ABSTRACT
The replacement of defective organs with healthy ones is an old problem, but only within a few years has this issue been put into practice. Improvements in the whole transplantation process have been increasingly important in clinical practice. In this context are clinical decision support systems (CDSSs), which have reflected a significant amount of work to use mathematical and intelligent techniques. The aim of this article was to present consideration of intelligent techniques used in recent years (2009 and 2010) to analyze organ transplant databases. To this end, we performed a search of the PubMed and Institute for Scientific Information (ISI) Web of Knowledge databases to find articles published in 2009 and 2010 about intelligent techniques applied to transplantation databases. Among 69 retrieved articles, we chose according to inclusion and exclusion criteria. The main techniques were: Artificial Neural Networks (ANN), Logistic Regression (LR), Decision Trees (DT), Markov Models (MM), and Bayesian Networks (BN). Most articles used ANN. Some publications described comparisons between techniques or the use of various techniques together. The use of intelligent techniques to extract knowledge from databases of healthcare is increasingly common. Although authors preferred to use ANN, statistical techniques were equally effective for this enterprise.

METHODS
We performed a search of Pubmed (http://www.ncbi.nlm.nih.gov/pubmed/) and Institute for Scientific Information (ISI) Web of
Knowledge (http://apps.isiknowledge.com) databases. Our inclusion criteria considered articles containing the search descriptors present in the title, abstract, keywords, and subject in 2009 and 2010. As exclusion criteria, we considered: the absence of a full text, a topic unrelated to transplantation databases or application of mathematical methods, and documents that were not original, such as literature reviews, letters, and comments. The searches used are as follows.


ISI Web of Knowledge: Topic=(“Transplantation” AND (“artificial intelligence” OR “Decision support systems” OR “Artificial Neural Networks” OR “Decision Trees” OR “Fuzzy Logic” OR “Decision Support Techniques”)) AND Year Published=(2009 OR 2010).

RESULTS

We found 69 articles including 2 common to both databases. We excluded 59 of these due to the above exclusion criteria, leaving 8 files for reading. There were 3 more articles in 2010 than in previous work.8 The following techniques were identified: Artificial Neural Networks (ANN), Logistic Regression (LR), Decision Trees (DT), Markov Models (MM), and Bayesian Networks (BN).

Table 1 summarizes the applications and techniques used in these articles.

Five of the 8 articles described the use of ANN. Nilsson et al9,10 developed a predictive model for survival and donor-recipient matching using ANN. Using a database of 70,759 records from heart transplantation,9 they selected the most important variables, achieving a correlation of 0.59 between ANN and Kaplan-Meier results. In a database of 59,698 records of heart transplantations10 as well, the model selected 14 donor and 21 recipient important variables, observing that the best donor-recipient matching achieved a survival 5-year-transplant rate of 77%.

Hummel et al11 applied ANN to a database of 145 kidney transplant recipients seeking to predict nephrotoxicity and acute cellular rejection (ACR) after the first year posttransplantation. For nephrotoxicity, the authors achieved accuracy (ACC) of 75.68%, whereas for ACR, it reached 80.89%.

Oztekin et al12 compared ANN, LR, and DT applied to a database of 16,604 heart-lung transplantation records. They showed that ANN and LR achieved similar results to predict survival at 9 years with accuracies of 82.4% and 81.9% respectively. These methods showed better performances than DT (ACC = 74.9%). Similarly, Caocci et al13 showed that ANN outperformed LR to predict the occurrence of acute graft-versus-host disease (aGVHD) among a database of 78 stem cell transplant recipients with an accuracy 83.3%.

Using a more probabilistic approach, Pidala et al14 employed MM to predict the optimal type of stem cells for transplantation (peripheral blood or bone marrow), based upon estimated survival after transplantation. The survival curves produced by the model were similar to those observed by meta-analysis. The authors also found that the life expectancy of those who receive peripheral blood stem cells was in most cases greater than that of those who received bone marrow stem cells. Also using MM, Saab et al15 compared the cost-effectiveness of 2 models of hepatitis B prevention in liver transplant recipients.

Finally, Stajduhar et al16 compared several BN algorithms among a database of 137 patients seeking to predict relapse after bone marrow transplantation. They observed which variables were important for this type of classification, achieving an accuracy rate of 77.43%.

DISCUSSION

The use of ANN seems to be preferred for knowledge extraction from transplantation databases. Consistent with the review of Hummel et al,8 we noted the application of ANN in most articles. Some of these compared ANN with other learning techniques; ANN outperformed DT12 and LR.13 Moreover, ANNs were used to predict survival,9,10,12 risk of a bad match between donor and recipient,9,10 occurrence of diseases after transplantation,13 and rejection or nephrotoxicity.11 It can also be used in conjunction with other techniques such as simulations based on Monte Carlo models.10 Despite the good results presented in these publications, one must be careful to not generalize them. Many articles showed results of applications to specific databases, which were used only during training, while some

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used databases with few data. When used in clinical practice or in various databases, the results can be different. Only Stajduhar et al\(^{16}\) extrapolated their methodology to different databases, achieving significant results in all of them.

It is worthwhile to emphasize the wide applicability of mathematical and computational techniques. We can find applications to different types of transplantation such as bone marrow, heart, lung, and kidney. Hummel et al\(^{8}\) also found applications in previous studies of liver and pediatric transplantation.

In conclusion, the use of intelligent techniques to extract knowledge from transplantation databases is increasingly common. The preference for and efficacy of ANN is evident. Moreover, statistical techniques such as MM have proven effective equally to achieve the proposed objectives. It is clear that mathematical and computational techniques can work well with transplantation databases. We hope that this work will contribute to increase researchers interest in applying intelligent techniques to knowledge discovery in organ transplant databases and serve as a guide to choose the best techniques to apply in their problems.

REFERENCES