**MSc Project Report**

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Identifying Feature Importance in Pediatric Post-Mortem Outcome with Machine Learning Models

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Acknowledgements

Contents

[1 Abstract 4](#_Toc16663059)

[2 Introduction 5](#_Toc16663060)

[2.1 Background 5](#_Toc16663061)

[2.2 Literary Review 5](#_Toc16663062)

[2.3 Report outline 5](#_Toc16663063)

[2.4 Aim and Objectives 5](#_Toc16663064)

[3 Methods 7](#_Toc16663065)

[4 Data 8](#_Toc16663066)

[4.1 Source 8](#_Toc16663067)

[4.2 Data Cleaning 8](#_Toc16663068)

[4.3 Missing data 8](#_Toc16663069)

[4.4 Normalisation vs Standardisation 8](#_Toc16663070)

[5 Analysis 9](#_Toc16663071)

[5.1 Create models 9](#_Toc16663072)

[5.2 Tune models 9](#_Toc16663073)

[6 Results 10](#_Toc16663074)

[7 Conclusion 11](#_Toc16663075)

[7.1 Project Summary 11](#_Toc16663076)

[7.2 Project Evaluation 11](#_Toc16663077)

[7.3 Recommendations for Future Work 11](#_Toc16663078)

[References 12](#_Toc16663079)

[Appendix A – Example Project Code 13](#_Toc16663080)

[Appendix B – Example RDV structure 13](#_Toc16663081)

[Appendix C – Detailed output from and analytic process 13](#_Toc16663082)

[Appendix D – Deliverables on Attached CD ROM 13](#_Toc16663083)

[Random Thoughts 14](#_Toc16663084)

# Abstract

Post mortems are complex procedures that utilise a significant amount of hospital resources, yet despite this, cause of death is only determined in 45% of cases. The event itself can be very traumatic for the parents of the child, yet is essential for providing further clinical understanding of the patient’s cause of death. Given this, there is an imperative to extract the greatest possible value from the data. Here, we investigated whether machine learning could be used to derive novel insights from the prediction of post mortem outcomes.

A post mortem database containing 7000 records across 300 variables was analysed and categorised into stage of examination (external and internal). The outcome of the examination was summarised as either ‘cause of death determined’ or ‘not determined’. From these summarised data, cases were filtered by children aged <= 2 years, resulting in a dataset of 3,100 post mortems.

Following this, decision tree, random forest, and gradient boosting machine models were iteratively built for each stage of the post-mortem examination and compared using their accuracy metrics.

The naïve decision tree model using external examination data had a predictive performance of 67%. Model performance notably increased when trained on internal examination data. At each stage of the examination, a core set of data items, of which the final set included age, BMI, and heart weight were highlighted using model feature importance as key variables for determining post mortem outcome. The use of increasingly complex modelling techniques was able to boost the predictive performance of the model by as much as 10%.

This project clearly shows the value of collecting clinical procedural data which can then be modelled using machine learning techniques to inform clinical practice. With more time, further modelling, including unsupervised clustering could be undertaken to derive further insights.

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# Introduction

## Background

Great Ormond Street Hospital for Children NHS Trust (GOSH) is the country’s leading centre for treating sick children. With the UCL Great Ormond Street Institute of Child Health, GOSH is the largest centre for paediatric research outside the US.

Specialist Paediatric Pathologists perform perinatal, infant and childhood post-mortems including hospital referrals, forensic cases and those on behalf of Her Majesty’s Coroner.

The Pathology Department has established a research database containing details of all post-mortems performed between 1996 and 2017.  The database was originally used specifically for research into Sudden Unexpected Death in Infancy (SUDI). Since then it has been utilised for a number of other projects investigating SUDI, stillbirths and various aspects of paediatric autopsy procedure.

Currently the database holds 7000 records, each record representing an individual post-mortem. Up to 300 items of data can be defined for each post-mortem.

The purpose of this project is to use data science analytic techniques to develop operational strategies that can be applied to paediatric post-mortems to prioritise which data is required to achieve the target of specifying the cause of death.

## Literary Review

Synopsis of project proposal but NOT a copy. Concentrate on parts that are directly relevant to the project.

## Report outline

Highlight some key aspects of the report, include some interesting graphics clearly annotated.

## Aim and Objectives

Take from project proposal; amended based on experience undertaking project?

The aims of this project are:

1. To develop a routine to extract data from the existing Post-mortem Research Database into an entity attribute value schema that will make the data more readily available for data analytics.
2. To apply the Decision Tree Analytical method to the extracted data to develop operational strategies that can be applied to paediatric post-mortems to prioritise which data is required to achieve the target of specifying the cause of death.
3. To investigate ensemble strategies, specifically Random Forests and Gradient Boosting to see how these techniques can improve on the basic Decision Tree method.
4. If time permits a final aim would be to consider if the approach of Neural Networks could be employed to enhance the results.

# Methods

Explain how the data was gathered and analysed

This section may be divided into sub-sections describing the conceptual design work and the actual implementation separately. Any problems or difficulties and the suggested solutions should be mentioned. Alternative solutions and their evaluation should also be included.

* Reproducible results - Develop Project pipeline
  + PM Research Database => EAV Schema => Summary and Study based Attributes => RDV production => RDV Adjustments => Run models => review results
* Python
  + Data Engineering
  + PyCharm IDE
  + Testing and Profiling
* R code
  + Analytics and visualisation
  + Models evolved through three stages
    - Individual model
    - Model run for all PM stages
    - Model as a function called with multiple random keys.
* Use of GIT Hub

Notes from Machine Learning Coursework Requirements:

1.1 This part should normally describe clearly the method used in your assignment and any relevant parameters (e.g. for neural networks this includes number of hidden nodes, layers, type of activation functions etc.), and the rational for using this method. If you are using a particular library or tool, you still need to describe how the method/algorithm that you are using operates. Citing the library, tool, etc., and mentioning the library functions that you have used is not enough to get a high mark.

1.2 This part should describe any special techniques/algorithms used as part of your methodology. For example, the algorithm used for training a neural network and its parameters – e.g. if you use Rprop backpropagation then initial learning rate values used should be stated. Also, this part should describe any normalisation techniques used, or other pre-processing or balancing methods, and whether you have used some form of cross-validation, or weight decay, providing details of the particular method. Citing the library, tool, etc., and mentioning the library functions that you used is not enough to get a high mark.

## Data Engineering

### Extract, Transform, Load (ETL) Process

‘The process of pulling data out of one database and place it into another database. Within this process the data is cleans and transformed to be in a more appropriate schema for analytics.

### Missing Data

### Data Wrangling

the process of transforming and mapping data from one "raw" data form into another format with the intent of making it more appropriate and valuable for a variety of downstream purposes such as analytics.

## Analytics

### Creating models

### Tuning models

# Data

Explain why the data matches the objectives.

## Source

* The nature of the data is that it is not normal
* Use of EAV schema to structure and clean data
* Introduce summary data for analytics and reporting

|  |
| --- |
| HL7® Fast Healthcare Interoperability Resources (FHIR®, pronounced "fire") is a next generation standards framework that leverages the latest web standards and applies a tight focus on implementation and was developed by healthcare standards developing organization, Health Level Seven International® (HL7®) |
| A FHIR resource can contain data about a patient, a device, an observation, and more. For a full list of FHIR resources, see the FHIR Resource Index |

## Missing data

* Gestation in days at birth.
* Balanced data

## Normalisation vs Standardisation

* Z score
* Normalisation for Age
* One-hot encoding

# Analysis

Explain what analysis was undertaken and why.

## Create models

## Tune models

# Results

Describe the results of the analysis.

Notes from Machine Learning Coursework Requirements:

Experiments, findings and discussion: you must present and discuss your results. You are expected to run several experiments and calculate basic statistics to summarise performance. Your report must include at least two figures which graphically illustrate quantitative aspects of your results, such as training/testing error curves, performance for sets of learned parameters, algorithm outputs, descriptive statistics, etc.

In this part, you should provide a detailed account of your experiments and results and discuss your findings. You can use Excel or other packages to provide charts - like the figure below, which uses error bars (Box and Whisker Charts in Excel), to show the performance of your algorithm in terms of generalisation. For example, the figure below shows generalisation with respect to number of hidden nodes used in a neural network based solution. Alternatively, one could use tables to provide the same information by giving for each number of hidden nodes the average value, the minimum value, and the maximum value of generalisation performance (in percentage of successfully recognised patterns) in the tests.

You could also discuss the cost of the computations, e.g. referring to the number of training iterations required or the number of error function evaluations (see figure below for the neural-network based solution discussed above)

In machine learning, overall results are also presented in tables like the one below that shows average performance in terms of recognition success as well as average classification success per class for two methods tested on the same dataset. Confusion matrices can also be used.

Method Class 1 (%) Class 2 (%) Average success (%)

Method 1 83 96 93

Method 2 73 93 88

# Conclusion

## Project Summary

Provide an overview/summary of your work and findings.

## Project Evaluation

Identify areas for improvement; discuss what you could have done better (particularly important if you failed some of your targets or your results as not as expected)

## Recommendations for Future Work

# References

Archer, K.J., 2010. rpartOrdinal: an R package for deriving a classification tree for predicting an ordinal response. *Journal of Statistical Software*, *34*, p.7.

Luellen, J.K., Shadish, W.R. and Clark, M.H., 2005. Propensity scores: An introduction and experimental test. *Evaluation Review*, *29*(6), pp.530-558.

(Example of using RPART package)

Therneau, T.M. and Atkinson, E.J., 1997. An introduction to recursive partitioning using the RPART routines.

# Appendix A – Example Project Code

Python Functions

Python ODBC

R Model

# Appendix B – Example RDV structure

Basic

Adjusted

# Appendix C – Detailed output from an analytic process

RDM file output

# Appendix D – Deliverables on Attached CD ROM

# Random Thoughts

* Python vs R
  + Why used when
* Reproducible results
* R code; evolved through three stages
  + Individual model
  + Model run for all PM stages
  + Model as a function called with multiple random keys.
* Balanced data
* Methods before data?
  + Include Software architecture in methods?
    - Tools and programing language
      * Why use R over Python?
    - Project pipeline
      * PM Research Database => EAV Schema => Summary and Study based Attributes => RDV production => RDV Adjustments => Run models => review results
  + Testing and Profiling
* Agile approach
  + Reviewed progress from last week
  + Set objectives for the coming week