Comparing Adaptive Bayesian Network, Artifickal Neural Networks, Classification Trees and Classical Logistic Models in Quantitative Risk Assessment: the Case Study of Foreign Body Injuries in Children

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Abstract

Risk Assessment is the systematic study of decisions subject to uncertain consequences. A wide range of techniques have been developed to address it using a quantitative approach. They can roughly be classified as engineering, statistical or causal modeling techniques. While engineering techniques are mainly devoted to simulate the causal process that lead to an adverse outcome, statistical modeling strategies rely on observed data and have been successful applied across various disciplines.
An increasing interested has been focused on causal modeling techniques like Bayesian Networks since their capability in combining in the probabilistic framework different type of evidence including both subjective beliefs and objective data; overturn previous believes in the light of the new information being received, and make predictions with incomplete data.
In this paper we proposed a comparison among Bayesian networks and other classical Quantitative Risk Assessment techniques such as neural networks, classification trees and logistic regression. The aim is directed to evaluate among a set of tools which best can be applied to guarantee the safety of children who are exposed to the risk of inhalation/insertion/aspiration of consumer products. Results showed that Bayesian networks appeared to have both the easy of interpretability and accuracy in making classification, thus outperforming all other methods.

Keywords: Bayesian network; children; classification trees; foreign body injuries; neural networks; quantitative risk assessment.

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1. Introduction

Quantitative Risk Assessment (QRA) is the systematic study of decisions subject to uncertain consequences by means of tools and techniques of probability theory and statistics (Royal Society 1992).
One of the key features of QRA is its effort to look at whole systems and not isolated parts. Each possible adverse event is followed through to its consequences and at the same time the consequences of different adverse outcome can be combined.
A wide range of techniques have been developed to address the risk assessment problem. They can roughly be classified as engineering, statistical or causal modeling techniques (Cox 2002). Engineering approach is based on the idea that risk exists objectively and the risk analysis is a tool for expressing it by probabilities and expected values (Aven and Kristensen 2005). Engineering techniques are mainly devoted to simulate the behavior of the system which is going to be assessed. In health risk assessment, among the most common techniques are Compartmental flow models and other continuous simulation models, Monte Carlo uncertainty models, Discrete- event simulation models, while Fault trees and Event trees are a major tool in Safety and Reliability Analysis (Vose 1998; Roy, Bhatt et al. 2003; Clark, Setzer et al. 2004; Wreathall and Nemeth 2004) .
Statistical risk modeling relies on observed data, on covariates and responses, rather than attempting to simulate the causal process that lead to the adverse outcome. The task is challenging because typically it is not known *(i)* which aspects of covariates are relevant to the response; *(ii)* the mathematical form of the relation among variables and response probabilities; *(iii)* how unobserved variables can affect the observed relation (Cox 2002). Among techniques that have successfully applied in risk analysis across various disciplines are logistic regression, artificial neural network and classification and regression trees (Levy, Wolff et al. 2002; Floerl, Inglis et al. 2005) .
While statistical and engineering approaches are complementary, causal modeling can combine elements of both. Indeed the risk assessment problem is being successfully addressed in a wide range of application domains using Bayesian Networks (Heckerman, Mamdani et al. 1995; Fenton, Krause et al. 2002). The success of BNs in Quantitative Risk Assessment is due to their capability to: (*i*) combine in the probabilistic framework different types of evidence including both subjective beliefs and objective data, (*ii*) overturn previous belief in the light of the new information being received, and (*iii*) make predictions with incomplete data. The compositional modeling characteristic of the engineering approach is captured by the ingoing-outgoing relations in the network, while the conditional probability distribution of each variable may be determined by machine learning algorithms.
In this paper a comparison among some statistical and causal modeling in the quantitative risk assessment framework was proposed. The aim is directed to evaluate among a set of tools which best can be applied to guarantee the safety of consumers. Unsafe consumer products are involved in thousand of injury in children caused by inhalation, ingestion, aspiration and insertion of foreign bodies (FB) (Gregori, Snidero et al. 2005). In general, probabilistic methods enable the characterization of uncertainty associated with the dimensions and the shape of the objects involved in injuries (Rimell, Thome Jr et al. 1996; Stool, Rider et al. 1998; Rider, Milkovich et al. 2000). We looked at the application of such techniques for the evaluation of the risk to experience a severe injury. Accordingly to (DTI 1999), an injury was defined "severe" when the injured child was hospitalized for at least one day. Following a

short presentation of data source and modeling techniques, results are summarized and discussed.

2. Materials and methods

2.1 Data source

The Susy Safe surveillance registry (Gregori 2006) collected data on FB injuries in children aged 0-14 according to the International Classification Disease ICD9-CM 931-935. A total of 7296 cases were registered in one Pakistani and 28 European hospitals at the end of March 2007. Data encompassed four main aspects of the FB injuries: the characteristics of the children (age, gender); the characteristics of the object (shape, consistency and dimensions); circumstances of injury (presence of parents, activity); hospitalization's details. With regard to the FB dimension, volume, which was calculated as the volume of the smallest regular geometrical solid containing the FB, and the ellipticity (the ratio between the maximum and the minimum size reported) were calculated.

2.2 Statistical methods

A Bayesian network and three different classes of predictive models were implemented to quantify hospitalization risk. Model fitting and model validation, except for Bayesian Network, was carried out using the R statistical programming language version 2.5.1 (R Development Core Team 2007). A 10-fold cross validation was carried out in order to evaluate the performance of the models which was summarized by the area under the ROC curve (Harrell 2001). Furthermore a sensitivity analysis was carried out for the "Hospitalization" node to identifying the most influential variables on injury severity. For categorical states, sensitivity is calculated as the degree of entropy reduction or mutual information, which measures how much uncertainty about a specific event is expected to decrease when a new finding is available, and the expected reduction of real variance (Bhattacharjee and Dunsmore 1991; Pearl 1991; Laskey 1995; Kewley, Embrechts et al. 2000).

2.2.1 Bayesian Networks.
A Bayesian Network (BN) is a graphical representation of the joint probability distributions over a set of random variables. It consists of a series of nodes representing variables connected by arrows forming a graph that has no cycles. The arcs specify the independence assumptions that must hold between the random variables. The resulting network is known as directed acyclic graph (DAG), (Jensen 2001). Each node in a Bayesian network is associated with a set of probability tables. For those nodes without ingoing arcs, the probability distribution is a prior distribution which requires supplying a set of initial values. Learning a BN from data involves the task of structure learning, that is, identifying the graphical structure of the network, and parameter learning, that is, estimating the conditional probability distributions to be associated with the network's graph (Pearl 2000). Among the algorithms created for performing structural learning, the K2 algorithm (Glymour and Cooper 1999) was chosen. The structural learning was carried out on a subset of 672 cases without missing values.

In the learned network graph, the "Gender" node ingoing or outgoing links were missing. However, according to literature, a dependency exists between age, gender, and injury severity (Rivara and Mueller 1987; Matheny 1988; Health 1997). Thus links between these nodes were manually created. With respect to parameter learning, continuous variables were discretized and a sequential learning with fading was carried out (Spiegelhalter and Lauritzen 1990) in order to make conditional probabilities updated as soon as additional evidence becomes available. The BN was implemented using GeNie (Decision Systems Laboratory - University of Pittsburgh 2006) to develop the structure and Netica (Norsys Software Corporation 2006) for the learning parameters and the validation phase.

2.2.2 Artificial Neural Networks.
Artificial Neural Networks denote a set of information processing paradigm inspired on the biological nervous system behaviour. In particular, the Multilayer Perceptron (MLP) is the most popular neural architecture where neurons are grouped in layers and only forward connections exists (Ripley 1996). Several feedforward neural networks architectures with back-propagation learning method were implemented. All neural networks contained from 10 to 25 neurons in a single layer and one neutron in the output layer. In all calculations the layers were fully connected. The least number of misclassifications given as the average on the validation datasets was obtained for the network with 17 neurons in the hidden layer. The same strategy was adopted to implement a neural network with two hidden layers. The resulting best network had 12 and 8 neurons in the two hidden layers.

2.2.3 Classification trees.
Classification tree (CT) is a nonparametric method based on recursive partitioning of a sample into subgroups. At each step the most significant predictor is used to split the sample into subset until no improvement is achieved in the classification accuracy (Breiman, Friedman et al. 1984). A classification tree was developed by binary recursive partitioning using all predictor variables described in table 1 (Berchialla, Snidero et al. 2007). To avoid overfitting the data, 10-fold cross validation was used on the training dataset to determine the optimal size of the tree. The best size was selected according the 1SE rule, by which the largest tree with cross validated error within one standard deviation of the minimum was chosen (Venables and Ripley 2002). The pruned tree was thus used to obtain predictions on the validation dataset.

2.2.4. Logistic regression.
Logistic regression model (LR) is a widely statistical tool used to fit probability of an event by a linear function of the explanatory variables (McCullagh and Nelder 1989). A logistic regression model was constructed using backwards variable elimination. The backward variable elimination was based on sequentially eliminating variables from an initial model consisted of all the predictor variables. At each step the variables is removed from the current model that results in the greatest reduction of the AIC criterion. The rule of eliminating variables was continued until no further reduction of the AIC criterion is obtained (Harrell 2001).

3. Results

In table 1 the input variables used in the models were listed. The structure of the Bayesian network was depicted in figure 1 (see Table 1 for a description of nodes) and the classification tree was shown in figure 3. Logistic regression parameter estimates were shown in Table 2 and in Table 3 model performances were presented. The sensitivity analysis (Table 4) resulted in a list of variables ranked according to the gain they prodived in variance reduction. It could be observed that in the BN, nodes which are closer to “Hospitalization” one show a greater impact in predicting hospitalization. On the other hand, the influence of those which are further away tends to be diluted due to the uncertainty introduced by the intermediate nodes. In the logistic regression, backward variable elimination yielded a reduced model with 6 out of the 12 original variables.
The combination of events, features, and processes causing diverse natural phenomena could be taken as a scenario. The capability to predict scenarios and compute an occurrence probability is a valuable tool for risk assessment because it allows for extrapolation of hazard and prevention. BNs can handle this feature in a very straight way. To illustrate this point we calculated the hospitalization risk of different scenarios that may be encountered. In Figure 2 was presented an example of how a BN deal with scenarios. After setting the evidence (a male experienced an incident while playing with a cylindrical shaped object) the probability of hospitalization is computed making use of the Bayes Theorem. Thus in this scenarios it was estimated that the care-givers were absent in the 60% of cases. Entering new evidence is also possible to check how output measure varies. For example, if a needle shaped foreign body, e.g. a fishbone, is swallowed while the child is eating, the probability of a male to be hospitalized is about 40%, whereas for a female is slightly lower (38%). BN was used to compute the probability of observing a given injury characterized by the type of foreign body, its shape, consistency and volume, the children’s age and gender (Table 5) The most probable location of the foreign body (most probable ICD) along with the most probable removal techniques required were reported in addition to the probability of experiencing a hospitalization.

4. Conclusion

In this paper a comparison among techniques which are widely used in Quantitative Risk Assessment was proposed. A causal approach using Bayesian Networks was adopted to carry out a risk analysis on foreign body injuries in children. Thus it was compared to a set of competing statistical risk modeling methods: (i) logistic regression models (LR); (ii) artificial neural networks, MLP; (iii) classification trees, CT. Children’s hospitalization was identified as the outcome measure of injury severity and it was studied in relation to the injured child characteristics and accident details.
Artificial Neural Networks (ANNs) along with Classification Trees are a rich tool in dealing with noisy or incomplete data. A drawback of ANNs is, however, that there are no standard methods for constructing the architecture. In our study we set up two MLP models: a single hidden layer feed-forward multiperceptron, which is the common type encountered in literature, and a two hidden layers feed-forward multiperceptron. Despite the different degree of complexity yielded by the models, their accuracies were not dramatically different.
Classification tree approach is also a method extremely robust to the presence of irrelevant variables and variables with little predictor value. Besides a non impressive

total accuracy, CT showed to be capable of better identifying injuries at a higher risk of severity (96% of sensitivity). Furthermore contrary to ANNs, which are “black box” models of difficult interpretation, it provided a way to extrapolate decision rules for achieving threat reduction in the form of a ready-understandable flowchart.
Logistic regression is a popular statistical method which can generate excellent prognostic models, also for easy of interpretability of estimated parameters. Although LR is not adept at modeling grossly nonlinear complex interaction, in our study it showed indeed its ability to capture non-linear effects outperforming MLPs and CT, which also were affected by a low specificity.
However our analysis showed that BN outperformed all methods in terms of accuracy. Moreover, advantage of BNs relies on the fact the complex causal relationships among factors are explicated in a graphical model which incorporates uncertainty via the conditional probability associated to each node (Pearl 2000). In our model, relationships among variables were discovered by learning algorithms but at the same time they were allowed to be modified to embody prior knowledge.
BN model gave a picture of the influence of critical factors on the injury severity. Also it allows for the comparison of the effect of different foreign body characteristics (volume, foreign body type, shape, consistency) and children features (age, gender) on the risk to experience a hospitalization. Results from sensitivity analysis also suggest that models do not always provide identical interpretation for the same covariates, thus a tool which allows for a ready interpretation of relationships among risk factors is of great usefulness.
The absence of an independent sample to perform an external validation of the statistical methods constitutes the major limitation of this study.

4.1 Final remarks

Since Susy Safe surveillance registry is set up to constantly receiving new cases, we chose to treat BN as an adaptive net giving more recent cases a higher weight than the older ones. As a result we built up a net that while receiving cases and updating information on foreign body features (size , shape and consistency) is able to quickly respond for instances to changing product safety design regulation. Beside the foreign body location and the removal technique used for the FB extraction, BN confirms the role of foreign body type along with its shape and consistency in determining risk of severe injury. Also the complex relationships among risk factors shows that there is not a single cause related to the severity of the injury but a more complex pattern of events concur to the adverse outcome. As a matter of fact parents and care-givers should be aware of objects which pose a risk for children. Education is a primary strategy in reducing foreign body injuries in children.

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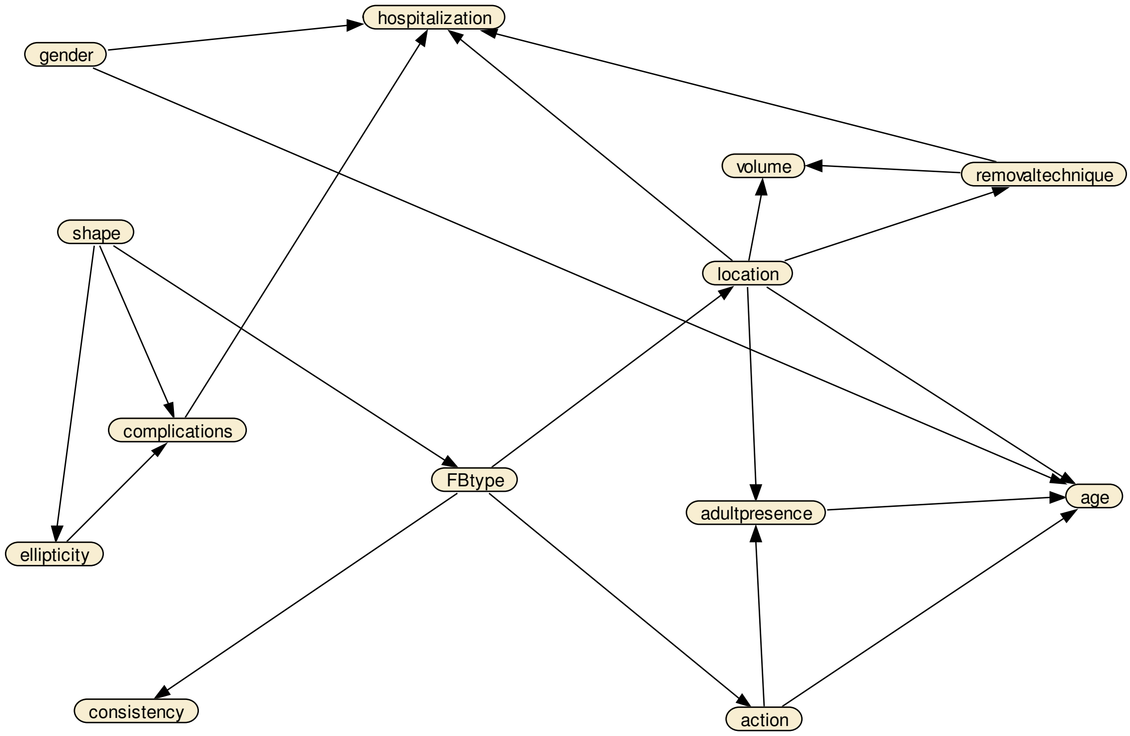

Figure 1. Bayesian network structure. Labelled rectangles represent node and arrows represent conditional dependence relationships.

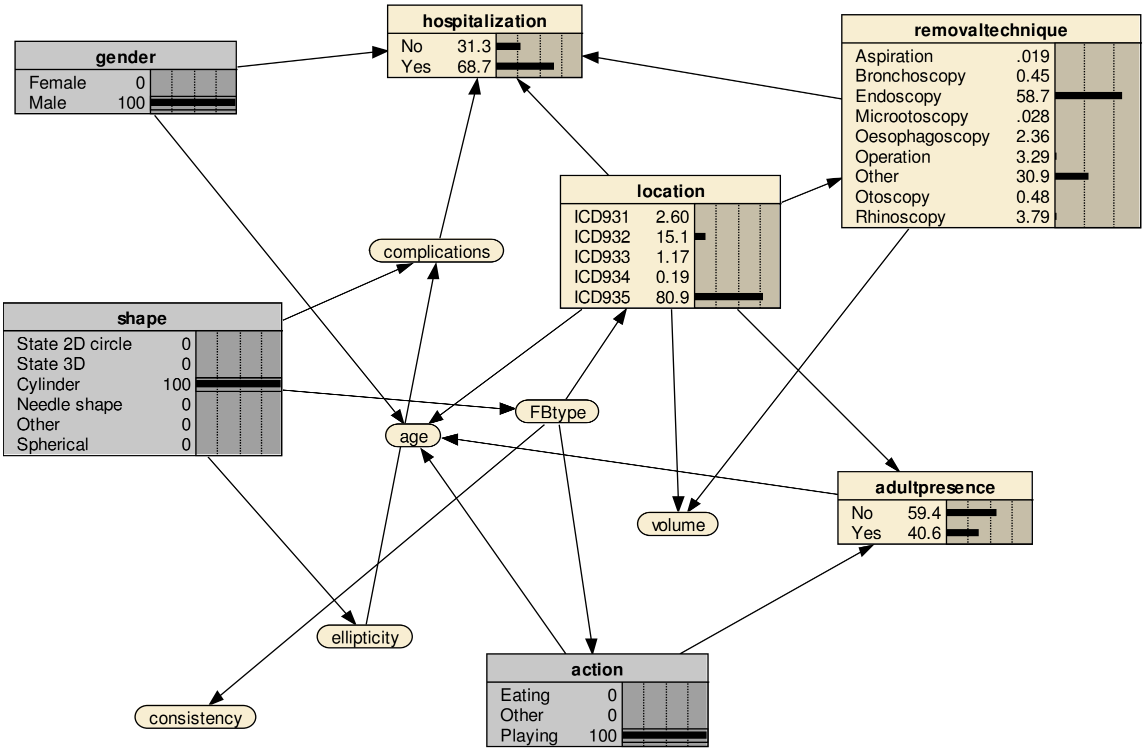

Figure 2. A scenario of a male playing with an object with a cylindrical shape (97% of probability to play with a button) is depicted. The child has 68.7% of probability to experience a hospitalization.

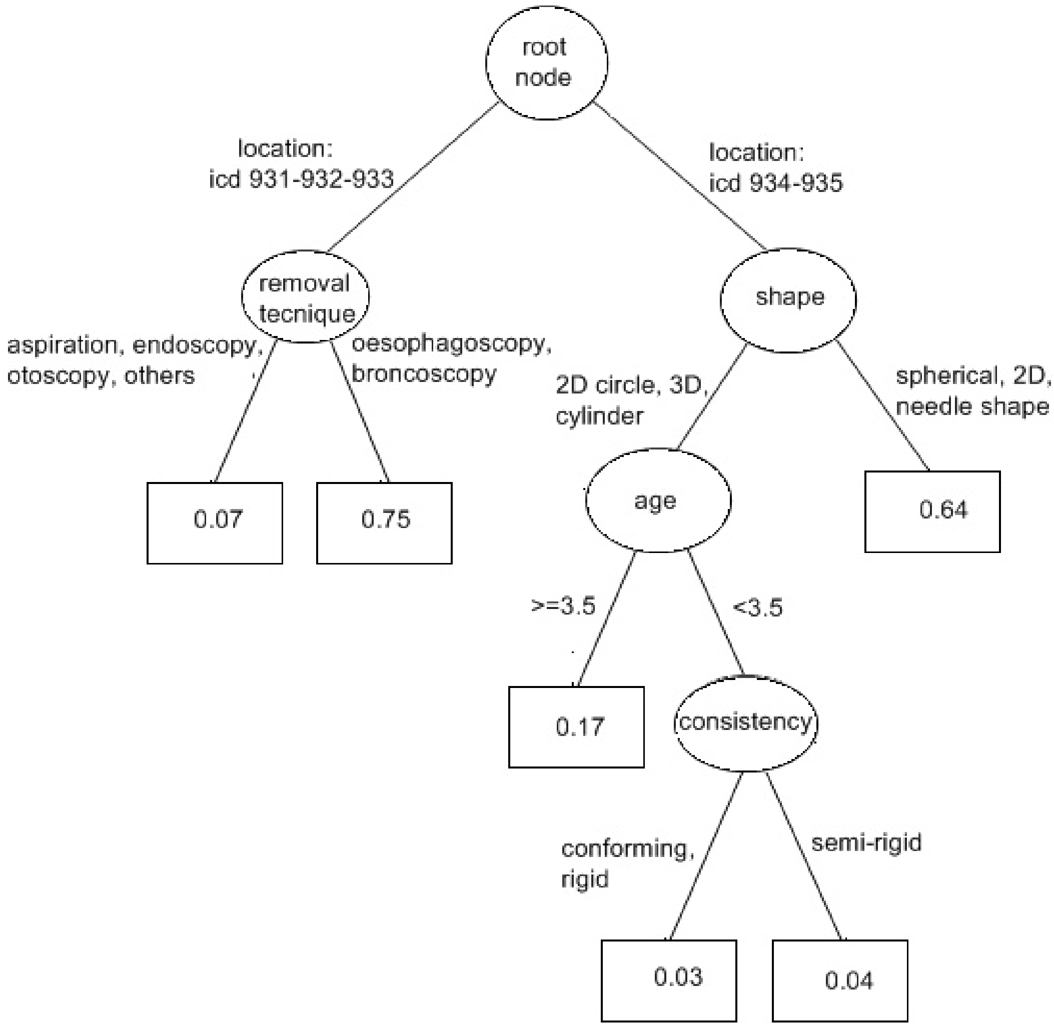

Figure 3. Classification tree. Prior probabilities at each group have been treated as equal. Terminal nodes are symbolized by rectangles; non terminal nodes, by ovals. Splitting criteria are specified in the nodes. The probability of experiencing a hospitalization is given within the node accordingly to the set of rules specified.

Table 1 Definition of variables and their states in the Bayesian network. Continuous variables were discretized on the basis of quintile (Age and Volume nodes) and tertile (Ellipticity node).

Node description	**Variable description**	**State description**
Age	Continuous	Age class: 0-1, 2, 3-4, 5-6, 6-14
Gender	Discrete	Female, Male
Location	Discrete	ICD931-935
Hospitalization	Discrete	No, Yes
Complications	Discrete	No, Yes
Removal tecnique	Discrete	Aspiration, Bronchoscopy, Endoscopy, Operation, Microotoscopy, Otoscopy, Other
Foreign body type	Discrete	Accessorize, arthropod, battery, bean and pea, bone, button, capo, coins; cotton, earplug, fruit and stone; jewellery; metal; nut; other inorganics; other organics; papers; pearl, ball and marble; pebble; pins and needle; plastic; stationery; stick, sweet, toys
Shape	Discrete	2D circle; 3D; Cylinder; Needle shape; Other; Spherical
Consistency	Discrete	Conforming, Rigid, Semi-rigid
Ellipticity	Continuous	1, score from 1 to 2, greater than 2
Volume	Continuous	Score up to 33.5, score from 33.5 to 65.4, score from 65.4 to 140, score from 140 to 400, up to 4710
Adult Presence	Discrete	Adult absent, Adult present
Activity before accident	Discrete	Eating, Playing, Other

Table 2. Results of Logistic Regression model.

Variable	Effect	p-value
Location		
ICD933	1.35	0.029
ICD934	3.79	<0.001
ICD935	2.44	<0.001
Gender		
female	0.89	0.045
Removal technique		
Aspiration	0.37	0.053
Bronchoscopy	3.35	<0.001
Oesophagoscopy	3.43	<0.001
Operation	2.64	0.023
Otoscopy	0.03	0.042
Shape		
2D circle	1.36	<0.001
Cylinder	1.45	0.003
Needle shape	1.47	<0.001
Other	1.82	<0.001
Consistency		
Conforming	0.87	0.04
Semi-rigid	0.80	<0.001
Age	0.80	0.003

Table 3. Area under the ROC curve was used to assess the performance of the models: Bayesian Network (BN); Logistic Regression (LR), Multilayer Perceptron (MLP) with 2 and 1 hidden layers; Classification tree (CT).

	AUC	SENS	SPEC
BN	92.31% (89.94-94.68)	95.19%(93.1-97.28)	90.06%(88.08-92.04)
LR	87.03%(84.99-89.05)	89.2%(86.5-91.9)	83.1%(80.75-85.45)
MLP (2 layers)	78.67%(76.64-80.7)	85.33%(81.73-88.93)	54.47%(50.76-58.18)
MLP (1 layer)	74.45%(71.25-77-65)	81.42%(77.52-85.32)	55.16%(51.51-58.8)
CT	72.29%(70.27-74.31)	96.14%(94.06-98.22)	41.74%(39.58-43.9)

Table 4. Sensitivity analysis was carried out on Hospitalization variable to determine the covariates that have the most influence on the injury severity.

BN		MLP 2 layers		MLP 1 layers		CT		LR
Variable	%	Variable	%	Variable	%	Variable	%	Variable
location	60.1	location	48.3	location	45.4	location	37.2	location
removal technique	35.7	removaltechnique	27 .6	removaltechnique	25.5	removaltechnique	20.8	removaltechniqu
foreign body type	30	shape	15.1	shape	12.4	shape	13.2	shape
shape	5.23	foreign body type	10.2	foreign body type	6.8	age	5.9	age
consistency	3.37	consistency	2.3	consistency	3.7	consistency	3.1	consistency
volume	1.84	volume	1.8	volume	2.3	foreign body type	2.4	gender
action	1.79	action	1.8	action	1.09	action	1.2	
age	1.26	age	1.2	age	1.2	volume	0.98	
ellipticity	0.82	ellipticity	0.7	ellipticity	0.4	ellipticity	0.3	
adultpresence	0.21	adultpresence	0.6	adultpresence	0.5	adultpresence	0.19	
gender	0.02	gender	0.1	gender	0.09	gender	0.03	
complications	0.007	complications	0.01	complications	0.002	complications	0.001	

Table 5. Predicted probability of observing evidence on foreign body and children characteristics. The probabilities of the most probable FB location (ICD) and removal technique required are reported along with the probability of experiencing a hospitalization given that an accident occurred..

	Observation pattern									
N	foreign body type	age	gender	shape	consistency	volume	ellipticity	Probability of observing evidence	The most probable ICD	The most probable removal technique
1	batteries	2	m	spherical	rigid	70	1	5.8	935 (90%)	endoscopy (81%)
2	pebble	1	m	3D	rigid	140	1.4	2.5	932 (71%)	endoscopy (43%)
3	plastic	3	f	3D	conforming	95	>2	5.35	932 (61%)	endoscopy (39%)
4	fish bone	5	m	needle shape	conforming	140	>2	5.1	934 (52%)	endoscopy (41%)
5	pearls	6	f	spherical	rigid	>400	1	7.62	934 (53%)	endoscopy (38%)
6	stationery	4	m	cylinder	conforming	33.5	>2	6.85	934 (57%)	endoscopy (43%)
7	toy	2	f	spherical	rigid	102	1.3	3.16	933 (57%)	other (39%)
8	nut	6	m	spherical	rigid	200	1	4.95	934 (95%)	bronchoscopy (62%)
9	button	3	m	2D circle	rigid	>40	2	1.73	935 (64%)	other (65%)
10	stick	4	m	needle shape	rigid	NA	NA	1.15	933 (92%)	other(62%)