# Advanced Prediction of Physiological Decompensation


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## Background

Physiological decompensation occurs when the body cannot regulate its functions at a working level and the patient's physiological status deteriorates. Events such as cardiac arrest, respiratory failure, and kidney failure all represent different subsets of this decompensation. Early detection of decompensation is essential for saving lives and providing clinicians with valuable information to execute potential life saving interventions. The current standard of early decompensation detection is the National Early Warning System (NEWS2); however, it lacks any predictive approach as it does not reflect patterns over time. Thus, clinicians need a tool that can encompass better features and predict whether an ICU patient will face physiological decompensation.

## Methods and Approach

Data was taken from the MIMIC-III Clinical Database, including demographics, vital signs, and lab tests. Our overall dataset consisted of the ICU stays of adult patients (>15 years of age as per MIMIC guidelines) who had a length of stay of greater than or equal to 48 hours. We started with developing a mortality predictor, as mortality is arguably the strongest label for physiological decompensation. The goal was to predict mortality within 24-48 hours from a sample 24-hour time window within a patient's ICU stay. We used three different models and performed k-cross validation on the latter two for feature selection and model validation using a 70-30 training-testing split.

## Results

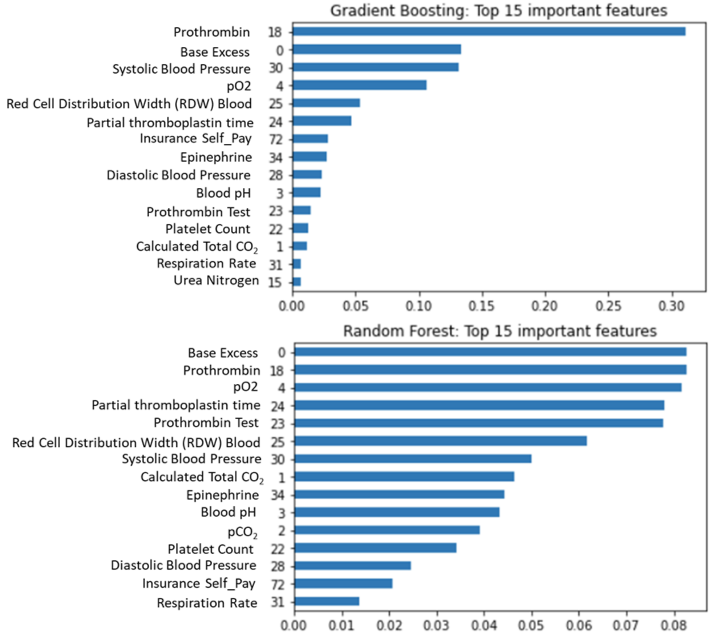


**Figure 1 – Top Features for Gradient Boosting and Random Forest**

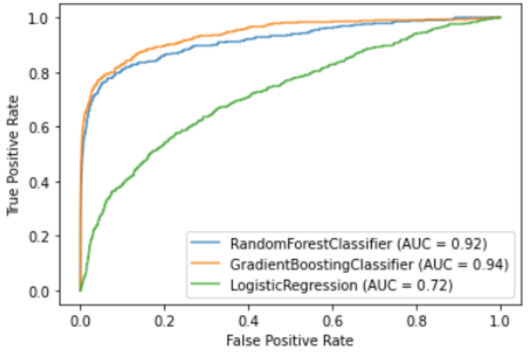


**Figure 2 – Mortality Predictor – AUC of Logistic Regression, Gradient Boosting, and Random Forest**

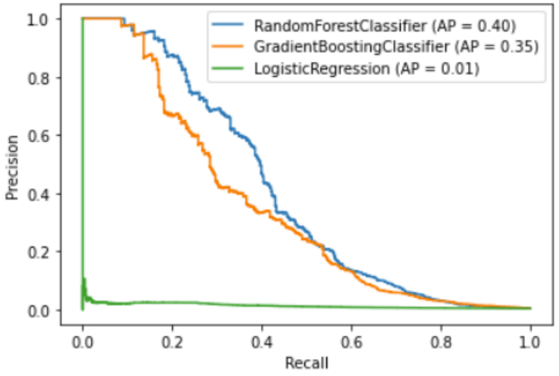


**Figure 3 – PR Curves of Models in Figure 2**

So far, our gradient boosting and random forest models outperform our logistic regression model, which was expected. Top features also overlap between gradient boosting and random forest feature selection, indicating the overall importance of these features.

## Conclusion and Future Direction

We found that our mortality predictor performance was consistent with literature, as well as the feature selection done via gradient boosting and random forest, as many of our top features were notable for their correlation with mortality.

We first plan to further improve this mortality model by looking at time weighting, expanding feature selection, and then looking at other models' performances, including recurrent neural networks. After, we will move onto the inclusion of other labels that comprise physiological decompensation and look to create an overall predictor of physiological decompensation utilizing time series data combined with risk scores.