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ORIGINAL PAPER

DEEP LEARNING FOR THE PREDICTION OF TRANS-BORDER LOGISTICS OF PATIENTS TO MEDICAL CENTERS

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ABSTRACT. Background: Covid 19 impacted many healthcare logistics systems. An enormous number of people suffer from the effect of a pandemic, infection diseases can spread rapidly within and between countries. People from the Kingdom of Cambodia and the Lao People's Democratic Republic are most likely to cross-border into Thailand for diagnosis and special treatment. In this situation, international referral cannot predict the volume of patients and their destination. Therefore, the aim of the research is to use deep learning to construct a model that predicts the travel demand of patients at the border.

Methods: Based on previous emergency medical services, the prediction demand used the gravity model or the regression model. The novelty element in this research paper uses the neural network technique. In this study, a two-stage survey is used to collect data. The first phase interviews experts from the strategic group level of The Public Health Office. The second phase examines the patient's behavior regarding route selection using a survey. The methodology uses deep learning training using the Sigmoid function and Identity function. The statistics of precision include the average percent relative error (APRE), the root mean square error (RMSE), the standard deviation (SD), and the correlation coefficient (R).

Results: Deep learning is suitable for complex problems as a network. The model allows the different data sets to forecast the demand for the cross-border patient for each hospital. Equations are applied to forecast demand, in which the different hospitals require a total of 58,000 patients per year to be diagnosed by the different hospitals. The predictor performs better than the RBF and regression model.

Conclusions: The novelty element of this research uses the deep learning technique as an efficient nonlinear model; moreover, it is suitable for dynamic prediction. The main advantage is to apply this model to predict the number of patients, which is the key to determining the supply chain of treatment; additionally, the ability to formulate guidelines with healthcare logistics effectively in the future.

Keywords: International Referral, Healthcare Logistics, Deep learning, Logistics model, Covid 19

INTRODUCTION

The Covid 19 has affected many healthcare logistics systems. An enormous number of people suffer from the effect of a pandemic. Infectious diseases can spread within and between countries. The government has policies to control the virus, such as lockdowns, social distancing, severely restricting travel, and many other activities globally. During the pandemic, travel behavior changed in four respects: demand for travel, the purpose for which travel was carried out, modes of travel, and the convenience of travel [Yang et al. 2021]. People from the Kingdom of Cambodia and the Lao People's Democratic Republic are most likely to cross the border into Thailand for diagnosis and special treatment. In this situation, there is unpredictability in the number of patients and

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their destinations. This outbreak has been significantly consequential and controlling the number of trans-border movements is of the utmost importance. Therefore, international health organizations are invited to assist in terms of management, sourcing, procuring, and distribution of aid in any type of humanitarian crisis [Alam et al. 2021]. Coordination of their efforts induces components of clinical treatment, especially the demand of a patient to cross the border, seeking better healthcare facilities, which causes referral back difficulties and challenges.

Logistics flow helps meet the growing demands of the public hospital network in the supply and distribution of products. Properly implemented logistics processes in the public hospital network can directly affect the quality of health services, reduce the risk of treatment, and increase satisfaction of health prosumers [Majchrzak & Bober 2016]. Healthcare supply chain management differs from other industries. It is a complex network consisting of many different parties at various stages of the value chain [Kritchanchai et al. 2019]. A significant number of logistical challenges have also been noted and are one of the six interrelated components of a healthcare system defined by WHO. These logistics and supply chain management issues include the relationship between access to equipment, medicines, and supplies [Babatunde 2020]. Additionally, the decision-making process presents strategies to improve efficiency along the healthcare value chain. [Sousa et al. 2019]. The management of medicines must be related to the appropriate level of the patient. Ensuring patient safety during hospitalization, as well as outside the hospital [Granillo 2020]. These data are crucial for the provision of proper medicinal products to the patient for whom they were prescribed. Information can pose a serious threat to the health and lives of patients [Gawrońska and Nowak 2017].

The northeastern region of Thailand borders two neighboring countries, the Kingdom of Cambodia and the Lao People's Democratic Republic (Lao PDR). The borders are located in the Provinces of Ubon Ratchathani, Sisaket and Surin. In terms of public health, Ubon Ratchathani Province accommodates a high-capacity level of the public health management system. It is a prominent health center and since it is a frontier city, it attracts a large number of patients.

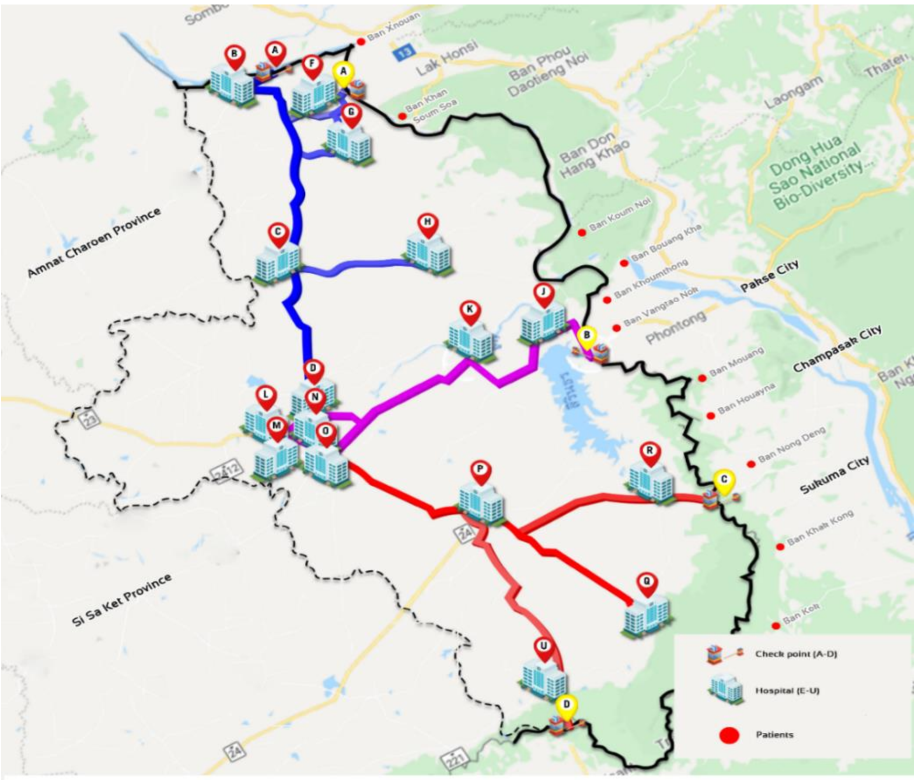

Fig.1. The health center and a frontier city

According to statistics, in 2018, more than 58,000 patients crossed the border for treatment in Thailand. Most of them are from the Lao People's Democratic Republic. They passed through the Chong Mek checkpoint to receive examination services (Figure 1). On average, approximately 60% of patients were treated at frontier hospitals, while approximately 40% were referred to the secondary hospital, due to the increasing trend of transboundary patient access. The Public Health Office must collect information to monitor, prevent, and control of disease and border disasters. Furthermore, the development of the cross-border referral system is similar to medical logistics. The health control officer or the personnel working in referral centers in cross-border locations should know the process of referral, repatriation, and consultation, including hospital hubs and local health service areas. Their priority is to select a hospital depending on the symptoms of the disease, service, and other information provided by the patient. They must show ingenuity in maintaining quality standards and putting the potential on full display. The covid 19 outbreak has been significant to the hospital. The hospital should improve the referral system, forecasting the travel demand of patients from international referral. Volume should be considered before preparing the service [Yang et al. 2019]. In terms of cross-border, the hospital must plan to manage resources and potential risks. Emergency rescuers should be prepared for both regular and disaster situations [Setzler 2007]. One of the performance indicators following hospital policy is that the operations of communication in the referral center are more convenient, fast and more efficient [Wajid and Unnikrishnan 2020]. Thailand, Laos, and Cambodia found different patterns of patients crossing the border; Laotians usually pass by personal vehicles or public vehicles, Cambodians like to pass by taxis or ambulances. Covid -19 is a major game changer in terms of travel patterns. Before the crisis, patients could travel by all modes of transport and directly from the health control centers to the hospitals. After the pandemic, the patient cannot cross the border, particularly in emergency cases characterized by their inherent uncertainty and the spatial distribution of the incoming demands. Delivery and distribution determine the criteria for using different channels. The heads of health control centers should monitor the volume of equipment as well as the inventory of medical material. Health care operations conducted in a warehouse are generally divided into reception, storage, order picking, sorting, and shipping. Treatment must consider reducing the gap between revenue and cost. In the Big Data era, analytical techniques such as data mining and deep learning are being used in inventory management to provide accurate and up-to-date information to make better decisions.

In recent years, the hospital has had a significant role in saving lives. One of the most widely used techniques for analyzing the actual problem is using the neural network model to predict the patient and the routing. In the future, this approach should be integrated with other approaches to better define the routing between hospitals and support a solution to the routing management problem [Kergosien et al. 2013]. In most research studies, the genetic process is preferred because it has better results than other methods [Inanç and Şenaras 2020]. Therefore, we propose a method to route vaccine distribution to hospitals. Sub-district health nurses using the bee colony method to determine the most optimal value for the fastest transit times. Von et al. [2019], suggests in-hospital management for referrals using mathematical equations under the conditions of workload, delivery time, patient symptoms, start and end time as mentioned above, in end-to-end patient care involved in all transportation, when the patient reaches the doctor, equipment and personnel must be sufficient and ready to accommodate the patient promptly. According to Lapierre and Ruiz [2007] gave a guideline for managing medical supply using a balanced schedules model and testing in real hospitals and the results showed that efficiency was improved. A review of the literature from 1990 to 2018 found that the model was divided into the supply chain model and the logistics model [Khanra et al. 2020]. The ability to discover new medical knowledge is constrained by prior knowledge that has high-dimensional time series data. They develop improved and more comprehensive approaches to studying interactions and correlations among multimodal clinical time series data [Belle, Ashwin 2015].

In this logistic model, emergency medical services include quantitative analysis, such as finding the lowest referral cost. Finding an emergency medical stop Vaccine management operating table of the emergency medical unit and qualitative analysis such as disaster planning. [Tlili et al. 2018]. The benchmark for emergency medicine efficacy in cross-border referral logistics is the starting point for having a service visitor or a customer. Medical expertise plays a role in deciding which hospital to choose. Analytic goals of medicine are prediction, modeling, and classification [Raghupathi and Raghupathi 2014]. Classification techniques include logistic regression, naive Bayesian methods, decision trees, neural networks, Bayesian networks, and support vector machines [Lee and Yoon 2017]. Therefore, the number of service users is the key to determining the support plan and the ability to formulate guidelines or methods to deal with problems effectively and performance indicators following the hospital policy province, health service area and ministry level. Based on the issues mentioned earlier, this research aims to develop a model to analyze the volume of border patients while also collecting spatial data location of hospitals near the border. The multilayer artificial neural network is one of deep learning, whose model differs from other mathematical methods and features due to the flexibility to obtain results in a nonlinear way. Ability to simulate datasets, training, learning, and improving weights close to results. The deep learning ability to adjust neural networks to learn a new environment and its forecasting capability can predict the amount of travel demand for patients across borders at each particular border. This study contributes to derived locations of the inter-reference that can handle all demand. The model allows the different data sets to predict the demand for the cross-border patient for each hospital that encompasses strategic and tactical planning decisions.

METHODOLOGY

This is a survey to study the demand for cross-border patients who wish to be admitted to network hospitals. With the outbreak of the covid 19 virus, these hospitals face huge risks in their day-to-day operations; moreover, take precautions against the virus. If border control and the hospitals use the deep learning model to predict the number of cross-border patients, they will be better prepared for planning and management.

In this study, a two-stage survey is conducted to collect data. The initial phase collects data on policy and planning. Interviews are conducted with 90 experts at the strategic group level of The Public Health Office, Commander of the Border Disease Control Division, The Hospital Director and the accident and emergency supervisor in Thailand's three northeastern frontier provinces. Next, observing patient travel behavior, route selection, vehicle type, cost by specifying a single starting point to the central hospital and finally choosing the best possible path. The areas outlined in this research were the Provincial Public Health Office, the hospitals near the border of the Lao People's Democratic Republic, a total of 28 hospitals. On the Cambodian border, a total of 28 hospitals were identified.

Study Area; Primary Hospital and Secondary Hospital.

The research team conducted this study with a list of hospitals in frontier cities; Ubon Ratchathani Province, Sisaket Province, Surin Province. Locations, as shown in Table 1. It consists of 1 permanent border crossing point, a total of 7 local, as shown in Table 2

Table 1. Researched Hospitals

No.	Name of Hospital	Frontier city	Nearby Country
1	Khemarat Hospital	Ubon Ratchathani	Laos
2	Natal Hospital	Ubon Ratchathani	Laos
3	Pho sai Hospital	Ubon Ratchathani	Laos
4	Sirinthorn Hospital	Ubon Ratchathani	Laos
5	Khong Chiam Hospital	Ubon Ratchathani	Laos
6	Buntharik Hospital	Ubon Ratchathani	Laos
7	Na Chaluay Hospital	Ubon Ratchathani	Laos
8	Nam Yuen Hospital	Ubon Ratchathani	Cambodia
9	Nam Khun Hospital	Ubon Ratchathani	Cambodia
10	Sapphasitthiprasong	Ubon Ratchathani	Medical hub
11	Kantharalak Hospital	Ubon Ratchathani	Cambodia
12	Khun Han Hospital	Ubon Ratchathani	Cambodia
13	Phu Sing Hospital	Si Sa Ket	Cambodia
14	Sisaket Hospital	Si Sa Ket	Medical hub
15	Buached Hospital	Surin	Cambodia
16	Sangkha Hospital	Surin	Cambodia
17	Kap Choeng Hospital	Surin	Cambodia
18	Surin Hospital	Surin	Cambodia

Table 2. Border Checkpoints Studied

No.	Border Checkpoints	Provinces	Border Crossing Areas
1	Trade relief point	Khemmarat district	Ban Tha Prachum, Lao PDR
2	Chong Ta U	Buntharik district	Champasak, Lao PDR
3	Trade relief point	Nam Yuen District	Phra Viharn, Cambodia
4	Permanent border	Natal District	Salavan Province, Lao PDR
5	Chong Mek	Sirindhorn District	Champasak,Lao PDR
6	Chong Sa Ngam	Phu Sing District	Udonmeechai, Cambodia
7	Chong Chom	Kap Choeng District	Udonmeechai, Cambodia

Deep learning for demand prediction

The decision system is an artificial intelligence-based problem solving tool designed to improve logistics in hospitals. The aim is to eliminate inconsistencies in hospital flows. [Dossou et al. 2021]. A Multilayer Perceptron Neural Network is a Neural Network of the feedforward type. This research is a forecasting model, deep learning techniques are adopted for diagnosing, classifying, and predicting [Ghaderzadeh and Asadi 2021]. Public datasets have training and testing datasets that are used to train and validate methods. Deep learning is suitable for complex problems as a network. The definition of an ideal model for healthcare logistics, case-based reasoning and generalization reasoning could be used [Galetsi and Katsaliaki 2020]. The MPL is an extremely powerful tool for solving various types of partial differential equations. The model includes three sets of layers: input layer, hidden layer(s) and output layer. The most commonly used multilayered network is backpropagation; MLP is trained based on that algorithm that follows a learning procedure based on error correction neurons that compute the data and undergo iterations [Arcos et al.,2018]. Then, the output layer predicts the output. The formulation of MLP output is as follows Eqs. (1):

$$a = f\left(X_{ij} + W_{ijk} + b\right) \qquad (1)$$

where a is the output, x is the input, w is the weight i to j hidden k, b is Biased. The research used multilayer perceptron algorithms to develop the MLP models, 70% (data sets) of the original data sets were randomly selected as the training set, and the remaining 20% (datasets) were used as the test set [Celikoglu 2011]. The random size is 1,000 pieces of data which never-before-learned. Radial basis functions are simple for implementing and solving high-dimensional partial (or ordinary) differential equations in complex domains. In most cases, such as the multiquadrics (MQ), inverse multiquadrics (IMQ) and Gaussian (GA), the accuracy of the RBF solution [Ilati and Dehghan 2015]

The MPL defines three data layers in this network: the input layer, two hidden layers, the output layer, and the data processing by the transfer function. The data are close to the real value used in batch training, Gradient Descent optimization. Covariates are used to control the differential influences between variables and their distribution, such as soft max function, Sigmoid function, Hyperbolic Tangent, Gaussian function [Ha et al. 2015]. For this research, the Sigmoid function is used for the hidden layer, and Identity is used for the hidden layer (Figure 2)

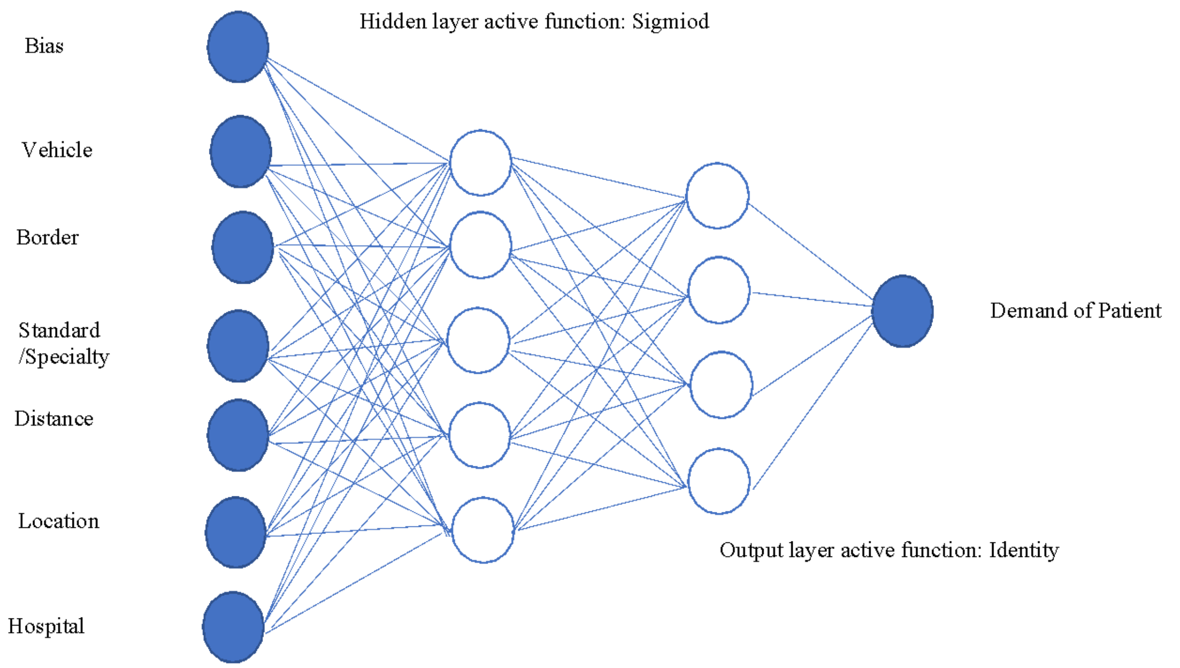

Fig.2. Multilayer Perceptron variables and active function.

Sigmoid functions are also useful for many machine learning applications in deep learning; they can be used as an activation function in an artificial neural network. The sigmoid function is defined as follows:

$$Sigmoid\ functions = \frac{e^x}{e^x+1} \quad (2)$$

An identity function is a function where each element in a set is multiplied and where the output is the same as the input. The identity function is defined as follows:

$$Identity\ function\ g(x) = x, for\ each\ x \in R, R\ is\ the\ real\ data \quad (3)$$

Determining the influential factors is considered one of the most fundamental steps in determining the international referral system. Therefore, the criteria used in the present research were adopted based on previous studies and the Ministry of Health requirements. The process resulted in 100 data. A set of variables, including information criteria of models, estimation information, formal statistical tests on residuals, and forecasting results. The parameter list is as follows;

$Demand_{patient}$: The volume of patients, Laotian or Cambodian, crossing the border from *i* to hospital *j*

Veh: This term refers to a type of vehicle for crossing point; ambulance or other.

Bor: The frontier border near Thailand.

Std: Standard hospital or specialist hospital.

Dis: This term refers to the distance from the origin *i* to the destination *hospital j*.

Loc: The location of the hospital to which the patient is willing to be referred.

Hos: This term refers to binary 1 hospital or binary 0 health center.

The accuracy of the validation proposed for this research instrument was carried out to verify the validity and accuracy of basic research instrument quality checks. The instrument was tested for accuracy, confidence, consensus or multiple choice of statements, questions, judging criteria, or evaluation, and the difficulty with different methods of operation by using statistical criteria such as analysis of the inner confidence of Pearson's Correlation Coefficient. The model validation of the goodness of fit compares the model's training and test traffic results with the actual survey values and explains the correctness. In this part of the paper, a comparative study was carried out to compare the performance and accuracy of the proposed MLP, RBF and R in order to a more comprehensive and better comparison, both statistical error analysis and graphical analysis approaches such as cross-plots and error distribution plots were used as criteria to evaluate the models. The essential statistical parameters used in this study include the average percent relative error (APRE), root mean square error (RMSE), standard deviation error mean, and correlation coefficient (R).

ANALYSIS AND RESULTS

Demand Forecasting: With regards to forecasting, this is conducted based on this model, the demand is a different original and different destination. The patient has a goal to travel to get diagnosed with professionals.

An effective model is forecasting demand from multi-location with appropriate location and standard hospital. The result of the nonlinear model was considered in Eqs. (4)

$$Demand_{\ patient} = \sum_{i:j} Veh\, w_j + \sum_{i:j} Bor\, w_j \sum_{i:j} Std\, w_j + \sum_{i:j} Dis\, w_j \sum_{i:j} Loc\, w_j + \sum_{i:j} hos\, w_j + bias \qquad (4)$$

Weight output layer, w_i=(0.453, 4.986,-1.182, -0.944), *bias*=-0.054

Forecasting performance comparison

The MLP network structure has two hidden layers as displayed and six variables. Variables include distance, a type of vehicle, border near Thailand, hospital or health control, stand of the hospital stand, or specialist hospital and location. In the summary of the MPL model, there were fewer errors in training than in testing and holding samples. Average percentage relative error (APRE) 4.031, root mean square error (RMSE) 269.8, standard deviation error means 460.4, and correlation coefficient (R) 0.877

For the RBF, the average percent relative error (APRE) 8.196, root mean square error (RMSE) 431.2, standard deviation error means 534.2, and correlation coefficient (R) 0.888

For Regression analysis coefficients of all six predictors as given correlation coefficient (R) 0.859

Table 3 Statistical parameters of the developed MLP

Statistical parameter	Value		
	MLP	RBF	R
The average percent relative error	4.031	8.196	
Root mean square error	269.8	431.2	431.2
Std. Error mean	460.4	534.2	512.1
R	0.877	0.888	0.859

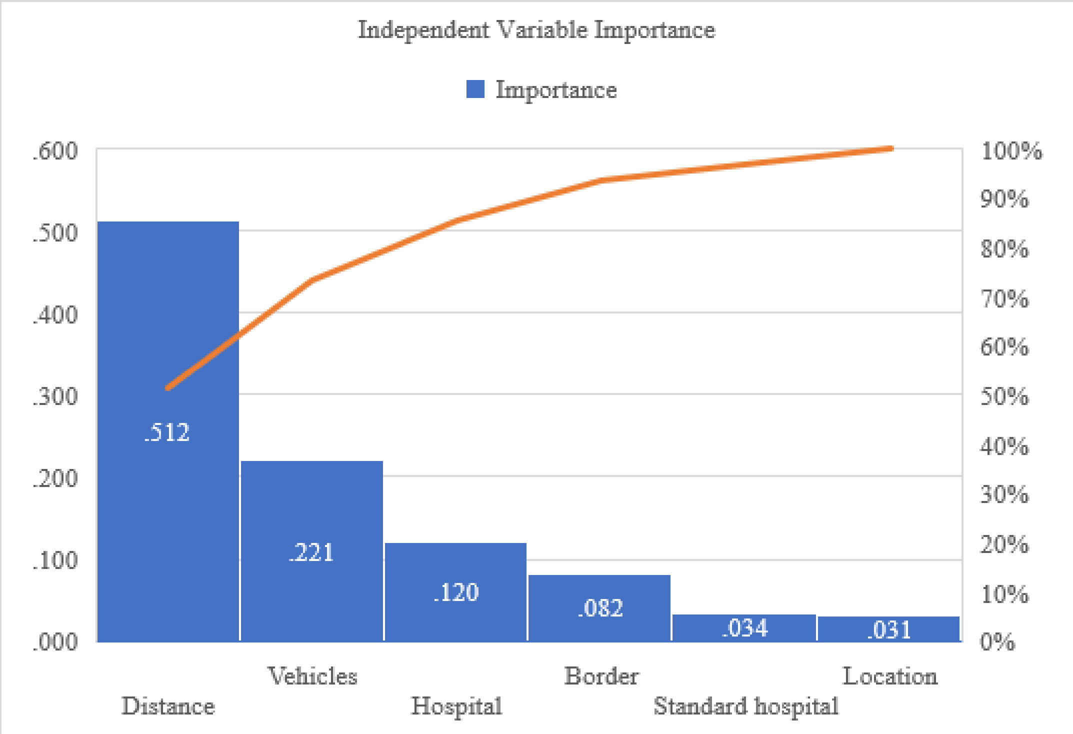

Fig. 3. Multilayer Perceptron variables and active function.

The result shows that MLP performs better than ordinary regression in terms of the amount of variation in the dependent variable explained by the model. The prediction is due to the fact that the MLP model can be used in the future with high consistency. Finally, the most important model is the distance 0.512, vehicle 0.221, hospitals 0.120, border 0.082 and standard hospital location 0.31 (Figure 3)

Both Cambodia and Lao People's Democratic Republic have an international referral policy of referral for patients to receive further treatment abroad. Regarding the referral of patients from the Lao People's Democratic Republic to Thailand, patients from there must coordinate with the border control offices. The immigration police must know the process of referring in and out and referring of any return details. The healthcare center's main activities are as follows:

Customer Service: There is an ambulance service which transports only Cambodian permanent border crossings for emergency hospital treatment in Thailand. Cambodian patients must coordinate with the immigration police to inform The Eastern Economic Corridor (EEC), Accident and the Emergency Department and ambulance staff of hospitals to have available ambulances to transport Cambodian patients. Some patients may contact the EEC directly to request an ambulance service. Most of the patients were found to have accidents injuries, followed next by antenatal and childbirth, then patients with cerebrovascular disease accounted for the final numbers. In addition, the hospital has patients suffering from chronic diseases such as anemia, diabetes, high blood pressure, plus patients requiring follow-up treatment.

Order Processing: For patients who wish to change hospitals to continue their medical treatment at the initial destination hospital. If the patient has symptoms that are not critical the doctor will assess the patient's condition and issue a referral to the patient for further examination or treatment, including being referred out.

Transport: According to the operating levels of the specific units, emergency response kits can be divided into four main categories as follows:

The first response unit (FR) is responsible for assessing and providing primary care to emergency patients, such as lifting and moving the injured, as well as providing basic resuscitation.

The basic life support unit (BLS) serves as a more capable operation than a basic life support unit, such as administering oxygen, performing basic procedures, and providing care for the injured other than proactive support.

The Advanced Life Support Unit (ALS) provides an elevated level of emergency care similar to the care of patients in a hospital emergency department, such as fluid administration, intravenous administration, and intramuscular defibrillation, airway care, and other proactive assistance.

Reverse Logistics: Reverse logistics or repatriation. There is an ambulance service for referred patients. The deceased are sent to the communicable disease control unit checkpoint at the border crossing, but there is no ambulance service to refer the deceased back across the border.

CONCLUSIONS

One of the major problems of international referrals is demand forecasting. Many healthcare organizations forecast using the gravity model and the regression model. The parameters include spatial data and nonlinear data. Therefore, this paper presents deep learning which is suitable for complex problems as a network. The findings of this research suggest that the deep learning model performs better than RBF and regression models. The model allows the different data sets to forecast the demand for each hospital. Based on the identification of the knowledge gap, this approach could be recommended for healthcare logistics to determine the treatment supply chain and the future ability to formulate guidelines effectively with healthcare logistics effectively.

In addition, this study tried to train multiple data sources to build model bases that could be used for predictive analysis. The field of healthcare logistics must utilize the best available supply chain system to provide the best treatment possible to its patients. The impact and responsibilities of the destination countries are relative to the political risk. The main activity must be to coordinate with the immigration police before crossing the border. The border office must know the process of referring in and out ;additionally, referring any return details. Furthermore, opportunities or challenges can interface with applications in medicine and clinical decision support. The deep learning approaches could benefit the healthcare field, such as applications related to these methods when used in the context of precision medicine, Diagnosis classification, Prediction of Disease, and so on. However, we also note limitations and need for improved methods development and applications, especially in terms of simplicity of use and accuracy.

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