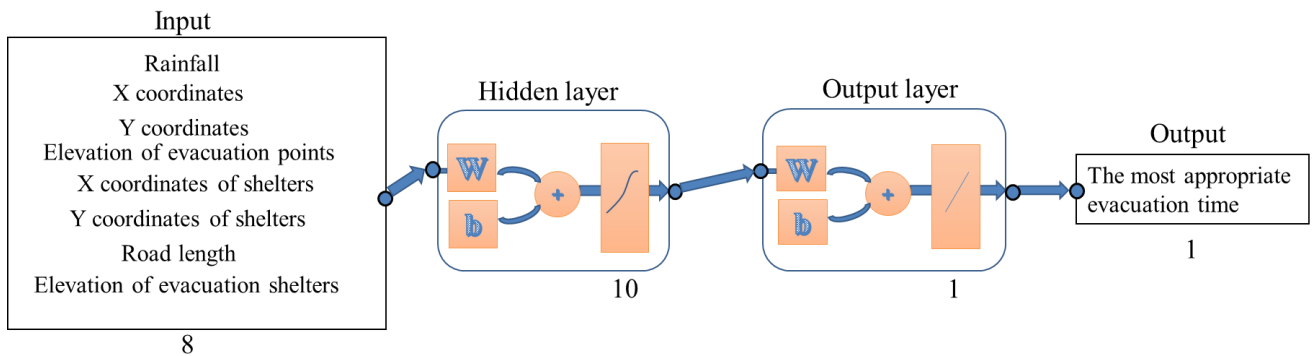


Figure 5. The structure of the network

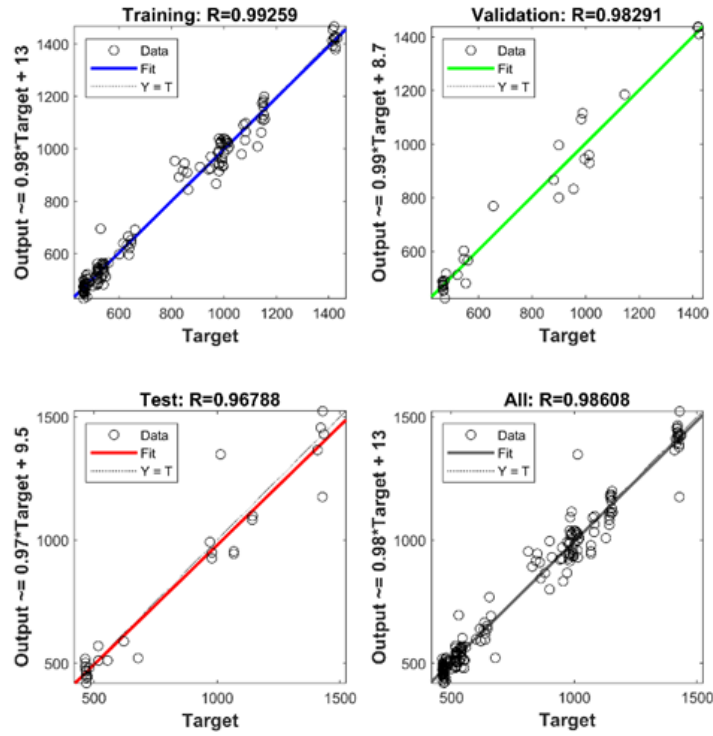


Figure 6. The results of deep learning

In this paper, 200 sets of data are used to build the deep learning model. Figure 5 shows that the model has 8 sets of input data, including rainfall, location coordinates and DEM data of evacuation points, location coordinates and DEM of shelter, and road length. Output data is appropriate evacuation time. The number of hidden neurons is set to 10. The input data and output data will be randomly divided into three sets, 1, 70% will be used for training. 2, 15% will be used to validate that the network is generalizing and to stop training before overfitting. 3. The last 15% will be used as a completely independent test of network generalization. This paper uses matlab2019 software to build the deep learning model, the training algorithm is Levenberg-Marquardt (trainlm) algorithm, and set the algorithm's epochs = 40. The result is shown in Figure 6. Figure 6 regression plots display the network outputs with respect to targets for training, validation, and test sets. The target means the evacuation start time derived from the value of equation (1). According to the characteristics of the regression plots, the output data is equal to the target data, where the data should fall along the 45 degree line. The closer it is to the target data, the higher the accuracy of the result. It is shown from figure 5 that the fit is reasonably good for all data sets, with R values 0.99, 0.98 and 0.96 respectively

4. CONCLUSIONS

This paper attempts to build an evacuation model based on the deep learning method, in order to determine the best start time of evacuation when flood occurs. Through the result analysis. it can be found that the results of training set, validation set and test set are close to the target data, and the fitting results are good, with high R value. Based on the above results, the following conclusions can be drawn.1. The score function of this study can be used to calculate the most appropriate evacuation time, the calculation cost is high and time consuming.2, Deep learning methods can be applied to the calculation of the most appropriate evacuation time. With higher accuracy, less time consumption and high efficiency.3. There is no specificity in the data of this study, which shows that the training model has a satisfied probability in theory. but considering that the flood evacuation behavior belongs to the behavior with geographical characteristics, which has a strong uncertainty. the strength of the probability remains to be discussed. In a word. this study proves the applicability and feasibility that flood evacuation time by deep learning method from the method and theory. which has strong social and scientific significance. It can provide prior knowledge and theoretical support for related research.

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