# Developing a Decision Model for Asthma Exacerbations: Combining Rough Sets and Expert-driven Selection of Clinical Attributes

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**Abstract.** The paper describes the development of a clinical decision model to help Emergency Department physicians assess the severity of pediatric asthma exacerbations. The model should support an early identification (at 2 hours) of those patients who are having a mild attack and those who are having a moderate/severe attack. A comprehensive approach combining rough sets and expert-driven manual feature selection was applied to develop a rule-based decision model from retrospective data that described asthmatic patients visiting the Emergency Department. The experiment involved creating the following four potential decision models differentiated by the subsets of clinical attributes that were considered: Model A using all attributes collected in the retrospective chart study; Model B using only attributes describing the patient's history; Model C using only attributes describing the triage and repeated assessments; and Model D using attributes from Model C expanded with some of the attributes from Model B identified by expert clinical knowledge. Model D offered the highest assessment accuracy when tested on an independent retrospective data set and was selected as the decision model for asthma exacerbations.

**Keywords:** rough sets; asthma exacerbations; decision rules; manual feature selection; decision model

## 1 Introduction

Asthma exacerbations are one of most common reasons for children to be brought to the Emergency Department (ED). These visits, and the subsequent hospitalizations required by a large proportion of these patients, account for nearly 65% of all direct costs of asthma care. Children with asthma, compared to their non-asthmatic counterparts, use more prescriptions and require more ambulatory care visits, ED visits and hospitalizations [1].

Management guidelines for children with asthma exacerbations coming to the ED are aimed at three levels of attack severity: mild, moderate, and severe [2].

Early identification of the severity of an asthma exacerbation has implications for the child's management in the ED. Patients with a mild attack are usually discharged home following a brief course of treatment (less than 4 hours) and resolution of symptoms, patients with a moderate attack receive more aggressive treatment over an extended observation in the ED (up to 12 hours), and patients with a severe attack receive maximal therapy before ultimately being transferred to an in-patient hospital bed for ongoing treatment (after about 16 hours in the ED).

In clinical practice, a decision on the severity and subsequent disposition of an attack is ideally made as soon as possible after arrival of the patient to the ED to ensure key therapies have been instituted. Underestimation of severity may result in inadequate treatment, premature discharge and a possible return visit, while overestimation of severity may result in an extended ED stay and unnecessary utilization of hospital resources. As information available on arrival is not sufficient for accurate disposition [3], disposition decisions are made later in the management process – usually between 1 and 4 hours. In our research we assumed the decision would be made at 2 hours [4]. One the one hand, is early enough to provide adequate therapies, and on the other hand, clinical information available at that time allows for accurate dispositions.

There have been many attempts to identify pertinent risk factors associated with pediatric asthma [5] and to develop prediction models [6] or severity scores [7] for asthma exacerbations. However, to date, no clear clinical decision model or widely used asthma score exists. In this paper, we discuss the development of a decision model to support physicians in making early disposition decisions about asthma exacerbations and discerning between two groups of patients: those with mild attacks and those with moderate/severe attacks. We dichotomized the original severity categories into two outcomes because of the importance of early identification of patients with a mild attack that can be safely discharged home while ensure that patients with moderate or severe attacks are identified to receive maximum therapy (e.g., systemic steroids). We used data transcribed from the ED charts in a retrospective study to construct four rule-based decision models using clinical attributes suggested by a medical expert and clinical practice guidelines. Models were verified on an independent testing data set acquired through the same retrospective chart study.

The paper is organized as follows. We start with a description of the retrospective chart data. Then we present our approach to developing decision models that combines rough sets with manual feature selection driven by expert clinical knowledge. This is followed by a description of considered models and the results of their preliminary evaluation leading to the selection of the best one. Finally, we conclude with a discussion.

## 2 Retrospective Chart Study

The data used to develop the decision model were collected through a retrospective chart review of patients presenting to the ED of the Children's Hospital of

Eastern Ontario (CHEO) between November 2000 and September 2003. This clinical center appropriately represents a potential sample of pediatric patients with asthma, and the collected data can be considered a representative picture of the asthma exacerbations amongst the pediatric population.

The processed pediatric asthma workflow is as follows. First, when child with asthma exacerbation arrives at the ED, a triage nurse gathers basic information on the patient's presenting complaint and evaluates the child's general condition. At this point the patient's breathing is also assessed for the first time (the first assessment is labeled as the triage assessment). After this first assessment the patient is registered, and then awaits a physician evaluation. During this physician-led evaluation, more information about child's condition is collected, including the patient's history, social environment, presence of known risk factors signifying more serious disease, outcomes of previous exacerbations, and the length and severity of symptoms during this exacerbation. At this point, the physician begins management of the asthma exacerbation, including repeated bronchodilator treatments at intervals from every few minutes (continuous) to every few hours, along with systemic corticosteroids for most patients. All management decisions are recorded in patient's ED chart. Moreover, throughout the patient's ED stay, he/she is reassessed by the physician or by the ED nurse to check response to treatments. Depending on a variety of external factors (patient's condition, clinicians' workload, etc), these re-assessments are performed at irregular intervals and they are partially or completely recorded in the chart.

Table 1 lists commonly evaluated and documented clinical attributes associated with asthma exacerbations that could be transcribed from ED charts. Attributes #1–#22 were collected during registration and physician evaluation and they describe patient's history, attributes #23–#32 were collected during the triage assessment and repeated assessments. We considered two sets of these attributes – the first set characterizes the state of the patient on arrival and it was collected during the triage assessment, and the other set presents the patient's most complete picture recorded in a repeated assessment within an interval of 100 and 140 minutes from arrival. Finally, attribute #33 was calculated as the number of bronchodilator treatments (i.e., masks) provided to the patient between the triage and repeated assessment being considered.

Each patient's data was reviewed and a patient was assigned to one of the two groups using asthma exacerbation severity category documented in the ED chart and confirmed later by lack of a subsequent visit to the ED. This procedure allowed us to identify those patients where the initial ED visit resulted in a premature discharge and subsequent readmission to the ED. In this sense we considered the confirmed severity group as a gold standard during development of decision models.

A final sample of 239 ED patient visits for asthma exacerbations was identified during the study period. Basic characteristics of this population are given in Table 2. Although the distribution of visits between both decision groups is fairly well balanced, it can be seen that more patients treated in the ED experienced moderate/severe attacks.

**Table 1.** Clinical attributes

| # | Attribute | Domain |
|---|---|---|
| | *Registration and physician evaluation* | |
| 1 | Patient age | $< 3$ years, $3 - 7$ years, $\geq 7$ years |
| 2 | Primary care | family doctor, pediatrician, other, none |
| 3 | Chest clinic | yes, no |
| 4 | Current inhaled steroids | $< 1$ week, $1 - 4$ weeks, $\geq 4$ weeks, as necessary, none |
| 5 | Age of first symptoms | $< 1$ year, $1 - 3$ years, $\geq 3$ years |
| 6 | Previous oral steroids | $< 1$ month, $1 - 3$ months, $3 - 12$ months, $\geq 12$ months |
| 7 | Previous ED last year | 1 visit, 2 visits, 3 visits, $\geq 4$ visits, none |
| 8 | Previous admission | floor, ICU, none |
| 9 | Smokers in environment | yes, no |
| 10 | Dander in environment | yes, no |
| 11 | Carpets in environment | yes, no |
| 12 | Allergies to environment | yes, no |
| 13 | Allergies to pets | yes, no |
| 14 | Allergies to food | yes, no |
| 15 | History of atopy | yes, no |
| 16 | Family history of asthma | yes, no |
| 17 | Allergy exposure | yes, no |
| 18 | URTI symptoms | yes, no |
| 19 | Fever | yes, no |
| 20 | Duration of symptoms | $< 12$ hours, $12 - 48$ hours, $\geq 48$ hours |
| 21 | Bronchodilators in last 24h | $1 - 3$, $3 - 6$, $\geq 6$, none |
| 22 | Arrival to the ED | ambulance, parents |
| | *Triage assessment/Repeated assessment* | |
| 23 | Temperature | $< 38$ C, $38 - 39$ C, $\geq 39$ C |
| 24 | Respiratory rate | normal, mild abnormal, abnormal |
| 25 | Heart rate | normal, mild abnormal, abnormal |
| 26 | Oxygen saturation | $< 88$, $88 - 93$, $93 - 95$, $\geq 95$ |
| 27 | Air entry | good, reduced |
| 28 | Distress | none, mild, moderate, severe |
| 29 | Skin color | pink, pale, dusky |
| 30 | Expiratory wheeze | present, absent |
| 31 | Inspiratory wheeze | present, absent |
| 32 | Retractions | present, absent |
| | *Treatment summary* | |
| 33 | Number of treatments received | number |

**Table 2.** Characteristic of the learning data

| Characteristics | Value |
|---|---|
| Mean age | 5.7 years |
| % of visits in the mild group | 41.0% |
| % of visits in the moderate/severe group | 59.0% |

As expected, the majority of charts had incomplete data. Only three clinical attributes (all describing demographics and history) were specified on all charts – they were #1, #2, and #3 (also attribute #33 was provided for all visits, however, it was calculated from information available in charts). Moreover, nine attributes (#9–#11 and #17 for the registration and physician evaluation; #30–#32 for the triage assessment; #23 and #28 for the repeated assessment) had missing values for more than 60% of collected visits. We excluded these attributes from the analysis.

## 3 Development of a Decision Model

In order to develop potential decision models we used a rough set approach with cumulative indiscernibility relation [8] that allows dealing with incomplete data without prior preprocessing (e.g., replacing missing values of attributes by known ones or removing incomplete cases). This approach supports evidence-based medical decision making [9] since data used for constructing the decision model are not changed.

Cumulative indiscernibility relation assumes that a missing value of an attribute is equivalent to any other value of this attribute. This simplification does not distinguish between situations where values were collected but not recorded and where values were not collected as it was deemed unnecessary by the physician. However, this distinction can be rarely inferred from retrospective chart study, making this approach suitable for analyzing clinical data transcribed from charts (written medical records are rarely standardized in format and content). It has been also successfully applied in other clinical studies [10, 11].

Rough set theory offers a methodology for finding important attributes in the form of a core and reducts. However, for data described by a large number of attributes, also the number of reducts may be very large making selection of attributes difficult and ambiguous [12]. Therefore, we decided against automated feature selection as an approach that does not consider knowledge about a problem domain, and instead used expert-driven manual selection. This approach has proved successful for other clinical problems [13].

The experiment involved using the entire set of clinical attributes transcribed from charts and three subsets of attributes selected according to clinical knowledge. For each of the sets of attributes, we induced decision rules using the modified LEM2 algorithm that ensured robustness of created rules (each rule had to cover at least one case with known values of attributes in the rule's conditions).

Generated sets of rules were then coupled with a distance-based classification strategy [14] to form rule-based decision models. Finally, we obtained the following four potential decision models:

1. Model A using all clinical attributes included in the analysis (a baseline model),
2. Model B using clinical attributes collected during registration and physician evaluation (attributes #1–#22),
3. Model C using clinical attributes collected during triage and repeated assessment together with the number of bronchodilator treatments (two sets of attributes #23–#32 and attribute #33),
4. Model D using clinical attributes from Model C and extended by the attributes from Model B as per asthma guidelines [2] . Specifically we included the following additional attributes:
   - Age of first symptoms (attribute #5),
   - Duration of symptoms (attribute #20),
   - Timing since last oral steroids (attribute #6),
   - Possible allergens (attributes #12–#14),
   - Family history of asthma (attribute #16),
   - Social status of the patient (attributes #2 and #22) - patients coming from poorer families would likely not have a family physician and would be brought to the ED by ambulance).

## 4 Evaluation of Decision Models

In order to evaluate the quality of the four decision models, we conducted an experiment that compared their performance on new retrospective chart data. Data transcribed from the ED charts were used as input to a decision model, and the suggested dichotomized evaluation of a severity of asthma exacerbation was considered as an output and compared to the gold standard (verified severity group).

The potential decision models were evaluated on an independent data set describing 123 visits to the ED of CHEO between October 2003 and July 2004. The transcription process followed the same regimen as described for the retrospective learning data. General characteristics of the testing data are given in Table 3. Compared to the learning data (see Table 2), the percentage of patients with moderate/severe attacks decreased and the distribution of visits between groups became almost even (with slightly greater number of patients with mild attacks).

Results of the evaluation are presented in Table 4. Compared to the baseline Model A, Model B exhibited decreased accuracies for both dichotomized groups, thus suggesting that the corresponding set of attributes did not include information required for reliable prediction of severity. Model C was found to be much more accurate – it preserved accuracy in the moderate/severe group and significantly increased accuracy for the mild group (increase of 20%). Overall

Table 3. Characteristic of the testing data

| Characteristics | Value |
|---|---|
| Mean age | 6.0 years |
| % of visits in the mild group | 52.8% |
| % of visits in the moderate/severe group | 47.2% |

accuracy for Model C was also higher than for the baseline model. This implies that the attributes characterizing assessments and treatment allowed us to identify relatively well patients with mild asthma exacerbation, while there was still not enough information to identify patients from the other group (this group was underestimated).

**Table 4.** Accuracy of classification for considered decision models

| | Model | | | |
|---|---|---|---|---|
| Group | A | B | C | D |
| Mild | 60.0% | 43.1% | 81.5% | 78.5% |
| Moderate/severe | 63.8% | 58.6% | 62.1% | 74.1% |
| Overall | 61.8% | 50.4% | 72.4% | 76.4% |

Finally, Model D improved accuracy in the moderate/severe group (increase of 12%) and only slightly lowered accuracy for the mild group (decrease of 3%). Overall accuracy of this model was the highest, proving the importance of expanding the triage and repeated assessment set of the attributes with those suggested in the guidelines.

To further validate the results, we used McNemar's test [15] to verify statistical significance of differences in performance of potential models. The McNemar's test is often used in clinical problems to compare individual outcomes before and after intervention and in our experiment we used the test to compare classification outcomes of paired models associated with the same patient records from the testing set. The results of the McNemar's statistic are given in Table 5 and they show that statistically significant classification differences were obtained for all pairs except Model A and B and Model C and D (significance 0.95, threshold 3.841), and the largest values of McNemar's statistic were obtained for Model B and C and for Model B and D pairwise comparisons. Considering the best prediction accuracy of Model D, McNemar statistic provided additional argument for selecting this decision model for predicting the severity of asthma exacerbations.

**Table 5.** McNemar's statistics

| | Model B | Model C | Model D |
|---|---|---|---|
| Model A | 2.817 | 3.892 | 6.881 |
| Model B | – | 10.090 | 16.569 |
| Model C | – | – | 0.552 |

## 5 Discussion

Data transcribed retrospectively from patient charts is usually characterized by a large number of clinical attributes with many of them being considered by the physician in a specific context (e.g., when a severe problem is suspected). It means that values of these attributes are evaluated and recorded only for specific patients and appear only on a fraction of charts. Moreover, some attributes may be checked by the physician during examination, but as they were deemed unnecessary (e.g., their values would not contribute to a decision), they might be not recorded either. A fact that there is a large number of attributes and that many charts include incomplete information, makes development of a decision model a difficult and challenging task [16] as a model may be prone to superfluous information and offer poor performance in clinical practice. Therefore, the development of a decision model should start with identification of those attributes that are the most explanatory but also that make the most sense from a clinical perspective. Values of selected attributes may still be incomplete, so methods employed to develop a decision model should be capable to handle such a situation.

The rough set approach with cumulative indiscernibility relation [8] used in this study handles incomplete data in a manner that is consistent with those reported in literature [17] that suggest that the most promising results in terms of accuracy of prediction are obtained when missing values are handled directly or when incomplete cases are removed from the analysis (the latter approach is rarely feasible for medical data sets transcribed from charts as it would result in excluding a significant number of available cases).

Direct processing of missing values is also in line with principles of evidence-based decision making, where clinical decisions have to be made using the best available knowledge. Modifications of clinical data, where missing values are replaced by automatically selected known values, could result in creating artificial patterns that might be captured by a decision model developed from such data, thus significantly limiting its clinical reliability. The approach we have used allowed us to avoid this trap, and it also ensured robustness of discovered patterns (each rule was supported by at least one case with known values of attributes referenced by this rule, thus it was supported by a complete evidence).

Rough sets offer techniques and evaluation measures for automatic selection of attributes, but we argue that whenever it is possible, attributes should be evaluated and selected according to expert knowledge and clinical experience. As physicians often tend to consider too many clinical attributes, it is reasonable to compare their selection against practice guidelines to possibly limit the number of selected attributes. Even if an automatic feature selection is used and a created decision model provides good predictive performance, the selected attributes should be verified by an expert in order to ensure that they are appropriate from a clinical perspective. Otherwise, the clinical applicability of a developed model may be very limited.

Our study demonstrated that rough sets combined with manual feature selection based on expert knowledge proved to be a valid methodology for developing a rule-based decision model for asthma exacerbations. The model that offered the highest predictive accuracy and thus was finally selected, was based on attributes characterizing assessments and treatments combined with those describing patient's history and identified in the practice guideline reflecting expert knowledge. The study confirmed that data transcribed retrospectively from charts often includes superfluous information that may result in less accurate decision models, and thus prior selection of attributes is of high importance. It also demonstrated that manual feature selection based on expert knowledge is an important success factor.

The decision model for asthma exacerbations has not been validated in clinical practice, however, we plan to embed it in a decision support module for the MET (Mobile Emergency Triage) system [18]. MET with a module for triaging pediatric abdominal pain successfully underwent a 7-month clinical trial in the ED at CHEO [19]. The decision model in the abdominal pain module was developed using the rough set approach with cumulative indiscernibility relation. Results from the prospective clinical trial demonstrated that our model has classification accuracy similar to the accuracy of physicians. We plan to conduct a similar clinical trial of the MET system with the asthma module.

## 6 Acknowledgments

The research reported in this paper was supported by the grants from the Natural Sciences and Engineering Research Council of Canada, Canadian Institutes of Health Research and the State Committee for Scientific Research of Poland.

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