SMART INFUSION PUMP DATA ANALYSIS USING DECISION TREES

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Abstract – Smart infusion pumps are designed to reduce medication errors with the use of drug libraries that set dosage limits. The research objective is to identify factors that are associated with a higher rate of hard limit events using decision trees. Results show that the emergency and NICU profiles were found to have twice the hard limit rate than other profiles. Also, infusions for patients over the weight of 47.95 kg had double the hard limit rate than infusions for patients lower than 47.95 kg. These factors should be explored to identify associated factors that may lead to an increase in medication errors and to reduce hard limit rate to improve efficiency in pump usage.

I. INTRODUCTION

An infusion pump is a medical device designed to automate delivery of liquid drugs or other liquids into a patient over a period of time. A medical user (e.g., nurse, medical doctor) must program the pump by entering a combination of dose, time and/or rate in order to administer the prescribed medication. Medication errors have the potential of occurring due to user errors when operating an infusion pump [1].

Smart infusion pumps use drug libraries to prevent user entry errors by accepting drug dosage only within specified limits. Hard limits, specified by the library, are limits that cannot be exceeded; entering a value outside of the hard limit range will not be accepted by the pump and an infusion will not start until a value within the limits is entered.

The purpose of this research is to identify factors leading to hard limit events related to infusion pump usage using decision trees, an automatic analysis technique. This information can help inform actions to reduce medical errors and harm in healthcare institutions, as well as identify usability issues that should be addressed to improve workflow efficiency. This work has been approved by The Children’s Hospital of Eastern Ontario (CHEO) and Carleton University Research Ethics Boards.

II. METHODOLOGY

Smiths Medical’s Medfusion Model 4000 syringe infusion pump (Smiths Medical, St Paul MN, USA) is a smart infusion pump with a customizable drug library and device server system that collects therapy data (e.g., drug information entered for each infusion) and alarm data (e.g., empty syringe and hard limit alarms) [2]. Infusion data from 185 Medfusion pumps were obtained from CHEO from August 2011 to August 2012. This study uses the event history report that details all pump programming and function events (e.g., on/off, alarms).

A. Infusion Data

The infusion data set was filtered to only include continuous infusions for weight-based drugs, where drug dosage was entered in mg. It was not verified if the infusions that were started ran to completion or interrupted. A set of 41,040 infusions were extracted and separated into two classes: 1) infusions associated with a hard limit event (HL infusions; 1,269 cases), and 2) infusions that were not associated with a hard limit event (NoHL infusions; 39,771 cases). For each infusion, four input variables were saved: 1) hospital department, 2) patient weight, 3) dose and 4) flow rate.

B. Decision Tree Technique

Data mining techniques are used to gain knowledge in order to predict outcomes, discover associations and reveal patterns not obvious to the human observer. Manual analysis would be also time consuming, and may potentially be infeasible. A decision tree (DT) is a data mining technique largely used for classification and can be used to identify factors influencing data classification and differentiation. The DT technique applied was based from the classification and regression tree method using the MATLAB implementation [3]. One variable was used for each split and all splits were binary. Two trees were built using two split criteria (gini and entropy) to cross check for common rules [4]. No pruning or stop criterion was specified, so a full tree was constructed; however, only the first few splits of the tree were analysed, as the primary discerning factors would be near the root node.
III. RESULTS AND DISCUSSION

![Decision tree result that was built using the gini criterion](image)

The tree built using the gini criterion is presented in Fig. 1. The number of infusions and the percent of those infusions that are HL infusions are shown for each node. The primary factor used to categorize the infusions was hospital department. For the emergency department and neonatal intensive care unit (NICU), HL infusions represented 5.60% (n=237) of infusions, while for the remaining departments (general, pediatrics, hematology/oncology, and medical day units), HL infusions represented 2.82% (n=1290) of infusions. Weight was the secondary split factor. For patients over 47.95 kg, HL infusion rate was 6.63% (100 cases); and was 2.66% (945 cases) for patients under 47.95 kg. For the weight and profile factors, the split in the HL rate is doubled. The split in node 3 is ignored because there are only two infusions in node 6.

The tree built using the entropy criterion had the same first split in node 1 found in the gini tree. The weight factor was also found in the deviance tree close to the root node. The consistency of the profile and weight factor in both trees present consistency in the results.

The higher HL rate for emergency and NICU is consistent with other research findings: 1) higher levels of error occur in pediatrics emergency department due to conditions that favour a hectic environment (overcrowding and long work hours) [4]; 2) paediatric drug dosage is largely dependent on weight and weight may only be estimated in emergency cases [5]; and 3) NICU environment is complex with unique patients that have changing needs and is therefore prone to error [5].

Increased HL rate in large weights may be to a clinician administering a large dose (that does not fit into the maximum syringe size of 60 mL) via two infusions or unintentionally prescribing a weight-based dose that is over the adult limit. A large portion of paediatric medication is prescribed based on patient weight; however, if the patient is large enough, the weight-based dose may exceed the paediatric dosage limit, and at that point, the patient needs to be prescribed the standard adult dose.

IV. CONCLUSIONS

DT analysis reveals factors in identifying user errors that are consistent with the literature. The profile and weight factors should be further explored. Interviews with clinicians working in CHEO departments will reveal if literature findings properly characterize the CHEO environment in the emergency and NICU departments or if other factors influence user errors. Analysis was done on a limited set and should be applied to a large data set with bootstrapping to ensure robust and consistent factors are identified. Additional infusion variables could also be used as DT inputs.

The DT provides an automated method for highlighting the most important factors in a large set of complex data, and in this study, specifically for differentiating between infusions with and without a hard limit event. Results from this study are encouraging and demonstrate that DT may be a useful tool for analysis.

V. REFERENCES


