Abstract

Hypothermia is a medical emergency that occurs when there is a low body temperature (BT) from the normal BT of 37°C. Reportedly ranges from 33% to 69% during general surgical operations and often leads to extremely short and long-term complications.

The use of Interpretable Machine Learning Regressors for Mild Hypothermia Prediction in General Surgical Operations was leveraged in this work. Specifically, building, testing, and optimization of ELM, Linear, RF, Logistic, and SVM regression models were done with an accuracy of 98.76%, 98.79%, 98.69%, 73.28%, and 29.34% respectively achieved upon model tuning and hyperparameter optimization. SHapley Additive ExPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) based on physiological vitals were transparently provided.

This work can contribute to Society 5.0 by improving patient outcomes of general surgical operations, reducing healthcare costs, and increasing the efficiency and effectiveness of Intelligent Healthcare Systems.

Data Collection & Analysis

Pre and intra-operative clinical data of 6000 patients who underwent surgical operations at Seoul National University Hospital between Aug 2016 to Jun 2017 were collected with a vital recorder program. An 8000M Solar Patient Monitor connected to a laptop was used for patients’ vitals monitoring. Data were in both .csv and .vitals files containing waveform representations (Figure 2) for all elements captured, including BT, BP, heart rate, and vitals. Python script was used to convert the data and extract key features, an example seen in Figure 3.

- 1221 data downloaded and obtained in batches.
- Nulls 9 records with null values were dropped.
- Features Drop Caseid, Anesthesia type (only 1 out of 1221 operations were administered spinal anesthesia), and Op_start_diastolic directly proportional to Op_start_systolic pressure dropped.

Results

<table>
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<th>Table 1: Model Performance Scores</th>
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<td>Algorithm</td>
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Model Selection, Optimization & Explainability

Linear Regression, Random Forest Regressor, and ELM Regressor were trained with a train-test split ratio of 70% to 30%, and their output assessed.

1. Linear regression (LR): For a dataset with n independent features, predicted values can be estimated given the different values of the independent features, using equation 1 below.

\[ Y = \theta_0 + \theta_1 X_1 + \theta_2 X_2 + \theta_3 X_3 + \ldots + \theta_n X_n + \epsilon \]  

(1)

Fitting into the LR algorithm, the LR model produced a mean average percentage error (MAPE) of 6.76%.

2. Random Forest (RF): The target variable has a continuous distribution hence, the RF approach was utilized because it combines numerous decision trees to get a prediction. Without hyperparameter tuning, RF model gave a MAPE of 7.60%.

Hyperparameter tuning was done starting with 2 leaf nodes, a least MAPE of 6.68% was obtained with max leaf nodes of 15 which remained constant with a further increase in leaf nodes.

3. Extreme Learning Machine (ELM): The best performance of the ELM was achieved by setting the pairwise_metric to cosine, which also transformed the ELM into an RBF-ELM, with the ufunc and density parameters of ELM dropped. The concept of XAI used to explain and provide the interpretability of predicted results is presented. The sum of contributions of each independent feature should yield the total contribution of all features, \( \sum_{i=1}^{n} \phi_i = \phi(X) \).

4. SVM & Logistic Regressors: Support Vector Machine Regressor and Logistic Regression models were also trained. Both models presented a high variability with a MAPE of 58.24% and 29.23% respectively.

Shapley values and LIME were used as XAI techniques. Shapley values algorithm for calculating each feature contribution is obtained using equation 2. The concept of XAI used to explain and provide the interpretability of predicted results is presented.

Conclusion

Building an intelligent Healthcare system that would implement any of the regression models presented here would be important in validating the results obtained in this study using a real-life environment, an aspect that would also directly contribute towards smart healthcare systems development and adoption.

References
