



Estimation of the future fracture epidemiology in the patients applying to the emergency department with long short time memory method

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Abstract

Operation rooms, human resources and equipment planning are essential for increasing the effectiveness of diagnostic and treatment methods in line with the needs of emergency cases. In this study, 151822 patients admitted to the emergency department (ED) within 3 years were examined in three categories including gender, fracture sites and causes of fracture. However, fracture cases were treated as time series and Long Short Time Memory (LSTM) method was used to estimate the number of future fracture cases. In the learning phase, the number of monthly cases in the next 6 months was estimated using 30-month case numbers. The Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean relative Error (MRE) values of the error rate between the estimated and actual number of cases were given.

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1. Introduction

With the changing living conditions, trauma and fracture patterns also change [1]. Epidemiological studies are used to identify them and to plan health services. The ability to act based on knowledge is important in today's world. In the field of health, patient information creates an intense accumulation of data. There are several methods for proper evaluation and analysis of this data. In recent years, machine learning was introduced in the medical applications and showed its remarkable efficiency in clinical diagnosis and decision support [2]. Presently, the recurrent neural network (RNN) was well employed in solving time series prediction problems and achieved prominent results in many fields. Several variants of RNN have been developed, and among them, long short-term memory (LSTM) network is one of the most popular variants. LSTM learns long-term dependencies by incorporating a memory cell that can preserve state over time [3].

The answer to the question "What will happen in the future?" is important in providing health services. The artificial neural network method is also emphasized in

the literature in predicting future patients [4]. Artificial neural networks have also started to be used in the field of orthopedics [5]. Our study stands out with the use of this method to predict future fracture patients. Current orthopedic literature in this area is generally in the direction of fracture diagnosis from patient images [6]. There are also studies suggesting the diagnosis of a fracture in automated systems with deep learning methods [7]. The general challenge in healthcare today is that physicians have access to a large amount of data about patients, but they have little time and tools to analyze them. The intelligent clinical decision supports in this direction are important for health service delivery planning, cost calculation and personnel distribution planning. These methods are used in future patient estimates [8]. There are few studies using the LSTM (Long Short Time Memory) model to predict patients who have had a heart attack [9, 10]. LSTM has been using for a long time in solving forecasting problems and analyzing big data [11]. However, no studies on the future prediction of orthopedic cases admitted to the emergency departments have been found in the recent literature.

With the presented study, using the LSTM method,

complex and heterogenic patient information and future patient prediction were made. According to this study, patients with limb fractures were examined epidemiologically from 151.822 patients who have applied to the emergency department in the last 3 years. In the study, it was aimed to present the fractures epidemiologically according to age, gender groups, distribution throughout the year, fracture region - shape and causes of the accident. Besides, it was tried to predict future case projections using LSTM method. The availability of LSTM in this area has been studied.

2. Materials and Methods

2.1. Data collecting

Among 151.822 patients who applied to the emergency department of the Sivas Cumhuriyet University Medical Faculty in 2011-2013, 2.105 patients who applied for the extremity fracture were included in the study. The data were obtained by scanning backward from the registry. Age, gender, diagnosis and causes of accidents were noted. The patients were divided into four groups according to their ages as 18-40, 40-65, 65-80 and greater than 80 old. The distribution of fractures according to gender was examined. Open and closed fracture rates were noted. The broken regions are listed as shown in Table 1. The data analysis was done in SPSS (Ver.23) program. Data were examined by considering percentage distribution, frequency and arithmetic means.

2.2. Long short time memory (LSTM)

Although Neural Network (NN) has achieved success in many applications, it does not achieve the desired accuracy in time series prediction. Recurrent Neural network (RNN) architecture, which enables the addition of the effect of past data to the next output in the time series prediction, reaches higher accuracy than NN in this series. However, if past inputs are connected to a longer sequence, performance rates decrease due to the short memory of RNNs. Long Short-Term Memory, LSTM architecture, which has been developed as a different version of RNN, allows the creation of longer past input-output relations [12]. In this study, Vanilla LSTM architecture by Gers and Schmidhuber was used in LTSM method that has many versions [13]. The LTSM block consists of three gates named input gate, output gate, gate candidate and forget gate and a sub-block. The main idea of LSTM is that the current input of each block, x_t and h_{t-1} , which represents the short-term output of the previous

block and the long-term output from the previous blocks, takes c_{t-1} into account for obtaining the block output. An LTSM block generates the short term h_t and long term c_t , belonging to that block.

The output of the forget gate is a nonlinear function of the current input with the state from the previous block, expressed by the sigmoid activation function;

$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \quad (1)$$

where f_t is the output of forget gate, b_f is the bias for forget gate, σ_g denotes gate sigmoid activation function. W_f and U_f corresponds forget gate coefficients. This output is between 0 and 1, and generates information on whether to be processed in the previous state in the current block or not. The input gate generates an output to calculate c_t with a sigmoid activation function of x_t and h_{t-1} inputs.

$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \quad (2)$$

where i_t is the output of the input gate, b_i is the bias for forget gate, σ_g denotes gate sigmoid activation function. W_i and U_i corresponds to input gate coefficients. The output gate generates information about whether the information in the previous door will be moved to the next block or not.

$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \quad (3)$$

where o_t is the output of the input gate, b_o is the bias for forget gate, σ_g denotes gate sigmoid activation function. W_o and U_o correspond to input gate coefficients. The output gate generates information about whether the information in the previous door will be moved to the next block or not. If the long term memory information of the current block is c_t the cell candidate block output is generated with z_t .

$$z_t = \tanh(W_z x_t + U_z h_{t-1} + b_z) \quad (4)$$

$$c_t = f_t \times c_{t-1} + i_t \times z_t \quad (5)$$

$$h_t = o_t \times \tanh(c_t) \quad (6)$$

3. Results and Discussion

The recent Covid-19 epidemic also showed us that the estimation of the volume of patients is very important for planning for health service. Although

some operations could be postponed to reduce the effect of the outbreak by reducing the hospital burden with lower patient acceptance, fractured patients treatment could not be postponed because of the urgency of treatment. Our study shows that the method we use can be used in other diagnostic fields as well.

The extraction of future projections of the cases with LSTM was carried out by coding deep learning codes in the Matlab programming language. The total of 36-month case data is divided into two parts: 30 months for the training and last 6 months cases for the estimation. The error between the LSTM estimation and the number of cases for each month in 6 months and the actual number of cases was used to measure the performance of the future estimator presented.

3.1. Performance indexes

To assess prediction performance of LSTM based case prediction, three performance indexes were used. Mean absolute error (MAE) was calculated as

$$MAE = \frac{1}{n} \sum_{i=1}^n |f_i - \hat{f}_i| \quad (7)$$

Mean relative error (MRE) is calculated as

$$MRE = \frac{1}{n} \sum_{i=1}^n \frac{|f_i - \hat{f}_i|}{f_i} \quad (8)$$

Root mean square error (RMSE) is calculated as

$$RMSE = \left[\frac{1}{n} \sum_{i=1}^n |f_i - \hat{f}_i|^2 \right]^{\frac{1}{2}} \quad (9)$$

where f_i is the actual value, \hat{f}_i is the predicted value for n instants.

3.2. Simulation environment and result

The prediction model was set up with the Matlab Neural Network Toolbox Results (Matlab R2018a). More than one scenario has been established for the estimation of the cases. These scenarios are as follows.

Scenario 1: Estimation of the number of cases by gender for the next 6 months.

Scenario 2: Estimation of the number of cases for the next 6 months according to the occurrence of the case.

Scenario 3: Estimation of cases by fracture site classes for the next 6 months according to the fracture sites occurring in cases.

Open fractures constituted 8.8% (186 of all cases) of all fractures that applied to the emergency department. These fractures are; Fractures were 46.2%, tibia shaft 11.8%, ankle 7.5%, and tibia distal 6.5% fractures. The leading cause of open fractures was a direct impact to bone 73.7%. In our study, the spine, pelvis, talus, calcaneus and femur shaft open fractures were not observed.

According to the first scenario, 6-month estimation of the number of cases of men and women was made with LSTM, and their performance is shown in figure 1 and 2, respectively. In the estimation made for women, it is seen that there are approximately 20 cases between the number of cases realized in the first two months and the number of cases estimated, but the difference between the number of cases estimated for each month and the number of cases realized is less than 10. In the prediction of cases with male gender, a better estimation performance was obtained compared to women. Within the six-month forecast period, each case number error was estimated with ± 10 errors, and the RMSE value was found to be 9.8.

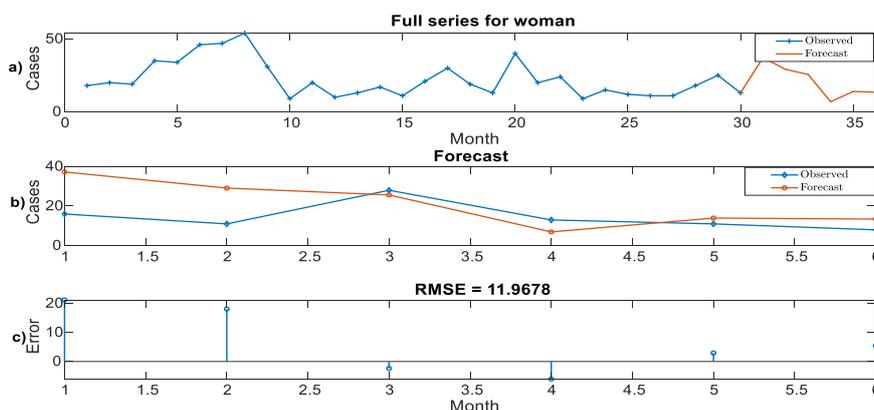


Figure 1. a) Full series of the case for woman (a), Predicted and actual case numbers (b), Prediction error for each month (c)

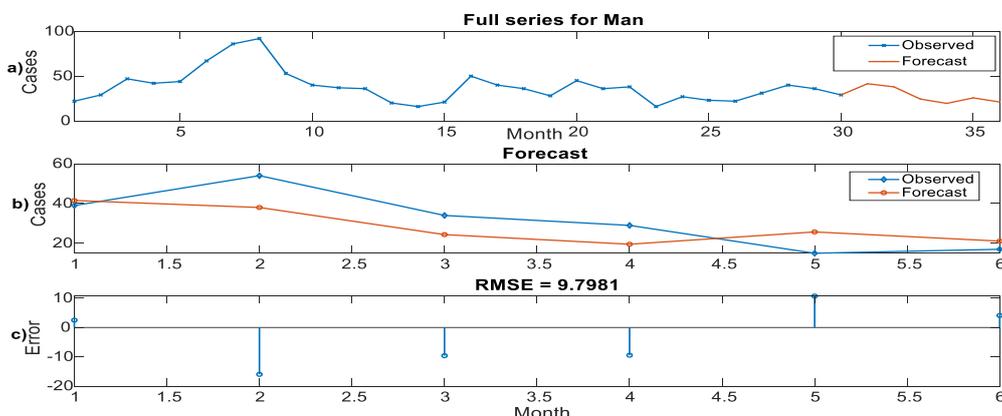


Figure 2. Full series of the case for man (a), Predicted and actual case numbers (b), Prediction error for each month (c)

In scenario 2, a classification was made according to the reason for the occurrence of the cases and an attempt was made to estimate the number of 6-month cases according to these classes. According to the reason of the broken cases, the cases were defined in eight classes which are a) normal falling, b) falling from the ladder, c) falling from a high place, d) the impact took as a result of the fight, e) sports injury, f)

traffic accident, g) stress and h) others not in another class. The number of cases for 30 months and the number of estimates and actual cases for the next 6 months are shown in Figure 3. The graph with the blue line shows the number of cases that occurred, while the red line shows the number of cases that were estimated.

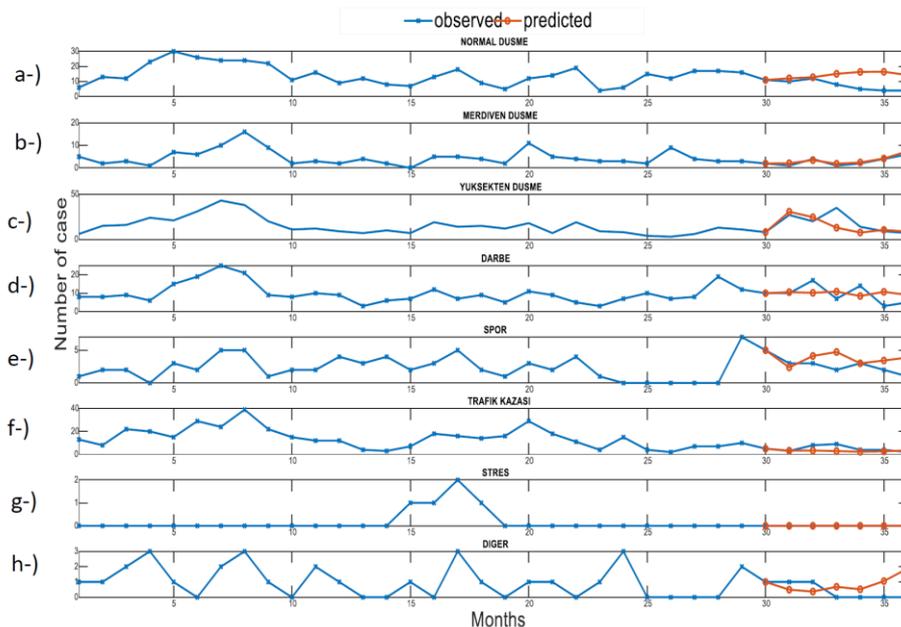


Figure 3. Observed and predicted case according to the cause formation

In scenario 3, cases are divided into two main classes as Upper limb and Lower limb according to fracture areas. Upper limb identifies cases to separate fracture sites and these fractures are Clavicula, Scapula, Humerus, Forearm, Hand-phalanx, Scaphoid, Spine, and Pelvis fractures.

Lower Limb fractures are classified according to 9 lower fracture regions and they are Femur, Patella, Tibia, Tarsal bones, Talus, Calcaneus, Foot phalanx, Ankle, Metatars fractures. In Table1, estimation performances of the number of cases according to the 6-month fracture region

are given. RMSE, MAE and MREs of the prediction errors of each major fracture region and the specific region where the fracture occurs are indicated in the table. Average RMSE, MAE

and MRE values of each class were calculated as 1.053, 0.839 and 0.358, respectively.

Table 1. Performance indices of 6-month forecasts by broken region

Broken region		RMSE	MAE	MRE
UPPER LIMB				
Clavicula		5,441	4,576	1,052
Scapula		1,463	1,266	0,476
Humerus	Proximal	1,290	1,045	0,135
	Shaft	1,460	1,147	0,806
	Distal	3,869	2,719	0,572
Forearm	Proximal	1,311	1,085	0,274
	Shaft	1,742	1,090	0,402
	Distal	2,119	1,841	0,137
Hand-phalanks		7,700	7,031	1,231
Schaphoid		1,856	1,538	0,000
Spine		0,545	0,351	0,934
Pelvis		3,118	2,738	0,188
LOWER LIMB				
Femur	Proximal	4,143	3,298	0,420
	Shaft	2,403	1,746	0,836
	Distal	1,041	0,810	0,963
Patella		0,806	0,702	0,361
Tibia	Proximal	1,489	1,178	0,933
	Shaft	1,221	1,176	0,028
	Distal	1,617	1,497	0,555
Tarsal bones		0,582	0,454	0,996
Talus		0,451	0,304	0,415
Calcaneus		0,730	0,373	0,000
Foot phalanks		0,378	0,285	0,083
Ankle		1,118	0,935	0,041
Metatars		1,695	1,322	0,769
<i>Mean</i>		<i>1,053</i>	<i>0,839</i>	<i>0,358</i>

4. Conclusions

Knowing the epidemiological distribution and rates of fractures is important for preventive medicine as well as health service delivery and planning. According to our study, fall-related fractures in childhood are more common, while osteoporotic fractures caused by minor trauma are observed in the foreground in elderly patients. Hand fractures that occur as a result of the direct impact on bone are more common in adults who form an active workforce. In long bone open fractures, which are difficult and costly to treat, tibial fractures are in the first place. Despite all preventive activities, motor vehicle accidents are the leading cause of fractures. Epidemiological studies

should be carried out at certain intervals according to changing living conditions and human activities. Removing future projections of fracture cases is very important for the programming of emergency and orthopedic clinical human resources, medical equipment and patient services. In this study, for the first time, a 6-month case number estimation from 30-month case numbers was made by using LSTM, which is one of the deep learning methods. Since the shape of the fracture affects the planning of the health service provided, the causes of the fracture again, satisfactory results were obtained in 3 different scenarios, according to the gender, the occurrence of the case and the fracture regions formed in the cases,

according to the fracture class classes for the next 6 months.

Conflicts of interest

The authors state that did not have conflict of interests

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