

Chapter 4.19

Medical Outcome Prediction for Intensive Care Unit Patients

Simone A. Ludwig

North Dakota State University, USA

Stefanie Roos

Darmstadt University, Germany

Monique Frize

Carleton University, Canada

Nicole Yu

Carleton University, Canada

ABSTRACT

The rate of people dying from medical errors in hospitals each year is very high. Errors that frequently occur during the course of providing health care are adverse drug events and improper transfusions, surgical injuries and wrong-site surgery, suicides, restraint-related injuries or death, falls, burns, pressure ulcers, and mistaken patient identities. Medical decision support systems play an increasingly important role in medical practice. By assisting physicians in making clinical decisions, medical decision support systems improve the quality of medical care. Two approaches have been investigated for the prediction of medical outcomes: “hours of ventilation” and the “mortality rate” in the adult intensive care unit. The first approach is based on neural networks with the weight-elimination algorithm, and the second is based on genetic programming. Both approaches are compared to commonly used machine learning algorithms. Results show that both algorithms developed score well for the outcomes selected.

INTRODUCTION

A study of the health care system in the United States reported that at least 44,000 people, and perhaps as many as 98,000 people, die in hospitals each year as a result of medical errors, many of

which could have been prevented. Medical errors can be defined as the failure of a planned action to be performed as intended or the use of the wrong action to achieve an aim. Problems that frequently occur during the course of providing health care are adverse drug events and improper transfusions, surgical injuries and wrong-site surgery, suicides,

DOI: 10.4018/978-1-61350-456-7.ch4.19

restraint-related injuries or death, falls, burns, pressure ulcers, and mistaken patient identities. High error rates with serious consequences are most likely to occur in intensive care units, operating rooms, and emergency departments (Institute of Medicine, 1999).

Medical decision support systems play an increasingly important role in medical practice to address the above stated problems. By assisting physicians with making clinical decisions, medical decision support systems are expected to improve the quality of medical care (Wennber & Cooper, 1999).

Sim et al. (2001) define clinical or medical decision support systems as software designed to be a direct aid to clinical decision-making, where the characteristics of an individual patient are matched to a computerized clinical knowledge base; patient-specific assessments or recommendations are then presented to the clinician and/or the patient for a decision. Numerous medical decision support systems have been developed to assist medical practice. In 2001, Kaplan reviewed 27 clinical decision support systems reported in the literature (Kaplan, 2001), while Metaxiotis et al. (2000) list 13 well known systems developed for diagnosis, test result interpretation and knowledge management. The range of clinical decision support systems spans the realms of home health care, to enterprise-wide systems, to medical research laboratories. When developing a new CDSS, several factors need to be considered to increase the likelihood that it will be integrated into the health care delivery in a variety of clinical environments. These factors need to be applied at all stages of the development life cycle of the CDSS. The criteria for a successful deployment of a CDSS can be divided into three main areas: (i) The data entry and the decision algorithms; (ii) the human-computer interaction, which includes the data acquisition and the manner in which information is requested from the system; and its usability; (iii) the output of the CDSS, including

the format and type of information supplied (Frize et al., 2010).

The application of machine learning methods in medicine is the subject of considerable ongoing research, which mainly concentrates on modeling some of the human actions or thinking processes and recognizing diseases from a variety of input sources (e.g. cardiograms, CAT (Computed Axial Tomography) / MRI (Magnetic Resonance Imaging) / ultrasound scans, photomicrographs, etc.). Other application areas are knowledge discovery (Neves et al., 1999), and biomedical systems, which include genetics and DNA analysis. The use of machine learning has also been applied to biomedical science related systems. There is already a growing interest in the application of learning systems for the interpretation of gene expression data (Brown et al., 1999; Slonim et al., 2000).

In a medical diagnosis problem, what is needed is a set of examples that are representative of all the variations of the disease. The examples need to be selected very carefully if the system is to perform reliably and efficiently. However, development of machine learning systems for medical decision-making is not a trivial task. Difficulties include the acquisition, collection and organization of the data that will be used for training the system. This becomes a major problem, especially when the system requires large data sets over long periods of time, which in most cases is not available due to the lack of an efficient recording system, or because of privacy issues. Another difficulty arises when trying to automate some processes as not all of them can be automated due to ethical and safety issues. Deciding what could and needs to be automated directly influences the design and implementation of the learning system.

The aim of this paper is to compare two classifiers with other machine learning techniques for the prediction of medical outcomes, such as the hours of ventilation necessary for patients in the Intensive Care Unit (ICU), and the prediction on whether the patient is likely to survive. Our two

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