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Supervised machine learning to allocate emergency department resources in disaster situations

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Abstract: **Despite implementing the Hospital Emergency Plan (HEP) in Morocco that manages the massive influx of victims in disaster situations, it is still difficult for healthcare decision-makers to deal effectively with these situations, which has negative impacts on the performance of the emergency department. Thus, managers need decision systems that help save lives and reduce disabilities. This paper aims to improve the HEP by developing a model based on supervised machine learning as a support tool, to allocate the needed human and materials resources according to injuries number. We propose applying a feedforward neural network (FFNN) and backpropagation. We evaluate the proposed model performance indicators. Our framework was conducted on previous experiences between 2009 and 2019 of 4 public hospitals in Casablanca city. The application of the developed model on our data sample showed that the FFNN provided satisfactory precision for the direct implementation and gave feasible solutions according to the available resources. Allocating resources can be performed using FFNN and capitalizing from lessons learned through previous experiences. In addition, this solution can be used as an international reference to provide a new solution that is more performant taking account of the available resources.**

Key words : Disaster situations, massive influx of injuries, emergency department, artificial neural networks, allocating resources.

I. Introduction

Disaster situations are incidents that generate a high number of patients at one time, exceeding the capacity of what the available resources can manage using the routine procedures. Every year thousands of people worldwide are affected by natural or human-made disasters [1]. These often dramatically affect their health, causing deaths and victims with different gravity degrees [2]. In these situations, the main challenge for hospitals is to save as much as possible of lives and reduce disabilities. Besides, the lack of resources is the biggest constraint in Moroccan hospitals [3], [4]. That is why allocating the needed resources for treating victims is essential, particularly for emergency departments (ED). Hence, several countries require their hospitals to have a disaster management plan to respond effectively to a high number of victims. In Morocco, the disaster management plan is called the Emergency Hospital Plan (EHP)[5]. The EHP describes only the organization process and does not allocate the necessary resources, which can lead to resources under-sizing or oversizing. Therefore, the hospital may be unable to treat all victims effectively. A significant number of studies have been devoted to the ED problems by searching for the best solutions to different situations considering capacity and cost constraints. These researches have been conducted on the strategic, tactical and operational levels. A review of relevant papers is presented in the following.

ED studies focused on medical care from patient transportation to hospitalization. Problems related to ambulance management have attracted several researchers considering patient transportation in normal and disaster cases [6]–[9]. Patient triage is another issue in ED, which helps physicians gain time in the medical process [10], [11]. Resource allocation in ED is the most discussed issue in the literature. The aim of which is to establish the best resources management [12]–[14]. For instance, some papers have focused on beds management [15], [16] and operating room scheduling as it helps prioritize emergency cases [17], [18]. ED modelling and simulation are the subjects of an increasing number of studies. They are valuable tools for system analysis that generate various solutions to emergency problems in both normal and disaster situations [19]–[21].

After this brief review, we observed that most papers converge toward a single objective: patient satisfaction by minimizing the time spent in the ED while maintaining the quality of care. These researches have used various methods such as meta-model, queues, linear programming, Markov chain, artificial intelligence algorithms and other methods. On the other hand, papers on managing ED issues in disasters situations are few. They have primarily tried to solve problems related to assigning ambulances and routes, blood supply and triage. Niko et al. [22] used a model based on a branch-and-cut solution method to determine the optimal emergency transportation network to perform emergency response trips with high priority in earthquakes disasters. Wang et al. [23] investigated emergency transportation in real-life disasters scenarios. They formulated the problem as an NP-hard integer linear programming model and proposed a hybrid ant colony optimization algorithm. Sung and Lee [24] modeled the triage in mass casualty incidents as an ambulance routing problem and determined destination hospitals for patient evacuation. They formulated the problem as a set partitioning problem and applied a column generation approach to efficiently handling a large number of feasible ambulance schedules. Dean et al. [25] developed a SAVE model for a mass casualty incident to evacuate victims to hospitals in the region effectively. Their model was based on mixed-integer programming. Glasgow et al. [26] developed a model based on simulation to supply blood to hospitals in the event of a mass influx of victims. They used the available quantitative and qualitative data to manage the possible scenarios and provide a model solution capable of responding effectively to these situations. Tai et al. [27] studied strategies to optimize red blood cell supply in mass casualty situations. They developed a computer simulation model of a transfusion system in a large trauma center. Their model used data from former civilian and military trauma registries. Abir et al. [28] developed a model based on simulation to predict peak capacity in the event of large numbers of burn victims in hospitals. Curran et al. [10] compared two methods of triage in the case of a mass influx of victims: The Canadian Triage and Acuity Scale (CTAS) method and the Simple Triage and Rapid Processing (START) Method. The comparison was based on the time spent per patient and the triage accuracy.

We notice that papers on ED issues in disaster situations have used different tools to achieve their objectives. Machine learning is one of these tools that several researchers have increasingly deployed [29]. However, to our knowledge, machine learning tools to size both human and material resources in ED in mass causality incidents has not been used in the literature. Previous experiences help decision-makers understand what happened, correct mistakes and learn from these experiences. Neural networks are supervised machine learning tools that learn and propose a predictive solution. In this context, we suggest size hospital resources, exploiting previous experiences, using a feedforward neural network (FFNN) to provide solutions based on real cases.

II. MATERIALS AND METHODS

A. Data cleaning and processing

Our investigation used data from four public hospitals in Casablanca city that serve more than 3 million inhabitants. One of these hospitals is a regional hospital, and the three others are provincial hospitals. Data included statistics on exceptional situations recorded from 2009 to 2019. Once the data were collected, it was necessary to exclude recorded cases that appear to be erroneous since the method followed in this paper is based on supervised learning, especially regression, which requires valid data. Hence, ED managers of the four hospitals were invited to participate in several focus groups to evaluate the collected data. The objective was to examine data veracity in order to remove irrelevant data. The review process was based on the personal judgments of the ED managers. The first sample included 475 cases of which only 384 were retained. Data cleaning and processing was the most difficult and time-consuming task because most Moroccan hospitals do not have information systems that allow recording data automatically [30].

B. 2.2. The basic concept of artificial neural network

FFNN contains three principal elements: input, output and hidden layers. Each constitutive unit (artificial neuron) is connected to other neurons in each layer. This connection is mathematically represented by the measure of the connection (weight) between two nodes in the network [31], [32]. To minimize the error function, these weights are changed in different learning process steps. The learning process eventually leads to the model being able to deal with any unknown data sets. Figure 1 represents the neuron model, which forms the basis for designing the ANN.

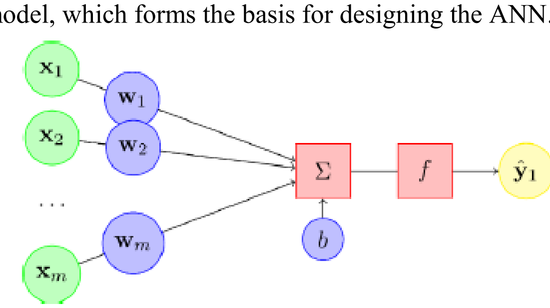

Fig 1: Nonlinear model of a neuron [33]

The following equations describe mathematically a neuron k:

$$Y = f(\sum_{i=1}^{n} W_{ij} X_i + b) \qquad (1)$$

The Xi are the inputs of the neuron, Y is its output. The weights wi of the connections represent the excitatory and inhibitory actions. The simple case calculates the weighted sum of these inputs Xi and adds a threshold value called (bias) represented by b in the figure. Then, it calculates the output Y through the activation function *f* used [33].

The activation function, denoted by ϕ(v), is used to limit the output of a neuron in terms of the induced local field v. Several activation functions may be used as an activation function. However, in order to satisfy the non-linearity requirement, sigmoid activation functions should be chosen

$$\phi(v) = \frac{1}{1+e^{-ax}} \qquad (2)$$

Where a is the slope parameter of the sigmoid function [34][35]. Either Mean Squared Error (MSE) or Root Mean Squared Error (RMSE), or Normalized Mean Squared Error (NMSE) can be used to measure the modeling performance of the given FFNN [36]. These are given in the following equations:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \qquad (3)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \qquad (4)$$

$$NMSE = \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \qquad (5)$$

Y and Ŷ are the observed data and modeling data, respectively. *N* is the length of the observed data [36].

C. *Description of the proposed algorithm*

After data processing to develop the appropriate model. The next step is to divide the data into two subgroups, group A contains 70%, and group B contains 30%. The choice of these percentages is confirmed through several trials to help the neural network train well on the data. Learning neural networks involves three steps (training, test and validation). In the proposed method the training and test phase was done by the data of group A; for this we used the algorithm of the gradient descent as well as the K-FOLD procedure of the cross validation [34]. The last step is the calculation of the error between the estimated prediction value and the real value in order to validate the reliability of the selected neural network. Figure 2 represents the algorithm used to predict the number of resources based on the number of victims.

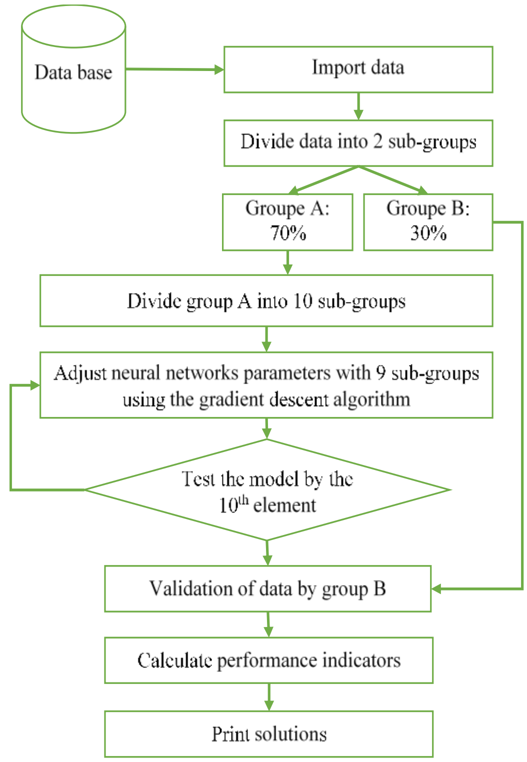

Fig. 2: Artificial neural networks algorithm

The input layer of this network contains victims' number, and the output layer gives the human and material resources using two hidden layers with ten neurons for each layer, as shown in figure 3. The activation function chosen is the sigmoid function.

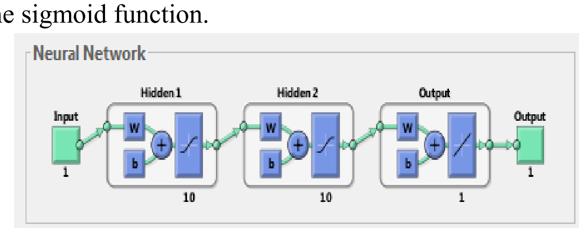

Fig. 3: Feedforward neural networks architecture

III. RESULTS

Our primary focus in this work was to demonstrate the feasibility/suitability of machine learning-based framework for the problem at hand and provide general model recommendations and suggestions. The FFNN was used with two hidden layers and ten neurons for each one.

The backpropagation training method was applied using the Levenberg-Marquardt algorithm. Ten-fold cross-validation and a search grid validated the error. The performance function used for learning was the mean squared error. To avoid overfitting, the total dataset was distributed in a training sub-dataset (70% to learn the network's node weights), a validation sub-set (15%: to stop learning and avoid over-training) and a testing sub-set (15%: to evaluate the model's ability to perform on previously unseen data). Table I summarizes the results, and figures 4 and 5 illustrate the regression indicators and MSE performance.

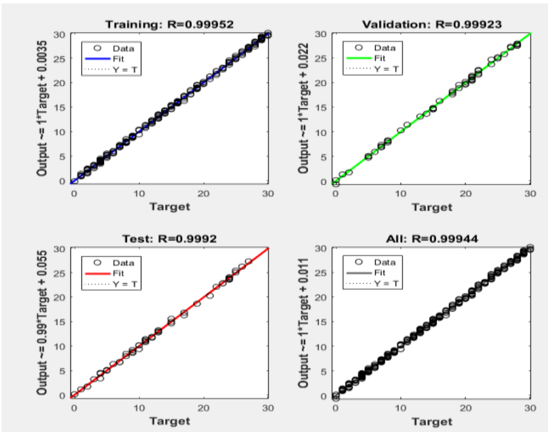

Fig. 4: Regression indicators

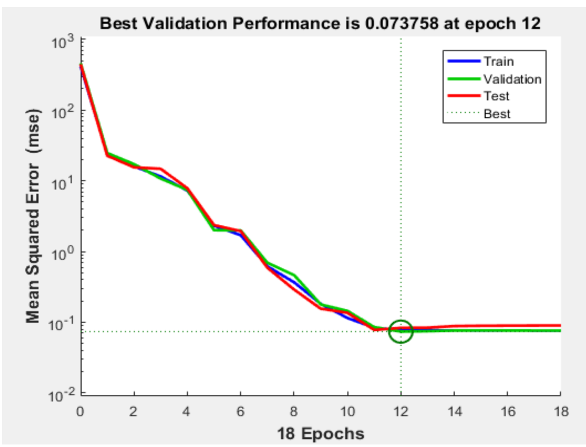

Fig. 5: Performance indicator MSE

To validate the approximation of activation function, the results are evaluated in terms of MSE, RMSE and NMSE. This precision is acceptable for our implementation. The results in the form of MSE, RMSE and NMSE are summarized in Table II.

TABLE II: MSE, RMSE AND NMSE VALUES

MSE	RMSE	NMSE
0.07375	0.2715	2.21E-04

The performance curve varies for different combinations of data and parameters. The model training process stops either when it reaches the mentioned number of epochs or when Mean Squared Error (MSE) is almost never improved after certain epochs. The circle in the performance curve shows the best validation performance. The performance index in table2 was lower in 12 epochs when the network had ten neurons in the two hidden layers, execution time (T=12seconds) and accuracy (R^2=0.99). The FFNN predicted each case (number of victims), and comparisons were made with real cases. Therefore, the FFNN can predict the number of resources based on victims' numbers when trained with the backpropagation algorithm. However, it can be seen that the FFNN has successfully predicted human and material resources, and the accuracy is close to one.

IV. DISCUSSIONS

Incidents that generate many victims can only be addressed through good management. This leads to a predictive preparation for this type of case. The different severities of victims require different kinds of interventions, from triage to surgical operations. Models based on feedback are essential references to adjust mistakes made in previous experiences. Such models could help hospital decision-makers in Morocco to determine the number of resources required in future cases. In this study, the calculated performance indicators like the error (MSE =0.07), execution time (T=12seconds) and accuracy (R^2=0.99), as well as the obtained results, show the effectiveness of the proposed model. Based on these results, the FFNN had a higher predictive rate. Neural networks are complex, flexible, and nonlinear, with properties not found in other modelling systems. These properties include robust performance in processing noisy or incomplete input patterns, high fault tolerance and the ability to generalize results. The prediction model developed with the FFNN accurately predicted the resources to be allocated for each number of victims. These results are similar to those of [37]–[40], which concluded that FFNN prediction is more accurate than other tools such as logistic regression. On the other hand, these results are more realistic than those of [14] because they take account of the available resources. However, to get more and more performance results, the dataset must be updated after each experience and have more resources like blood. In addition, the algorithm must filter the dataset for each case (road accident, plane crash, railway accidents, etc.). However, this work is a pilot study. It has some limitations related to the sample size, which is reduced and needs to be enlarged in future studies. Although the current sample achieved high accuracy regression, it still needs more cases to confirm the model's scalability for each kind of disaster situation.

TABLE I : RESULTS OF SIMULATIONS

Victim's number	Ambulances	Surgicals	Nurses	Nurses in operating room	Beds	Emergency doctor	Radiologs	Reamnimators	Operating rooms
677	68	68	68	54	541	102	27	27	20
38	4	4	4	3	30	6	1	2	1
122	12	12	12	10	98	19	5	4	4
450	45	45	45	36	359	67	18	18	14
245	24	25	25	20	196	37	10	10	7
347	35	34	35	28	277	52	14	14	10
127	13	13	13	10	102	20	5	5	4
524	52	52	53	42	419	78	21	21	16
845	85	85	85	68	676	127	34	34	25
672	67	67	67	54	538	101	27	27	20
929	93	93	93	75	744	139	37	37	28
447	45	45	45	36	357	67	18	18	13
189	19	19	19	15	151	28	8	8	6

V. CONCLUSION

Managing exceptional situations is a difficult task for hospital decision-makers. There is a need for a decision support tool to help make wise decisions under time and capacity constraints. The use of neural networks, notably the gradient descent algorithm and the FFNN multilayer, allowed processing data collected from previous experiences and finding relevant solutions to save victims lives using the available resources. The main objective of this research was to save human lives and reduce disabilities in exceptional cases, making use of the available resources in the hospital. We proposed a decision support tool based on previous experiences using FFNN. Results showed that learning from experiences is one of the best ways help to find optimal solutions. Our model was developed in the Moroccan context and can be extended to other contexts. This paper contributes to the literature on responding to disaster situations namely sizing the different hospital resources.

This paper reports the first study results concerning hospitals allocating resources in disaster situations modeled with ANN. Further studies to optimize the performance of allocating resources can be based on hybridization of others heuristic or the simulation of discreet events systems.

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