Interpretable ML Models for Prediction of Occurrence of Mild Hypothermia

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Abstract

Hypothermia is a medical emergency that occurs when there is a low body temperature (BT) from the normal BT of 35◦C. Reportedly ranges from 33% to 89% 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. SHapely 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.

Introduction

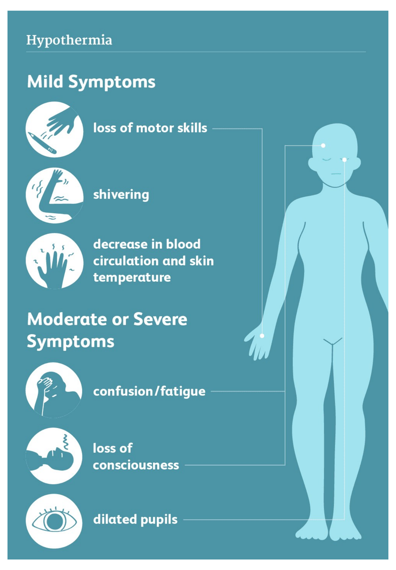


Figure 1. Signs and Symptoms of Hypothermia

The application of computational or artificial intelligence has increased recently in medical diagnosis. Machine intelligence-assisted decision-making technologies are frequently used to assist (but not to replace) a doctor in diagnosing a patient's sickness, giving rise to rapid growth in the design and usage of smart healthcare systems[1]. The use of AI to predict the time of occurrence of Hypothermia (particularly mild case - 32°C and 28°C), specifically looking at patients undergoing general surgery is presented[2].

Data Collection & Ananlysis

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.

Figure 2. Vitals Data Waveform Representation, BT representing Body Temperature for example

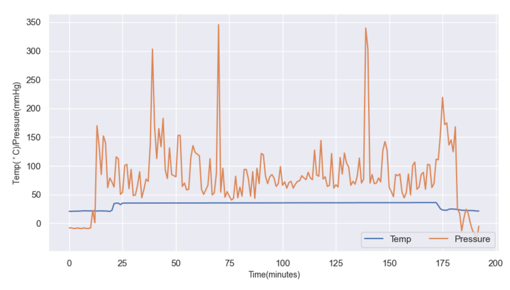


Figure 3. Trends and variations of temperature(°C) and pressure(mmHg) for a single patient

- **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.

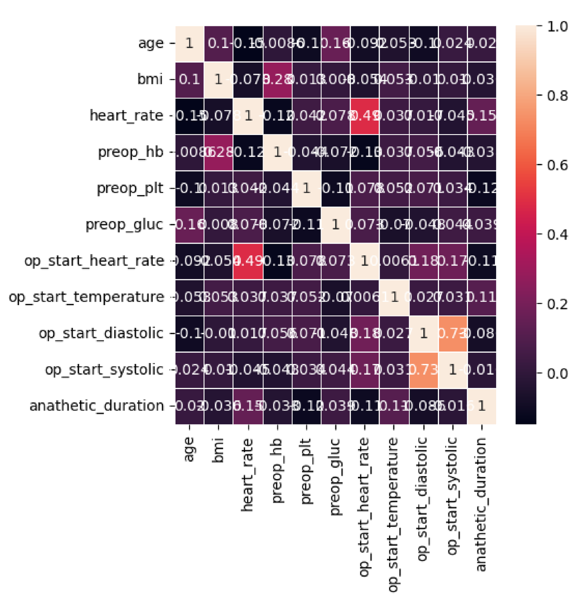


Figure 4. Heat Map of Data Features

Results

Table I. Model Performance Scores

Algorithm	MAPE	R-Squared	Accuracy
ELM Regressor	**6.68**	0.9876	98.76%
Linear Regression	6.76	0.9879	**98.79%**
RF Regressor	7.60	0.9869	98.69%
Logistic Regression	29.23	0.7328	73.28%
SVM Regressor	58.2	0.2934	29.34%

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.

$$Y = c + w_1X_1 + w_2X_2 + w_2X_2 + ... + w_nX_n + \epsilon \quad (1)$$

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

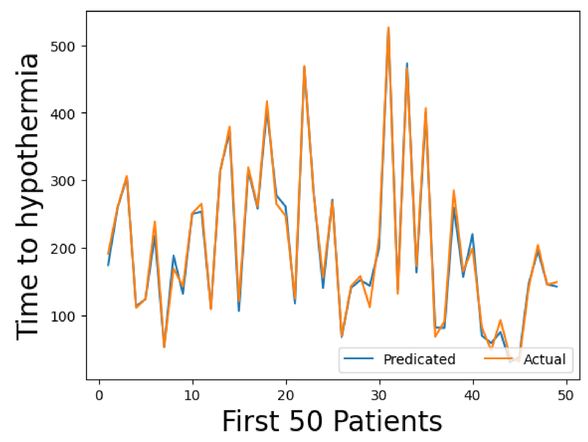


Figure 5. Line Graph Performance of LR

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%.

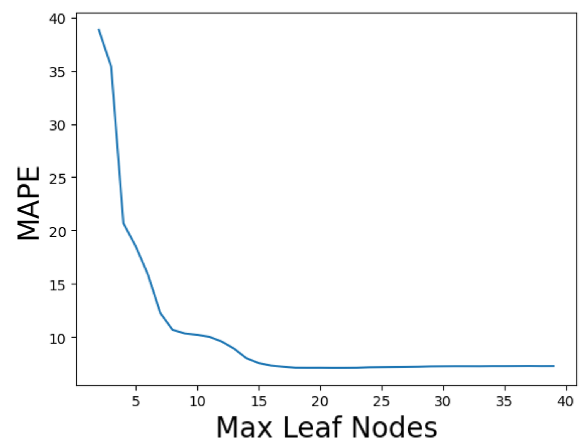


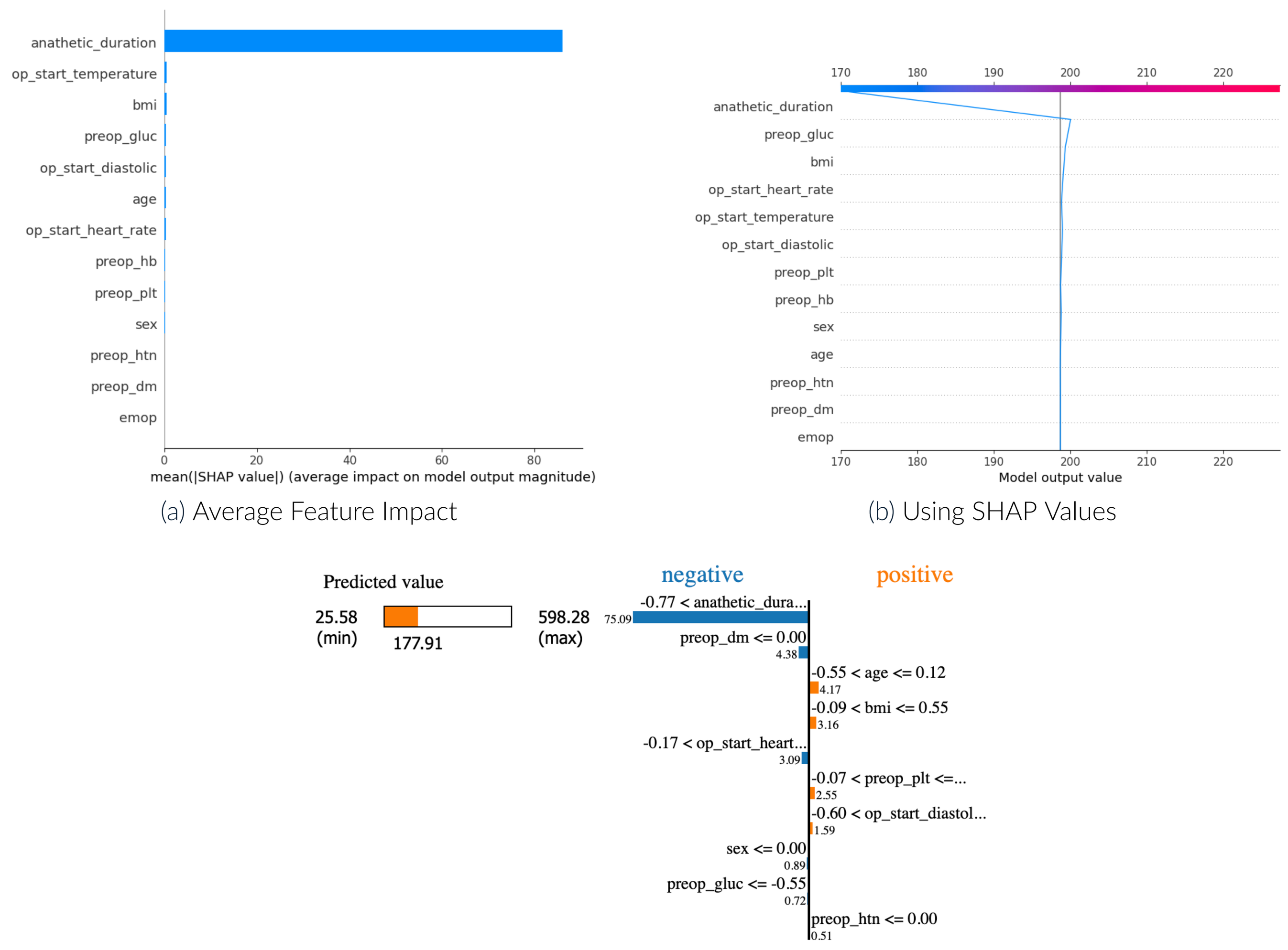
Figure 6. RF Performance with Varying max_leaf_nodes

Hyperparameter tuning was done starting with 2 leaf nodes, a least MAPE of 7.10% 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. include_original_features was set to True, and *alpha* set to 0.9. The performance of the model greatly improved, from an initial MAPE of 11.90% without hyperparameter tuning to 6.68%.

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.
The sum of contributions of each independent feature should yield the total contribution of all features, $\sum_{i=1}^{N} \phi_i = v(N)$.



(a) Average Feature Impact (b) Using SHAP Values

Figure 7. Model Explainability with LIME

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

[1] D. Saraswat et al., "Explainable AI for Healthcare 5.0: Opportunities and Challenges," in IEEE Access, vol. 10, pp. 84486-84517, 2022, doi: 10.1109/ACCESS.2022.3197671. https://doi.org/10.1109/ACCESS.2022.3197671

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