Mühendislik Bilimleri ve Tasarım Dergisi
6(3), 375 – 382, 2018
e-ISSN: 1308-6693

Journal of Engineering Sciences and Design
DOI: 10.21923/jesd.378742

Araştırma Makalesi Research Article

A FUZZY LOGIC BASED CLINICAL DECISION SUPPORT SYSTEM FOR EMERGENCY SERVICES

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Keywords
Emergency medicine,
Decision support system,
Fuzzy logic,

Abstract

Emergency departments are one of the most important units in the hospital where there are special units and many problems. At the beginning of these problems, emergency services are crowded and urgent patient care planning is difficult. The applications such as triage system are used for these problems. However it is known that such applications do not fully solve these problems. In this study, a fuzzy logic based clinical decision support system (CDSS) was developed for the classification of emergency patients. In the study, application complaints and medical data of 180 non-anonymous patients in Muğla Sıtkı Koçman University Training and Research Hospital were used. The 95 of the patients are female, 85 are male and the average age is 46. In order to analysis the performance of the performed system, the results of the application and the decisions of the specialist doctor were compared statistically (accuracy, sensitivity and specificity). Consequently, the accuracy of the realized system 83%, sensitivity 87% and specificity 76.6% was found. Provided that the most recent decision belongs to the expert physician, the development of this kind of CDSS is thought to be beneficial in terms of serious time and space in the emergency departments of the hospitals, especially during intensive periods.

ACİL SERVİSLER İÇİN BULANIK MANTIK TABANLI BİR KLİNİK KARAR DESTEK SİSTEMİ

Anahtar Kelimeler
Acil tıp,
Karar destek sistemi,
Bulanık mantık,

Öz

Acil servisler, her hastanede olan ve içerisinde özel birimlerin bulunduğu, birçok problemi olan en önemli birimlerinden biridir. Bu sorunların başında, acil servislerin kalabalık olması ve acil hasta bakım planlamasının zorluğu gelmektedir. Bu problemler için triyaj sistemi gibi uygulamalar kullanılmaktadır. Fakat bu gibi uygulamalarında problemlere tam olarak çözüm getiremediği bilinmektedir. Bu çalışmada acil servise gelen hastaların sınıflandırılmasına yönelik bulanık mantık tabanlı bir klinik karar destek sistemi (KKDS) gerçekleştirilmiştir. Çalışmada Muğla Sıtkı Koçman Üniversitesi Eğitim ve Araştırma Hastanesi'nde anonim olmayan 180 hastanın başvuru şikâyetleri ve medikal verileri kullanılmıştır. Hastaların 95'i kadın, 85'i erkek olup yaş ortalamaları 46'dır. Gerçekleştirilen sistemin performansını test etmek için uygulamanın sonuçları ve uzman hekimin kararları istatistiksel olarak değerlendirilerek (doğruluk, duyarlılık ve özgüllük) karşılaştırılmıştır. Sonuç olarak, gerçekleştirilen sistemin doğruluğu %83, duyarlılığı %87, özgüllüğü %76,6 bulunmuştur. En son kararın uzman hekime ait olması şartıyla bu tür KKDS'nin geliştirilmesi hastanelerin acil servislerinde özellikle yoğun olduğu dönemlerde ciddi zaman ve mekân açısından kazançlı olacağı düşünülmektedir.

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Alıntı / Cite

Ozkaraca, O., Acar, E., Peker, M., Turk, E. (2018). A Fuzzy Logic Based Clinical Decision Support System for Emergency Services, *Journal of Engineering Sciences and Design*, 6(3), 375-382.

Yazar Kimliği / Author ID (ORCID Number)	Makale Süreci / Article Process	
O. ÖZKARACA, 0000-0002-0964-8757	**Başvuru Tarihi /Submission Date**	14.01.2018
E. ACAR, 0000-0003-2251-112X	**Revizyon Tarihi / Revision Date**	07.03.2018
M.PEKER, 0000-0002-6495-9187	**Kabul Tarihi / Accepted Date**	25.06.2018
E. TÜRK, 0000-0003-0898-6778	**Yayım Tarihi / Published Date**	30.07.2018

1. Introduction

Emergency services which ensure public safety and health by addressing different health related cares are one of the busiest departments of hospitals. Emergency service process begins with the first physical examination of the patient and continues until the patient is discharged or hospitalized. The intensity of the emergency services is a serious problem all over the world. Healthcare administrators are working to develop solutions to both overcome the density and who may not be overlooked of serious patients' because of this crowd. One of the suggested methods for this purpose is triage (Erdem, 2011). Determination of priorities with the preliminary assessment made by auxiliary health personnel is called triage (McHugh, 2012; Mirhaghi, 2015; Mace, 2008). However, the processes of triage have some limitations such as flow charts of the triage are very specific and inadequate triage personnel or the high number of patients who should be done triage (Augustyn, 2007). Also, lower triage level patients, who have to abide unable to be predicted and often lengthy latency in pretreatment (Van der Linden, 2011). The usage of the computer-based systems can be beneficial in such cases. In addition, intelligent computer software system is being developed by researchers in recent years. These are referred to as a decision support system. Decision support system (DSS) is interactive computer software, which is aimed to assist users by means of heuristics and statistical methods while determining a diagnosis for a patient using his/her data.

We performed an effective clinical decision support system based on fuzzy logic for prevent the omission of the patients in crowded emergency departments that can be compatible with the triage system. In this study, we aimed to develop a system which is able to determine the severity of the patient without doing further tests. This system provides a decision who is redirected to the intensive care, service or discharged. Finally, we aim to see the success rate of this computer-based system, according to the triage system.

2. Materials and Methods

We present a novel generic clinical decision support system which is compatible with the triage system. The Ethics committee of the Muğla Sıtkı Koçman University (2015–00057) approved prospective study was performed on all consults completed by the physicians in emergency service during two months. A total of 150 patients was included in the training stage to perform the smart clinical decision support system, and 30 patients were included in the testing stage. We selected emergency department patient's ≥18 years old according to the recommendation of the physician. However, the physician does not have any information about the purposes of the study. Nine parameters (Age, Systolic Blood Pressure, Respiration Rate, Surface Temperature, Oxygen Saturation, Diastolic Blood Pressure, Comfort Value, Glasgow Coma Score, Pulse) are recorded to the patients' card by same nurses as soon as the patient came to the emergency room. Finally, the case of selected patients was recorded a week later. Medical and technological materials of the study are described as in the following subsections.

2.1. Basics of fuzzy logic

Fuzzy logic has been used extensively in recent years in medicine due to a simple and effective method (Torres, 2006). The term of fuzzy logic emerged from the fuzzy sets theory (Zadeh, 1965). Fuzzy logic is different from conventional (Boolean) logic. The proposition is considered 'right' or 'wrong' in conventional (Boolean) logic. The realization of a third condition is assumed to be impossible, and, in general, this type of situation is called as 'paradox'. However, the basic idea of the fuzzy logic, a proposition might be 'true', 'false', 'very true', 'very wrong', 'completely true', 'completely wrong', 'approximately right', 'approximately wrong' (Sivanandam, 2007). The simplest fuzzy model consists of a set of rules with an "if – then" structure:

IF <condition 1> AND ... AND <condition n> THEN <conclusion>

In this statement "*<condition 1>*" represents the actual value of some real-world variable.

The combination of the results in fuzzy rules and individual rules of assessment is carried out using fuzzy cluster operations. Operations on fuzzy sets are different from operations on non-fuzzy sets. The membership functions of A and B fuzzy sets are μA and μB as shown in Table 1. It contains possible fuzzy operations for OR and AND operators on these sets, comparatively. The most used operations for OR and

AND operators are max and min, respectively (Caponetti, 2017; Yildiz, 2010).

Table 1. Fuzzy set operators

	OR(Union)		AND(intersection)
Max	max{μA(x), μB(x)}	MIN	M in{μA(x), μB(x)}
A_{sum}	μA(x)+μB(x)−μA(x)μB(x)	PROD	μA(x)μB(x)
B_{sum}	min{1, μA(x) + μB(x)}	BDIF	max{0, μA(x) + μB(x) − 1}

The results of each rule are evaluated. Afterward, these results should be assembled to obtain a resultant. The fields which is derived from rules are merged with different ways. The operators are used as in Table 2 for the merging process and the final fuzzy output is obtained. The desired output is located with certainty by using one of the "defuzzification methods". Generally, the “Max” operator is used for accumulation (Yildiz, 2010).

Table 2. Accumulation methods

Operation	Formula
Maximum	$Max\{1, \mu_A(x) + \mu_B(x)\}$
Bounded sum	$Min\{1, \mu_A(x) + \mu_B(x)\}$
Normalized sum	$\frac{\mu_A(x) + \mu_B(x)}{Max\{1, Max\{\mu_A(x'), \mu_B(x')\}\}}$

2.2. Experimental environment and evaluation metrics

The achieved results from the performed system and decisions of the specialist physicians were evaluated with sensitivity, specificity, and accuracy of such evaluation criteria. Statistical measurements of sensitivity, specificity, and accuracy reveal a test’s basic reliability in the medical diagnostic test. They were used to enumerate how the test was good and consistent (Baratloo, 2015). Sensitivity is a term used in Biostatistics. It shows the ability to separate positive patients from all patients in a test. Specificity is an ability of the separates to real sturdy from within the all sturdy. The relationship between both the sensitivity and specificity measures is defined by the graphical approach of the ROC curve and this helps to make a decision to find the optimal model to determine the best threshold for the diagnostic test. One of the measures used when desired sensitivity and specificity combined to obtain a single measure is likely to accurate test results. Accuracy measures correctly figured out the diagnostic test by eliminating a given condition (Baratloo, 2015). Clinical decision support system should have high sensitivity, specificity, accuracy for the high positive and negative predictive value. These indicators can be found by the following formulas 1, 2 and 3.

$$\text{Sensitivity} = \frac{TP}{(TP + FN)} \tag{1}$$

$$\text{Specificity} = \frac{TN}{(TN + FP)} \tag{2}$$

$$\text{Accuracy} = \frac{(TN + TP)}{(TN + TP + FN + FP)} \tag{3}$$

Sensitivity, specificity, and accuracy can be defined for performed study as follows. For example, the patient will be referred to intensive care by the physician who is likely to be positive in the performed software tests’ result. Another measure of trueness that specificity is the probability of a negative result of the performed software for who have not been discharged by the physician. This gives the specificity of the system. It means that, if the sensitivity and selectivity increases, the degree of accuracy in the diagnosis of disease is an increase. The accuracy of the system can be defined in performed study as follow. For example; it is a possibility of the software results are in intensive care same as who will be directed to the intensive care unit. The possibility of being positive or negative of the software results who directed to the service or not directed to the service by the physician respectively. The meaning of the abbreviations for each decision (Discharge, Service, and Intensive Care) is given as Table 3.

Table 3. The meaning of the abbreviation in the statistical evaluation

Discharge	
TP	The number of patients that have been discharged and correctly identified by the developed software
TN	The number of patients that haven’t been discharged and correctly identified by the developed software
FP	The number of patients that should not be discharged from the hospital but discharged by the developed software
FN	The number of patients that haven’t been discharged by the developed software but discharged from the hospital by the doctor
Service	
TP	The number of patients that have been redirected to the service and correctly identified by the developed software
TN	The number of patients that haven’t been redirected to the service and correctly identified by the developed software
FP	The number of patients that have been redirected to the service by the developed software but have not been redirected to the service in fact
FN	The number of patients who haven’t been redirected to the service by the developed software but should be redirected to service.
Intensive Care	
TP	The number of patients that have been redirected to the intensive care and correctly identified by the developed software
TN	The number of patients that haven’t been redirected to the intensive care unit and correctly identified by the developed software
FP	The number of patients that have been redirected to the intensive care by the developed software but haven’t been redirected to the intensive care in fact
FN	The number of patients that haven’t been redirected to the intensive care unit by the developed software but should be redirected to intensive care

In order to find these metrics, we first compute some of the terms like False Negative (FN), True Positive (TP), False Positive (FP) and True Negative (TN) based on the definitions given in Table 4.

Table 4. Terms used to define sensitivity, specificity and accuracy (Anooj, 2012)

Outcome of the diagnostic test	Condition (e.g. disease) as determined by the Standard of Truth		
	Positive	Negative	Row total

Positive	TP	FP	TP + FP (total number of subjects with positive test)
Negative	FN	TN	FN + TN (total number of subjects with negative test)
Column total	TP + FN (total number of subjects with given condition)	FP + TN (total number of subjects without given condition)	N = TP + TN + FP + FN (Total number of subjects in study)

3. Proposed Model

The proposed system is aimed to determine where emergency service patients should be sent to next. The state of patients after emergency service is important for this study. Firstly, patients' parameters were recorded as soon as the patients came to the emergency services. Secondly, the physician's decision was recorded. Finally, the case of patients were recorded one week later. All patients who were recorded data were examined by the same physician and nurse. This physician and nurses did not know why the data was received for avoid of guidance and favoritism.

Nine significant vital signs of a patient are selected as inputs and the next recovery area (discharge, service or intensive care) is returned as the output. The inputs are patients' respiration rate, surface temperature (in Celsius), oxygen saturation (in percent), last measurement of systolic and diastolic blood pressure, Glasgow coma score, pulse, age and perceived comfort value (measured as an integer between 0 and 20). These comfort parameter values reflect the personal opinion of the physician. For example, if the patient has a heavy injury, a lot of pain and almost unconscious comfort value can be given between 15-20. However, if the patients have only a headache and fever, the comfort value can be given 0 - 5. Generally, these parameters are used for monitoring patients in the emergency department (Erdem, 2011). The comfort parameter is one of the most important parameters in this system. Normally, there is no such parameter in medicine. But it was used for the physician interpretation of the patient data. The comfort value can be any value between 0 and 20 reflecting the condition of the patient. If the comfort value zero corresponds to "very bad patient condition" while the comfort value twenty means "a very good patient condition". These inputs are passed to the fuzzy logic-based system that processes and produces the output. The output is displayed as a user-friendly graphical figure to the user. The user interface of the developed software can be seen in Figure 1. The software is quite simple to learn and use for physicians.

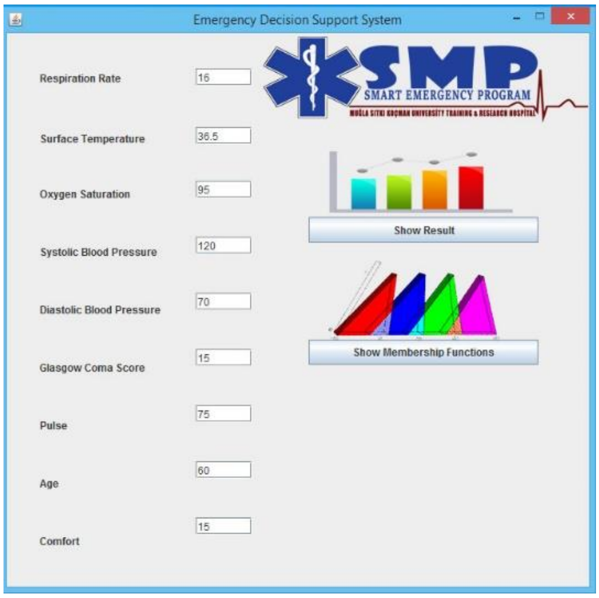

Figure 1. Screenshot of the constructed system

The fuzzy logic based system contains four main components as shown in Figure 2. These are knowledge base, fuzzification, fuzzy inference base, and defuzzification (Mendel, 1995). The steps performed by the fuzzy logic system are explained in subsections.

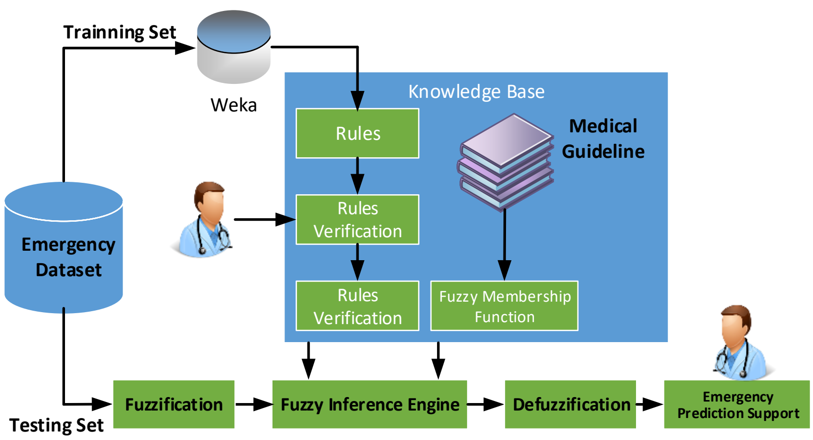

Figure 2. Illustration of the fuzzy logic based system

3.1. Membership Functions for Input Variables

The basic elements of the fuzzy logic is fuzzy sets which is a set with a smooth boundary. Fuzzy sets, are characterized by membership functions. In fact, this membership function is a fuzzy number and it is defined by a function which may assign the membership value between 0 and 1. Such a function is called the membership function.

In most cases, membership functions are derived from large data sets. Similarly, they can be designed by using probability density functions. However, in our work, the lack of existing data set in emergency service makes it difficult to use these methods. For this reason, we have consulted our expert to design the membership functions and define the domain of input variables. Trapezoidal fuzzy sets were used in performed systems for fewer rules and less linguistic value. Membership functions for the used parameters are shown in Figure 3 and 4.

The preparation of membership function is based on the desired system design data and choice of the appropriate shape. The membership function of the nine parameters and their limits were determined with the help of the physician. For example, we use systolic and diastolic blood pressure. This input variable is divided into 3 fuzzy sets. These sets are (Low, Normal and High); membership functions of the 3 fuzzy sets are trapezoidal.

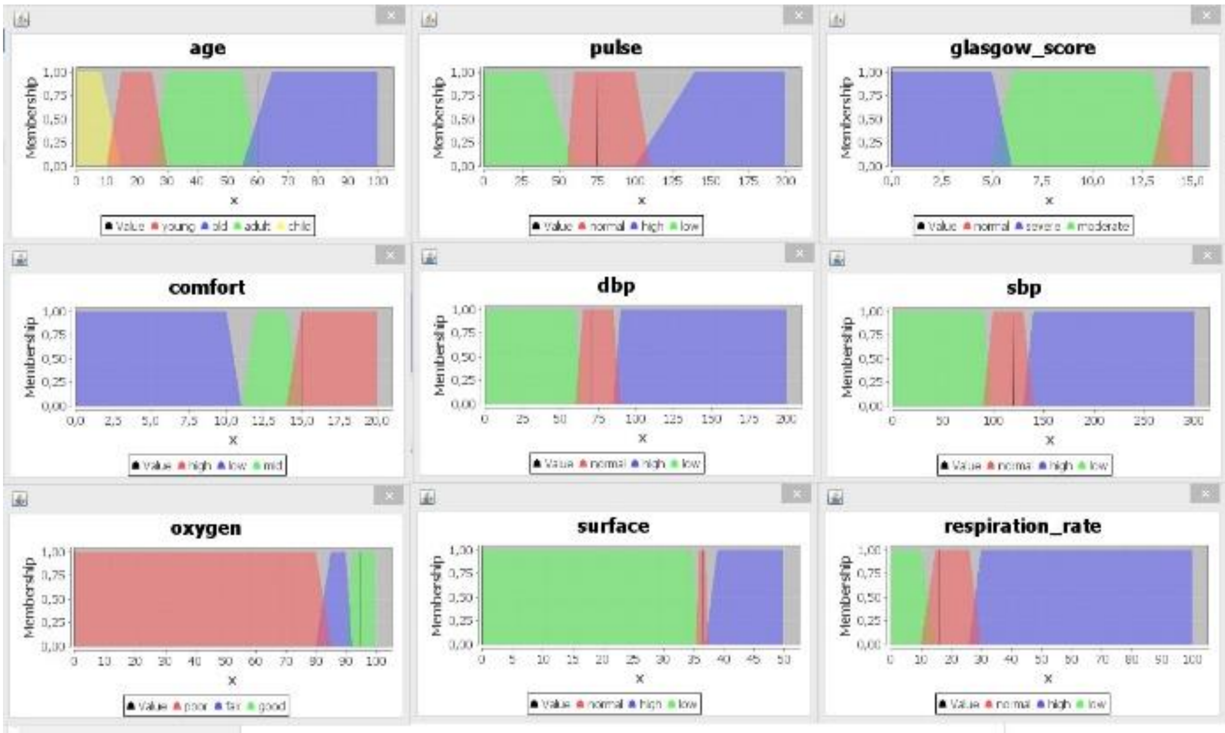

Figure 3. Membership functions for the clinical decision support system's basic parameters.

We use the Center-of-Gravity (COG) approach for the defuzzification process. It is the most commonly used defuzzification method because it provides a correct conclusion based on the weighted values of several output membership functions. Hence, the final decision of the system is calculated through the following formula 4 (Bryan, 1997):

$$Final\ Decision = \frac{\sum_{n=A}^{n=G}[(FO_n)(FGrade_n)]}{\sum_{n=A}^{n=G} FGrade_n} \qquad (4)$$

Where:
Final Decision = the number of clinical decision to be used for the patients
FO = the fuzzy output in counts for labels A through G (for a three-label output membership function)
F_{Grade} = the fuzzy grade level for levels A through G
The result of the performed system is shown with a black line to the physician as shown in Fig. 4.

Figure 4. Membership functions for the decision.

3.2. Designing fuzzy rules for the emergency

The proposed software makes decisions using fuzzy if–then rules. The overall system is driven by 20 rules. First of all, emergency service patients' data were evaluated with the Weka program. Apriori algorithm of Weka is used for the classification of the dataset and

67 rules were created. The Apriori is association-correlation rule algorithm which is used for the discovery of the frequent item in the data mining over transactional databases.

The rules in the realized system were established according to the expert views of the emergency physician. Their views are taken as the final decision in the establishment of fuzzy rule consequent parts under the light of 67 different alternatives. Hence, prior to actual data use, the fuzzy system model was obtained as a collection of IF-THEN rules as in Table 5. Such a fuzzy system is very flexible and can overcome the imprecise type of information.

4. Experimental Results

This study included all patients from a period of seven days who presented to the Muğla Sıtkı Koçman University Training and Research Hospital Center. Many patients come to the emergency department of our hospital in a day but most of them are unnecessary patient to take the assessment. We have used the data of one hundred and fifty patients in the training phase of the system. However, only thirty patients' data were used for the testing of the system.

The experimental results of the clinical decision support system for risk prediction are explained in this section. Here, the performance of the proposed system is evaluated by the sensitivity, specificity, and accuracy (Zhu, 2010). The accuracy, specificity and sensitivity of the system for discharge decision were calculated as 82%, 72%, and 100% respectively as shown in Table 6. However, after a week, the same patients were observed and the accuracy, specificity and sensitivity of the system were calculated as 97%, 93%, and 100% respectively.

Table 6. The comparison of the "Discharge Decision" according to the current and next state of the patients

Output of the System	Discharge (Current)	
	Positive	Negative
Positive	TP = 10	FP = 5
Negative	FN = 0	TN = 13

Output of the System	Discharge(A week later)	
	Positive	Negative
Positive	TP = 14	FP = 1
Negative	FN = 0	TN = 14

The physicians were decided to the "Service Decision" for ten patients. Therewithal, performed intelligent system has decided to the "Service Decision" for eight of them when they come to the emergency department. However, seven patients of them were in the service, one patient was removed from intensive care and two patients were discharged by physicians when examining the situation of these patients after one week. The accuracy, specificity and sensitivity of the system for discharge decision were calculated as 79%, 89%, and 60% respectively as shown in Table 7. However, after a week, the same patients were observed and the accuracy, specificity and sensitivity of the system were calculated as 97%, 95%, and 100% respectively.

Table 7. The comparison of the "Service Decision" according to the current and next state of the patients

Outcome of the system	Service (Current)	
	Positive	Negative
Positive	TP = 6	FP = 2
Negative	FN = 4	TN = 17

Outcome of the system	Service (A week later)	
	Positive	Negative
Positive	TP = 7	FP = 1
Negative	FN = 0	TN = 21

Finally, the decision of the intensive care unit's accuracy, sensitivity and specificity values were calculated as 88%, 100%, and 70% respectively as shown in Table 8. However after a week, accuracy, sensitivity and specificity values were calculated as 93%, 100%, and 77% respectively with a small margin. Because of this, the rules for intensive care patients are very clear and specific symptoms.

After these obtained results in our study, the average accuracy, specificity and sensitivity of the performed study was calculated as 83%, 87%, and 76,6% respectively when the patient as soon as came to the emergency department. Seven days later, these parameters were found as 92.3%, 95.6%, and 96% respectively.

Table 8. The comparison of the "Intensive Care Decision" according to the current and next state of the patients

Outcome of the system	Intensive care(Current)	
	Positive	Negative
Positive	TP = 7	FP = 0
Negative	FN = 3	TN = 16

Outcome of the system	Intensive care(A week later)	
	Positive	Negative
Positive	TP = 7	FP = 0
Negative	FN = 2	TN = 21

5. Discussion

In this study we found the usage of fuzzy logic clinical decision support system is an effective tool for accurate diagnosis of patients in emergency, when it has been made that hospitalization of patients or where to hospitalize.

Previous studies have shown that CDSS can improve physicians' performance and accuracy, but that the quality of any particular system may depend on the technical approach used to model medical information (Sperandio, 2014). Andreas Wicht et al. developed a web-based clinical decision support system (CDSS) for hemato-oncological patients. The results indicate that their approach is promising due to the evaluated in real time and under real conditions (Wicht, 2011). Behnood Gholami et al. designed a clinical decision support system for cardiopulmonary management and Intensive Care Unit Sedation based on the deterministic rule-based expert systems. According to the obtained results, decision support systems are very useful for medical systems (Gholami, 2012). In our study, the average accuracy, specificity and sensitivity of the performed study was calculated as 83%, 87%, and 76,6% respectively when the patient as soon as came to the emergency department. Seven days later, these parameters were found as 92.3%, 95.6%, and 96% respectively. The accuracy of the realized system is quite low when the patients first came to the emergency department compared to other studies listed in Table 1. However, this value is misleading because of medical reasons. For example, realized system has decided to the Discharge for the patient of number 1 as shown in Fig. 5. However, the physician had given service decision for precaution. Because the patient had chest pain and he could be having a heart attack. But, his condition was fine when we look at him a week later.

There was no heart attack. Performed system had guessed correctly. The accuracy of the realized system is 97% when we consider the data one week later. These findings show that clinical decision support system such as performed applications may be helpful to physicians for emergency departments.

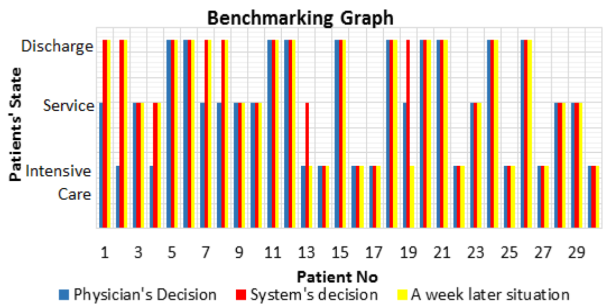

Figure 5. Comparative results of the system

6. Conclusions and Future Work

The demands in the emergency room is increasing day by day. In this case, it is difficult to meet the demand for sometimes. All over the world is looking for various ways in order to respond to extreme excess demand and to distinguish of the serious patients in this crowd. One of the most common methods are triage system for this purpose. For example; the waiting times was calculated as 92.5 minutes in USA (United States Government Accountability Office, 2009). The some medical ways is attempted for solution of these problems such as triage color code and distance healthcare (Duran, 2013). Triage system is patient assessment systems that is made a priority evaluation along with patients' vital signs and symptoms for early recognition of serious patients in the crowded emergency departments and deliver to early treatment. However, it is known that even Triage systems cannot fully eliminate these problems and several additional methods are being sought by researchers (Ozüçelik, 2013). It is obvious that the omitting of the critical patients and in particular delaying of the treatment of intensive care patients is causes vital issue. If you have experienced triage personals, you are able to recognize to the serious patients at the triage system. However, problems are increasing due to the both overcrowding emergency services and inadequate and/or inexperienced personals. At this point, computer-based smart systems can be useful for the solution of these problems. For example, the accuracy, sensitivity and specificity value of the performed CDSS is calculated as 88%, 100% and 70% respectively for patients that should be admitted to the intensive care. These proportions are reassuring. At this point, we believe that if CDSS is used in addition to the triage system, the patients could be treated in the early period due to the high success rate of its'.

Performed system have been identified to critical patients. The accuracy, sensitivity and specificity rates of the recognition of the patient who is discharged were calculated as 82%, 72% and 100% respectively in performed CDSS. Also, the accuracy, sensitivity and specificity values were calculated as 79%, 89% and 60% for hospitalized patients.

According to the performed study in the UK, emergency departments of hospitals is undergoing difficult times because of the crowd. This situation has become an international issue that concerns the whole world. The researchers reported that as a solution the less patients wait in there, the emergency department can be used as more effective. SD Somma and et.al are developed a rule called the 4 hours rule. According to this rule, all patients who admitted to the emergency room should be diagnosed and then admitted or discharged within 4 h. They have expressed that some problems were resolved thanks to this rule such as the overcrowding problems of the emergency services, omission of the diagnosed and delay in treatment of a serious patients was reduced (Somma, 2015). We conclude that we were highly accurate diagnosis that were discharged or services by using vital signs and initial assessment of the patient in performed CDSS. This system will reduce unnecessary tests and ensure the early discharge of patients from the Emergency Department. Another benefit of such a system is early determination of patients who have to directed to the service and early hospitalized patients reduce overcrowding of emergency room.

In this study, we propose a novel and efficient clinical decision support system using fuzzy logic which models a patient's data from emergency services. The system was tested by consulting the expert and the system showed fair accuracy. The usage of fuzzy logic clinical decision support system is an effective tool for accurate diagnosis of patients in emergency. We conclude that studies involving the use of such a Fuzzy Expert System in providing diagnostic and predictive medical opinions are highly promising for the future but these expert systems can never completely replace the clinician.

Conflict of Interest / Çıkar Çatışması

No conflict of interest was declared by the authors.

Kaynaklar

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