KidsBrainIT: Using machine learning to predict childhood brain trauma patients' length of stay

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Introduction

- Parents of critically ill children and intensivists are interested in **length of stay (LoS) prediction** in **paediatric critical care units (PCCU)**.
- **Traumatic Brain Injury (TBI)** is one of the leading causes **of mortality and disability in children** which can result in **long PCCU LoS and lengthy rehabilitation times**.
- No prior study has used **clinical grade bedside physiological data** within **the first 24 hours** of PCCU admission to **predict LoS in PCCU**.

Aim

To **classify** whether PCC TBI patient's **LoS** will be **greater than equal to 4 remaining days** using only the first **24 hours** of standard **physiology**, basic **demographic**, and **clinical** data after admission.

Methods - Data

- A **data informatics feasibility study** was conducted.
- KidsBrainIT Dataset (Figure 1) was used:
  - **Real world multi-national multi-centre** (16 PCCU from 7 countries) prospectively routinely collected data.
  - Originated from TBI paediatric patients (n = 214), aged 2 to < 16 years old.
  - First **international** fully anonymised paediatric dataset with **clinical grade physiological** recordings

KidsBrainIT Dataset:

Demographic Data:	Clinical Data:	Bedside Physiology Data (1 minute resolution):
Age, sex and centre	Glasgow Coma Score, Pupil Reaction Score, LoS	Standard bedside physiology measurements

Figure 1: The **KidsBrainIT dataset consists of 214 data files (16 PCCU in 7 countries) over 3 time periods.**

Methods - Data Challenges

1) Missing data:
- Patients have different sets clinically directed of physiology measurements.
- Measurement calibration.

Imputation

- Forward fill, or MICE using Bayesian linear regression.

2) Data collection artifacts:
- Measurement calibration.
- Measurement artifacts

Cleaning

- Cleaned by clinical expert.
- Removed data imputed.

3) Multicenter: Check LoS distributions are uniform between centers.

4) Relationship to age: Strong relationship with physiology baseline and age in children.

Adjust during modelling/use age corrected features where possible.

214 data files → ***Cleaning/ Exclusion*** → **171 data files** → ***Data Analysis***

Methods

Standard Methods (Figure 2):
1) Use model types suitable for **physiological time series.**
2) Extract **"summary features"** from physiological time series.

Ensemble Methods:
Uses the same approaches as above, however:
- Instead of fitting one model to all data, a model is fitted to **each physiology measurement**.
- A voting approach is used to combine classifier predictions.
- Not all patients have the same set of physiology measurements!

Inputs
- Demographic and clinical scores
- Physiological time series

Sequence based
Use ML methods that can be fitted directly to sequence-based data:
- Long Short Term Memory (LSTM)
- Recurrent Neural Network (RNN)

Physiological Summarisation (Feature Extraction)
Convert "variable" length physiological time series into a set of summary features, i.e. mean and variance
- Use standard ML algorithms

Output
Class label: Is the LoS >= 4 days

Sequence Based Methods

"Raw" physiological time series:
- Minute-by-minute physiology data.
- Long sequences which models can struggle with.

"Aggregated" physiological time series:
- Physiological time series aggregated into chunks (1, 2, 4 … hours).
- Typically, the "worst" or "last" measurement, central tendency and/or dispersion.

Feature Extractions Methods

Automatic Time Series Summarisation[1]:
- Extract summary statistics for each physiology measurement.

Secondary Insult Detection[2,3,4,5]:
- Secondary insults are detected and summarized into features.
- Evaluation of the patient autoregulation system (i.e. ordering of the MAP, CPP and ICPm).

Physiological Pattern Mining[6]:
- Identify physiological patterns which occur in the different patient populations which may be indicative of outcome.
- Dichotomic pattern mining.

Figure 2: Flow chart describing the modelling and feature engineering options for physiological time series.

Methods- Model Fitting

10-fold Cross Validation (CV):
Mean validation AUROC score as evaluation metric.

Hyperparameter search:
100 experiments per model architecture.

Binary Classifiers:
Logistic Regression, SVM, Naïve Bayes, K-Nearest Neighbours, XGBoost, Neural Network (Fully connected) and LSTM.

Results

- Feature engineering methods performed the best (Figure 3) with **automatic time series summerisation** (mean CV AUC=0.81) or **secondary insult detection** (mean CV AUC=0.81).
- **Ensemble modelling method** had the best performance overall (mean CV AUC=0.87)

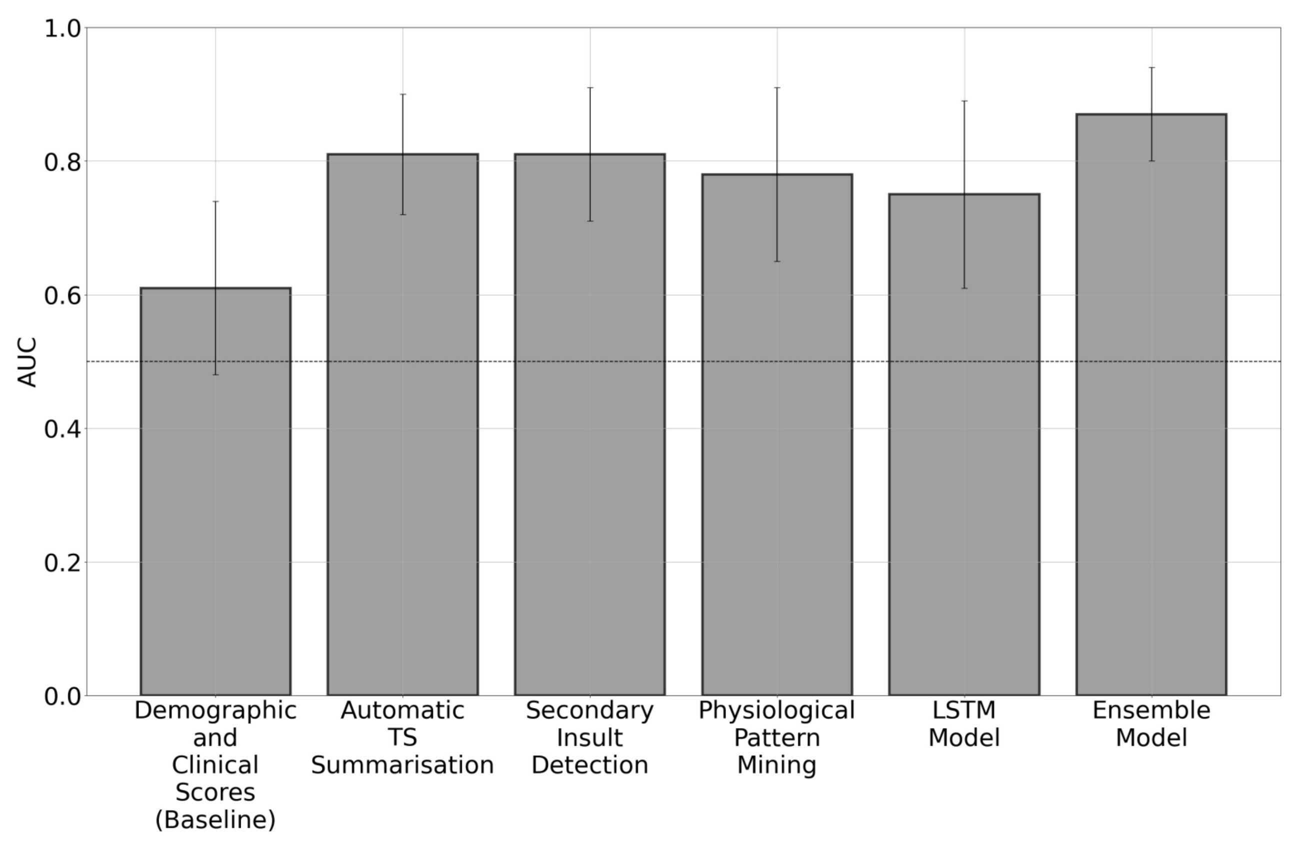

Figure 3: Average validation AUC scores using 10-fold cross validation of the best performing models for each of the techniques.

Error bars show the standard deviation of the AUC score for the 10-folds. Unless otherwise specified results shown use XGBoost models which performed the best.

Conclusions and Future Work

Data-driven PCCU LoS prediction for childhood TBI **is possible** using the **first 24 hours of bedside physiological data**.

Future work should include (i) **dynamic** prediction of the **remaining day-by-day LoS** for paediatric TBI, and (ii) prediction of LoS for **other pathologies**.

References

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Acknowledgements: Precision Medicine DTP, this work is supported by the Medical Research Council [grant number MR/N013166/1]

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