Original Article

An Artificial Intelligence Based Application for Triage Nurses in Emergency Department, Using the Emergency Severity Index Protocol

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Abstract

Background: In this article we present i-TRIAGE, an intelligent decision support system to triage patients in an emergency department. i-TRIAGE is an intelligent system, which created in line with the guidelines of an international used triage protocol, named Emergency Severity Index.
Aim: The aim was to create a user-friendly application to assist triage nurses in the procedure to get fast and correct triage decisions and in addition to suggest the most appropriate specialist doctor for each health problem, as there is no medical specialty or specialization of the emergency physician in the country. Also, it could be an educational triage scenarios tool for medical or nursing students.
Methodology: A database of 616 triaged patients from the University Hospital of Patras in Greece, was used to develop and test the system. i-TRIAGE tested in two methods of artificial intelligence (machine learning, fuzzy logic).
Results: The evaluation of the system was based on internationally used metrics and proved to have high success rates, especially in the application of fuzzy logic.
Discussion: The research team believes that i-TRIAGE may in the future be a useful tool for all nurses in an emergency department, to assist triage decisions.

Keywords: Triage Nurse, Artificial Intelligence, Decision Support, Machine Learning, Fuzzy Logic, ED-Triage, Emergency Severity Index.

Introduction

The provision of high-quality health services, in the Emergency Department (ED), is widely accepted and indisputable, that is the key indicator of measuring the quality of a health system. For this r reason, EDs must be adequately staffed with autonomous medical and nursing staff, be organized effectively with full logistical infrastructure and technological support and finally operate in accordance with international standards and protocols (Kipourgos 2015). The above need becomes even more urgent if we consider that the patient saturation coming to the EDs is increasing worldwide every day, and this will hardly change in the near future (di Somma et al. 2015). However, in Greece as well, the situation is not in a better position, as the insufficient development of primary medical care, the inefficient operation of outpatient clinics and the status of non-daily 24-hour on-call hospitals, have led to very high levels of attendance in Greek Eds (Agouridakis &Spirakis 2010) Therefore, according to the above, it becomes clear that triage in the EDs (ED Triage), is necessary and should be a basic condition for the establishment and operation of each hospital. The purpose of ED Triage is to classify patients according to the severity of the problem they are experiencing, as well as to identify those who cannot wait to be examined (Gilboy et al., 2020). Overtriage and under-triage are the most common mistakes and can cause delays or over-treatment (Welch and Davidson 2010).

Background

Emergency Severity Index (ESI) is an approved five-level triage protocol, developed by ED physicians Richard Wuerz and David Eitel in the U.S. (Wuerz et al. 2000; Gilboy et al. 1999), which is widely used worldwide (Tanabe et al., 2005). Wuerz and Eitel argued that the primary goal of an ED triage instrument is to identify patients who need to be treated with priority and safety, and that was responsibility of a triage nurse (Gilboy et al. 2020). ESI is a simple-to-use algorithm that ranks patients first by assessing the severity of a health problem (ESI level 1 or 2), and then resource needs for those who do not meet high-level criteria (ESI level 3, 4 or 5). The inclusion of resource needs is a unique feature of ESI. Acuity is determined by the stability of vital functions and the potential threat to life, limb, or organ. Resource needs are calculated based on previous experience with similar patients and they defined as the number of resources a patient is expected to consume in order to make a disposal decision (discharge, admission, or transfer). Each step of the algorithm guides the user to the appropriate questions to ask. Based on the data or answers received, a decision is made and the user is directed to the next step and finally to the definition of a triage level. ESI algorithm requires an experienced nurse, who starts at the top of the algorithm and who with practice will be able to move quickly from one decision point to the next.

The algorithm uses four decision points (A, B, C and D) to classify patients into one of five levels. The four decision points represented in the ESI algorithm are critical to the accurate and reliable implementation of the ESI (Gilboy et al., 2020).

The four decision points arise from four basic questions:

A. Does this patient need immediate rescue intervention?

B. Is he a patient who should not wait?

C. How many resources will this patient need?

D. What are the vital signs of the patient signs?

Our research team believes that computer science, through the field of Decision-making support systems (DMSS), could be a powerful ally for a health professional, who is responsible for all the above. To date, various DMSS have been developed. The value of these systems lies in assisting decision-makers and interactively supporting all phases of a user's decision-making process (Fernandes et al., 2020a; Gupta et al., 2007). At clinical level, DMSS's are called clinical decision support systems (CDSS) (Fernandes et al. 2020a) and provide health professionals with additional expertise and support to take a clinical decision. They are often used both for the early prevention of diseases and for their correct diagnosis (Troisi, 2021). They have also been used to prevent drug side effects, (Garg et al. 2005) manage pain, (Pombo et al. 2014) and triage patients in a ED (Fernandes et al. 2020b).

The development of the Artificial Intelligence (AI) in the last years, has favored the further clinical use of CDSS's. AI is defined as the field of computer science that deals with the ability of computers to do things that would require intelligence if humans did (Stewart et al. 2018). The concept of AI was introduced in the 1950s, but the lack of electronic data at that time delayed its widespread use (Ahmad and Jenkins 2022).

Our purpose through this paper is to present an AI-based application for ED-Triage, which based on the ESI protocol for triage patients in the emergency department and this application was called intelligent-Triage or *"i-Triage"*. We chose to create experienced AI systems using fuzzy logic and machine learning methods. Our expectation is not that these systems could replace the experts. On the contrary, we believe that they could be useful tools to assist in making a critical decision, and/or an extra educational material to familiarize new nurses and nursing students in ED-triage scenarios.

Methodology

Study design and population: The present study was designed to create intelligent systems of artificial intelligence and machine learning, which will then be evaluated according to international metrics and compared with the knowledge of experts in the field of ED-Triage. These are systems that have been trained by experts, in order to be able to function as an aid and support in clinical decision-making, as well as training tools for young nurses and nursing students. The study was conducted under the scientific supervision by Master's Program in Informatics for Life Sciences of the University of Patras and its population were patients who arrived at the emergency department of the University Hospital of Patras, for one month. All the patients were triaged by an expert triage nurse, using ESI algorithm.

Data collection: Data were collected through a PHP form, which was created for our study. The form elements were created by the first author of the article and according to the ESI protocol for ED-Triage. However, each item was evaluated by several experts (ED-Triage nurses, clinicians, academic members etc.) and the content validity index was calculated. The authors accepted the data that showed a validity index above 0.80. The reliability of the internal consistency of the form was assessed by estimating the Cronbach's Alpha value, with results >0.70, which was considered acceptable. In addition, a pilot collection was conducted between 40 patients, who did not participate in the final sample. The expert ED-Triage nurse was filling one form for each patient and after the SUBMIT selection, the information was saving in a database. The base consists of a table called *'triage_data'*, which consists of 186 fields. As the collection of research data was completed and a total of 616 cases were registered, the data was exported in a form of spreadsheets, for their study and production of the *i-TRIAGE* rules.

Functional architecture: Before explaining the structure of the intelligent system, it should be clear exactly what *i-TRIAGE* is all about. The goal is twofold, as on the one hand the patients should be characterized in five levels of severity of their health problem and on the other hand it should be decided who specialist physician should treat them, due to the lack of emergency physicians. Exactly for this reason individual subsystems were created, multiples of the number of medical specialties of the emergency department. Thus, according to the knowledge acquired and gathered, the functional architecture of *i-TRIAGE* was designed **(Fig. 1).** Looking at the picture, it seems that all the data when entering them constitute the Basic System (*i-TRIAGE*), which is then divided into individual subsystems, and which eventually reach the conclusion. Each subsystem has unique input and output variables, while all subsystems have some general input variables, which are common to all subsystems. Thus, a second distinction for input variables other than that made in the previous section, concerns the general variables (Basic system) and the specific variables (unique for each subsystem).

Implementation Issues

i-TRIAGE has been designed and implemented with the fuzzy artificial intelligence tool, *Fuzzy Clips* and compared to the *WEKA* machine learning tool.

When designing Fuzzy Clips, 6 fuzzy variables were created, which were:

- Blood pressure,
- Heart rate,
- Respiration rate,
- Oxygen saturation,
- Pain scale, and
- Body temperature

The *fuzzyTECH 6.06* software tool was used to design the graphs of the fuzzy variables. It is an especially useful and helpful tool for the development and optimization of fuzzy intelligent systems. For the operation of *i-TRIAGE*, in addition to the fuzzy input variables described above, a variety of variables with clear boundaries (clear variables) were created. Some of these variables concerned all *i-TRIAGE* subsystems, while there were some specific for each subsystem.

The reason the *i-TRIAGE* subsystems were created is to reduce complexity and optimize efficiency. Thus, as many subsystems were created as the corresponding medical specialties, as well as an additional system, which concerned the Resuscitation Team. Listed below are the subsystems and in parentheses the set of rules designed for each of them in the application of fuzzy logic:

• i-TRIAGE_path (Pathological system - 60 rules)

• i-TRIAGE_musc (Musculoskeletal system - 43 rules)

• i-TRIAGE_neuro (Neurological system - 10 rules)

• i-TRIAGE_cardio (Cardiac system - 11 rules)

• i-TRIAGE_uro (Urological system - 9 rules)

• i-TRIAGE_orl (Otolaryngological System - 15 rules)

• i-TRIAGE_gyn (Gynecological system - 6 rules)

• i-TRIAGE_derm (Dermatological system - 9 rules)

• i-TRIAGE_rt (Resuscitation Team System - 9 rules)

The user interface has been developed in an easy-to-use and friendly PHP environment, which was created with the online tool *"Free MySql Database & PHP generator"*. In this environment the user enters the data and by selecting the command *"SUBMIT"*, the corresponding intelligent experienced system is called and immediately on the screen returns the triage decision.

Ethical considerations and human protection: This study, which is in line with the Helsinki Declaration (1964) and follows the guidelines of the European Network of Research Ethics Committees(EUREC - Home n.d.) and the National Commission for Bioethics and Technoethics, was approved by the Committee on Research, Ethics and Deontology and consequently by the Scientific Council of the university hospital, where the first author works. In addition, complete anonymity and non-collection of personal information was ensured.

Results

In the *i-TRIAGE* test, we used two different methods. We first tried to implement and test the efficiency of the system using the WEKA machine learning tool using the J48 algorithm. The second method sought was the implementation through Fuzzy Clips, using six fuzzy variables, which were widely used in the production of rules for exporting output classes.

WEKA Machine Learning Model

When applied to the machine learning tool, all data were used as input variables, except for each patient number *(ID)* and the ED-Triage expert decision *(ESI_TRIAGE_SCALE)*. The explanation for this is that the machine learning tool, should only include clinical data to produce a decision tree. The machine learning tool chosen was WEKA and the algorithm was selected was *J-48 algorithm*. Also, the *"reduced error pruning"* selection was true, while the test method was *"cross validation: 10 folds"*. The highest success rate was achieved in the *i-TRIAGE_rt* subsystem (95%). Neurological and cardiological subsystems had similarly high success rates (~94%). *i-TRIAGE_derm* had the lowest success rate of 72%. *i-TRIAGE_path,* the system with the highest volume of cases and features, has a success rate of 86.2%, with 176 of the 204 cases being classified correctly. The rest of the systems ranged from ~ 85-90%. The **Table 1** analyzes the total percentages of the method in all subsystems.

Fuzzy Clips Model

The second method sought was the implementation of *Fuzzy Clips*, using six fuzzy variables, which were widely used in the production of rules for exporting output classes. The fuzzy variables that used, fully justify their existence both technically and bibliographically. The six variables used represent the patient's 4 vital signs (Blood Pressure, Heart Rate, Respiration Rate, Temperature), Oxygen Saturation (SPO2) and pain experienced by the patient on a pain scale of 1-10. As, the physiological limits of the variables of vital signs and SPO2 are very easily changed by factors such as age, environment, pre-existing pathology etc. and the feeling of pain that a patient feels, is completely subjective, fuzzy logic for these variables, was the best solution.

We used *i-TRIAGE* for a total of 616 patients, related to various health problems with triage decisions of all levels, according to the ESI triage protocol and which had to be treated by different specialists, due to the lack of emergency physicians.

To evaluate the *i-TRIAGE*, we used 4 metrics, commonly used for this purpose: accuracy, precision, sensitivity, and specificity (abbreviated as Acc, Sen and Spec respectively), defined as follows:

Acc = (a + d) / (a + b + c + d),

Prec = a / (a + c),

Sen = a / (a + b),

Spec = d / (c + d)

where, *a* is the number of positive cases correctly classified, *b* is the number of positive cases that are misclassified, *d* is the number of negative cases correctly classified and *c* is the number of negative cases that are misclassified. By *"positive"* we mean that a case belongs to the group of the corresponding initial diagnosis and by *"negative"* that it doesn't.

All systems in Fuzzy Clips, had 100% metric ratings, except for the pathological one which had incorrect categorization in the control set, in just 1 case **(Table 2).**

Figure 1. Functional architecture of *i-TRIAGE*

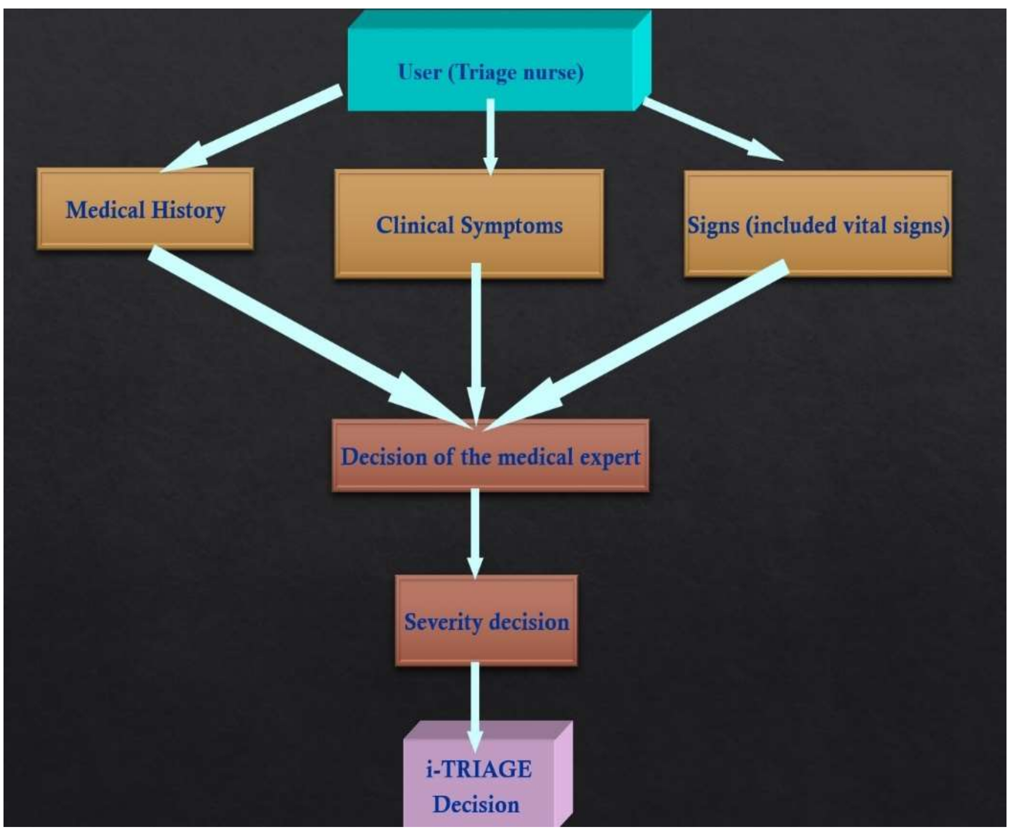

Table 1. Results of *i-TRIAGE* in WEKA

Evaluation results for *i-TRIAGE* in FUZZY CLIPS

Accuracy	0,99
Precision	0,93
Sensitivity	0,99
Specialization	0,99

i-TRIAGE in Machine Learning Model (616 patients)

i-TRIAGE Subsystem	Success Rate	Error Rate
i-TRIAGE_path (204 patients)	86,2745% (176)	13,7275% (28)
i-TRIAGE_musc (120 patients)	88,3333% (106)	11,6667% (14)
i-TRIAGE_neuro (34 patients)	94,1176% (32)	5,8824% (2)
i-TRIAGE_cardio (50 patients)	94% (47)	6% (3)
i-TRIAGE_uro (41 patients)	90,2439% (37)	9,7561% (4)
i-TRIAGE_orl (68 patients)	85,2941% (58)	14,7059% (10)
i-TRIAGE_gyn (34 patients)	88,2353% (30)	11,7647% (4)
i-TRIAGE_derm (25 patients)	72% (18)	28% (7)
i-TRIAGE_rt (40 patients)	95% (38)	5% (2)

Table 2. Evaluation results for *i-TRIAGE* in FUZZY CLIPS

Discussion

i-TRIAGE was designed and developed to serve as a valuable aid to an ED-Triage nurse. An already tested triage protocol was used (ESI), which among other things includes the availability of resources (Chmielewski and Moretz 2022; Gilboy et al. 2020). However, the innovation of the system lies in the fact, that it does not produce an effect only for the degree of severity of the health problem, but also proposes the respective specialist doctor, who will have to deal with the incident. The need for the latter came from the fact that in Greece the specialty or specialization of the emergency clinician is not established yet.

We already knew that AI is a very well-tested field at the clinical level. Representatively we mention applications in: Cardiology (Dorado-Díaz et al. 2019) and specifically in the fields of Atrial Fibrillation (Raja et al. 2019; Turakhia et al. 2019; Halcox et al. 2017), Cardiovascular Risk (Huang et al. 2017), Pulmonary Medicine (Topalovic et al. 2019), Endocrinology, in the field of diabetes self-management (Lawton et al. 2018), Nephrology (predict GFR) (Niel et al. 2018), Gastroenterology (Yang and Bang 2019), Neurology and specifically in the fields of Epilepsy (Regalia et al. 2019), Gait, Posture, and Tremor Assessment (Dorsey et al. 2018), Computational Diagnosis of Cancer in Histopathology (Campanella et al. 2019), Medical Imaging and Validation of AI-Based Technologies.(Liu et al. 2019) In addition, the current health crisis due to the pandemic from the new coronavirus was another challenge for artificial intelligence systems. We have seen applications of artificial intelligence in various areas: (1) providing early warnings, (2) monitoring and forecasting, (3) data analysis, (4) forecasting and diagnosis, (5) treatment and care and (6) social control.(Namdar et al. 2022; Artificial Intelligence against COVID-19: An Early Review | IZA - Institute of Labor Economics n.d.)

Also, we know from the literature that AI systems have been developed for ED-Triage. Most of them relied on variables such as age, gender, vital signs, and major health problem to produce the rules (Fernandes et al. 2020b). The writing team evaluated and decided to use fuzzy logic in some variables, and these were used extensively in the production of the rules. *i-TRIAGE* was tested in two different methods of AI. Both machine learning and fuzzy logic yielded high performance metrics, with the latter, however, being comparatively superior.

Limitations and Strengths: Artificial intelligence algorithms are often a controversial tool, which may also facilitate mistrust of their use. Many times, there is a bias from health professionals about the contribution of AI and issues arise that mainly concern ethical and legal implications. Also, patients currently trust health professionals more than a machine. A second constraint specific to *i-TRIAGE* refers to the fact that it was created using only variables that were studied in the specific patients in the study. So, a logical question is *"what sorting decision will the system make for a patient with different variables from those studied?"*

Knowledge and acceptance of the above restrictions have led us in the right direction. We believe, that one of the strengths of the system is that it was not designed to replace the human factor, but to be an intelligent information aid in making a difficult clinical decision. Thus, *i-TRIAGE* does not decide, but proposes a triage decision. In addition, young health professionals and students could become familiar with ED-Triage scenarios through the system, whereby the system also acquires an educational role. A second strength of the system concerns the large volume of patients studied. The 616 cases provided a wide range of clinical variables, and several triage rules were generated. However, in the perspective of clinical use of the system, the user can create new rules every time he encounters an incident for which there is no provision by the system. In this way the system will constantly learn and be enriched.

Implications for Emergency Nursing: Triage nurses in an emergency department see a large number of patients on a daily basis. The large volume of patients and the pressure of the need for immediate assessment and decision are variables that may lead to errors in decisions.

Knowing that the ESI is a reliable and widely used triage protocol, we thought we could aim to create an "intelligent" system, relying on artificial intelligence algorithms, to produce triage decisions. Of course, the role of the professional nurse cannot be replaced by a machine, which is why it is emphasized that the role of the system is to assist and suggest triage decisions.

We believe that the evaluation metrics achieved leave promising expectations for even greater use in the future, either using the i-TRIAGE as a training tool in simulated triage scenarios, or as an aid to a triage nurse. Finally, our system could also be used in health systems that do not have emergency physicians in the emergency departments, as it was created with the aim of recommending the right physician to handle each incident.

Conclusions: The procedure of ED-Triage is certainly not a simple and effortless process. However, it is a key indicator for evaluating the quality of health services provided. Also, the immediacy of dealing with an incident should be characterized by scientific subjective and objective criteria. For the above two reasons and as it is unacceptable and dangerous for patients to be treated in random order or in order of priority based on arrival time, the need for triage is imperative for all ED's. There are a variety of algorithmic triage protocols that used around the world. The protocol chosen for the needs of this work is ESI, which is a system of five levels (1-5) and which is used internationally (included Greece-Thessaloniki/General Hosp. Papageorgiou). Despite the limitations, current AI techniques are very capable of solving well-defined problems in a wide range of clinical areas. Such systems have the potential to enhance many aspects of emergency patient care. In this work, we present the design, implementation, and evaluation of *i-TRIAGE*, an intelligent system that deals with the triage of patients in an emergency department. The process was modeled based on the selection decisions of the experts and the existing literature. In testing this system, we used two different methods. We first tried to implement and test the efficiency of the system using the WEKA machine learning tool using the J48 algorithm. The results were satisfactory with the individual *i-TRIAGE* systems achieving a correct categorization rate of 72-95%. The second method sought was the implementation through Fuzzy Clips, using six fuzzy variables, which were widely used in the production of rules for exporting output classes. The effectiveness of the fuzzy logic has an obvious advantage compared to WEKA. All systems had 100% evaluation metrics, except the pathological one which had incorrect categorization in the control set, in just one case and metrics:Accuracy = 99%, Precision = 93%, Sensitivity = 99%, Specialization = 99%. In total, *i-TRIAGE* achieved correct categorization in 615 out of 616 cases of its total. In conclusion, our study showed that AI could help a nurse to get triage decisions in an emergency room and maybe in the near future *i-TRIAGE* be a clinical or/and educational tool.

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