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Multi-objective evolutionary algorithms for fuzzy classification in survival prediction

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ABSTRACT

Objective: This paper presents a novel rule-based fuzzy classification methodology for survival/mortality prediction in severe burnt patients. Due to the ethical aspects involved in this medical scenario, physicians tend not to accept a computer-based evaluation unless they understand why and how such a recommendation is given. Therefore, any fuzzy classifier model must be both accurate and interpretable.
Methods and materials: The proposed methodology is a three-step process: (1) multi-objective constrained optimization of a patient's data set, using Pareto-based elitist multi-objective evolutionary algorithms to maximize accuracy and minimize the complexity (number of rules) of classifiers, subject to interpretability constraints; this step produces a set of alternative (Pareto) classifiers; (2) linguistic labeling, which assigns a linguistic label to each fuzzy set of the classifiers; this step is essential to the interpretability of the classifiers; (3) decision making, whereby a classifier is chosen, if it is satisfactory, according to the preferences of the decision maker. If no classifier is satisfactory for the decision maker, the process starts again in step (1) with a different input parameter set.
Results: The performance of three multi-objective evolutionary algorithms, niched pre-selection multi-objective algorithm, elitist Pareto-based multi-objective evolutionary algorithm for diversity reinforcement (ENORA) and the non-dominated sorting genetic algorithm (NSGA-II), was tested using a patient's data set from an intensive care burn unit and a standard machine learning data set from an standard machine learning repository. The results are compared using the hypervolume multi-objective metric. Besides, the results have been compared with other non-evolutionary techniques and validated with a multi-objective cross-validation technique. Our proposal improves the classification rate obtained by other non-evolutionary techniques (decision trees, artificial neural networks, Naive Bayes, and case-based reasoning) obtaining with ENORA a classification rate of 0.9298, specificity of 0.9385, and sensitivity of 0.9364, with 14.2 interpretable fuzzy rules on average.
Conclusions: Our proposal improves the accuracy and interpretability of the classifiers, compared with other non-evolutionary techniques. We also conclude that ENORA outperforms niched pre-selection and NSGA-II algorithms. Moreover, given that our multi-objective evolutionary methodology is non-combinational based on real parameter optimization, the time cost is significantly reduced compared with other evolutionary approaches existing in literature based on combinational optimization.

1. Introduction

Severely burned patients require specialized medical care to minimize mortality [1]. Great efforts have been made to analyze this problem from the clinical, the epidemiological and national health system perspective [2–6]. Although the survival rates for burn patients have improved substantially due to medical care in specialized burn centers, patient mortality is still the primary outcome measure for burn care [7].

Early mortality prediction after admission is essential before an aggressive or conservative therapy can be recommended. Severity scores are simple but useful tools for physicians when evaluating the state of the patient. Scoring systems aim to use the most predictive pre-morbid and injury factors to yield an expected likelihood of death for a given patient [7]. In general practice, physicians only use a few scores, usually internationally accepted ones involving very simple calculations, such as the simplified acute physiology score (SAPS I-II), the acute physiology and chronic health evaluation score (APACHE II), or the sequential organ failure assessment

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(SOFA) [8,9]. However, their daily use in burn centers gives rise to a potential problem, since the above mentioned scores are not designed for critically ill burn patients.

Open burn wounds increase vulnerability to environmental contamination, the larger the burn size the more vulnerable it is to contamination. Burn-related deaths depend on the total body surface area (TBSA). Moreover, from the epidemiological point of view, sex, weight and age are also significant for mortality from burn wounds [1,10].

Some effort has been dedicated to predicting mortality using a scoring system after burn trauma based on these evidences. Baux and prognostic burn index (PBI) scores provide a mortality rate by summing age and TBSA [11,12]. Other authors also consider respiratory problems, such as the model presented in [13] using a respiratory score, the CapeTown score, which extends the Baux score with an inhalation score [14], or the score based on logistic regression presented in [15].

Some authors suggest that, for mortality prediction in burns, TBSA, age and inhalation injury outweigh other factors significantly enough to serve as the only components that need to be used to give a prediction [7], for example, the probability of death estimation described in [16]. On the other hand, the widely used abbreviated burns severity index (ABSI) considers gender, age, inhalation injury, %TBSA and presence of the burns severity score proposed in [17].

However, infections and co-morbidity are also relevant aspects to consider. Burn patients with larger burn injuries (over 30%TBSA) and those colonized by multiple resistant organisms require special precautions [1]. Indeed, 75% of deaths are currently related to infectious complications and inhalation injuries from burn wounds when the TBSA is over 40% [1,18,19]. According to [19], about 75% of mortality is related to infections.

If infections and co-morbidity are considered, the number of parameters to analyze increases considerably. The two main problems are the difficulty involved in selecting relevant parameters and the need to provide a survival model that can be easily interpreted by physicians.

Further efforts can be made to combine infection and co-morbidity factors in an attempt to provide a death estimation. For instance, in [4] a mortality prediction model is proposed based on multivariate analysis. In this sense, the combination of evolutionary computation and fuzzy logic, namely evolutionary fuzzy systems [20,21], helps to solve this kind of problem. In particular, we focus on rule-based fuzzy classification since rules can be easily interpreted by physicians [22–26]. In our proposal, these rules are obtained from the medical data sets using a multi-objective constrained optimization model which maximizes the classification rate and minimizes the number of rules of the classifier, subject to interpretability constraints. This optimization model is solved by using Pareto-based elitist multi-objective evolutionary algorithms [27–30].

The remainder of this paper takes the following form: Section 2 reviews the main works developed in the fields of fuzzy classification and evolutionary computation, particularly when applied to artificial intelligence in medicine. The main differences and advantages of our proposed approach compared to existing studies are shown. Section 3 describes a fuzzy optimization process for mortality scoring, where a fuzzy classification model is described and a multi-objective constrained optimization model is proposed to learn accurate and comprehensible fuzzy classifiers. In Section 4 two Pareto-based elitist multi-objective algorithms (niched pre-selection and ENORA) are proposed to learn fuzzy classifiers according to the proposed multi-objective constrained optimization model. In addition, the well known multi-objective evolutionary algorithm NSGA-II is briefly described. Section 5 includes the experiments carried out and the results obtained for the problem of classifying infection-related mortality in patients suffering from severe burns. In order to compare the results obtained by our algorithm and those obtained by other authors in the scientific community, this work also includes experiments for the well-known problem of the Iris data set classification. An analysis of the obtained results is also included. Section 6 discusses the novelties and benefits of our suggested methodology and the main conclusions of the paper are outlined.

2. Background

In this section we review some of the efforts made to lend weight to prediction of mortality using artificial intelligence techniques. We then analyze fuzzy classification and evolutionary computation techniques and their impact in the medical field.

2.1. Mortality scoring in artificial intelligence

There is increasing interest from the medical community to support mortality scoring by artificial intelligence techniques [31–35]. In particular, commonly used scoring systems have been deeply analyzed for critical patient care, such as APACHE or SOFA and severity and organ failure scores for Intensive Care Units (ICU) [8,9]. In [36,37] mortality prediction models are presented, combining APACHE score and artificial neuronal networks. The work described in [38] presents a case-based reasoning system using APACHE to support clinical decisions. In [9,39] SOFA-based models are analyzed to support mortality predictions in ICUs. In [40], the T-CARE system based on temporal case-based reasoning is presented to support severity scores in burns units.

In medical scenarios where mortality prediction depends on a large number of features, some authors propose the use of evolutionary computing. For example, in [41], the authors propose a survival prediction for breast cancer based on genetic programming. A Bayesian model optimized by a genetic algorithm is described in [42] for mortality prediction.

2.2. Fuzzy classification in medicine

One illustrative milestone of these first works is the MYCIN system, a diagnosis support system for infectious diseases in which the medical knowledge is provided from the physician's team in the form of rules [43].

Fuzzy sets [44] have been recognized for their ability to introduce notions of continuity into deductive thinking. Because its continuous nature, the behavior of fuzzy systems is more likely to be closer to medical reality than the behavior of classical systems. Additionally, fuzzy sets allow symbolic models to be used. Fuzzy sets can bridge the gap between the discrete world of reasoning and the continuity of reality, which is the main reason why they are considered useful in [45].

One of the most important areas of application in the fuzzy set theory is *fuzzy rule-based systems (FRBSs)*. These fuzzy logic systems constitute an extension of the classical rule-based systems, because they deal with *if-then* rules, whose antecedents and consequences are composed of fuzzy logic statements, rather than classical logic ones. In a broad sense, an FRBS is a rule-based system in which fuzzy logic is used as a tool for representing different forms of knowledge about a problem, as well as for modeling the interactions and relationships that exist between its variables. Due to this property, fuzzy logic principles have been successfully applied to a wide range of problems in different domains in which uncertainty and vagueness emerge in varying ways.

Fuzzy classification is one of the most common applications of FRBSs. Some examples of applications in medicine are the classification of medical images [46], interpretation of mammograms [47], classification of the malformation of cortical development [48] and