Respiratory Rate Estimation using PPG

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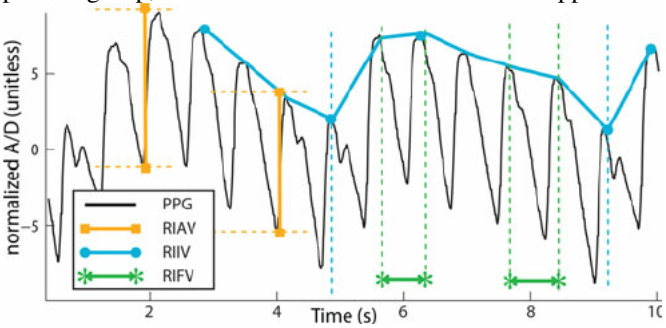
***Abstract*—Due to a shortage of noninvasive sensors for objective and accessible assessment, respiratory rate (RR) is an important vital sign marker of health that is frequently overlooked. Signal processing, waveform fiducial markers, and handcrafted algorithms have been used to generate RR from simple photoplethysmogram (PPG) respiratory modulations.The PPG signal has two components: an AC-like component caused by the synchronous change in blood volume caused by the heart, and a very slowly fluctuating DC component caused by factors such as respiration. So in this study, using this signal, we will try to obtain the respiratory rate with the help of Machine Learning techniques like Xgboost and elastic net regression. The data was obtained from the Physionet website, which had the BIDMC dataset, which included 53 patients. PPG sensor measurements were included in the dataset.**

***Index Terms*—PPG, XGBoost, KNN, Elastic net, Random Forest, Respirtory rate**

I. Introduction

External and internal respiration are two different ways of breathing. Internal respiration is the conversion of gases at the cellular level, while external respiration is concerned with gas exchange at the alveolar and capillary level. Respiratory rate (RR) is a popular diagnostic marker for respiratory dysfunction and malfunction, and it is often referred to as breathing rate or breathing frequency. A high RR is a good predictor of cardiac arrest and is strongly linked to in-hospital mortality. As a result, RR monitoring is critical for determining a patient's health state in the hospital, at home, or in the community. RR is currently measured in clinical practice by counting chest wall expansion, which is very subjective, inaccurate, and inconvenient.

For research and patient monitoring, noninvasive continuous measurement of RR has been emerging utilising any or a combination of impedance pneumography (IP), piezoelectric, acceleration, electrocardiogram (ECG), and photoplethysmogram (PPG) sensors.Pulse oximeters which produce PPG signals by shining light (using a light emitting diode) on the skin and monitoring the minute fluctuations in reflected or transmitted light intensity (using a photodiode).The PPG is modulated primarily by the respiratory, among other physiological functions, and manifests as three types of signal modulation: baseline wander (BW), which is influenced by changes in intrathoracic pressure and artery vasoconstriction during inhalation; amplitude modulation (AM), which reflects changes in stroke volume and intrathoracic pressure during respiratory cycles; and frequency modulation (FM), As a result, respiratory surrogate signals produced from PPG can be used to predict RR. PPG-based RR estimate has been the focus of recent study. Digital filtering, time and possibly frequency domain analysis, signal decompositions, feature based points produced respiratory surrogate waveforms and characteristics, signal quality estimations, and sensor fusion are all typical components of RR algorithms. Hand-crafted rules and empirical parameters tailored for specific algorithmic procedures, developed for a general or specific target patient group, are used in the above traditional approaches.



For estimating respiratory rate through PPG signals we used some machine learning techniques like statistical features (kurtosis , skewness , etc.) and for predicting models we used XGBoost regression and elastic net regression. Kurtosis.

The cumulative weight of a distribution's tails compared to the centre of the distribution is measured by kurtosis. A bell peak with most data within three standard deviations (plus or minus) of the mean can be seen when a batch of essentially normal data is graphed using a histogram.

Kurt = kurtosis = fourth central moment = standard deviation

Skewness- Asymmetry or distortion of a symmetric distribution is measured by skewness. It calculates the divergence of a random variable's distribution from a symmetric distribution, such as the normal distribution. Because it is symmetrical on both sides, a normal distribution has no skewness. As a result, if a curve is shifted to the right or left, it is said to be skewed.

skewness N = number of variables in the distribution Xi = random variable x = mean = standard deviation

Decision tree- One of the most widely used and useful models for supervised learning is the Decision Tree. It can

be used to tackle both regression and classification problems, albeit the latter is more widely used. There are three sorts of nodes in this tree-structured classifier. The Root Node is the first node in the graph, and it represents the complete sample. It can be further divided into nodes. The features of a data collection are represented by the interior nodes, while the decision rules are represented by the branches. Finally, the outcome is represented by the Leaf Nodes. This algorithm is quite useful for resolving decision-making issues.

XGBoost regression- Extreme Gradient Boosting (XGBoost) is an open-source toolkit that implements the gradient boosting technique in an efficient and effective manner. XGBoost has become the go-to method and often the primary component in winning solutions for a variety of issues in machine learning contests shortly after its development and initial release. Predicting a numerical value, such as a dollar amount or a height, is an issue in regression predictive modelling. For regression predictive modelling, XGBoost can be utilised directly.

Elastic net regression- Elastic Net is a regularised regression model that includes lasso and ridge regression, as well as l1 and l2 penalties. When the elastic net is employed alone, it becomes the ridge regression because it includes the lasso regression penalty. The coefficient of ridge regression is initially determined in the technique of regularisation with an elastic net. After that, we apply the lasso approach on the ridge regression coefficient to shrink it.

CatBoost Regression- CatBoost is based on decision tree and gradient boosting theory. The primary principle behind boosting is to successively integrate multiple weak models (models that perform marginally better than chance) to generate a strong competitive prediction model using greedy search.

Random forest- Random Forest Regression is a supervised learning approach for regression that uses the ensemble learning method. The ensemble learning method combines predictions from several machine learning algorithms to produce a more accurate forecast than a single model. Random Forest Regression is a powerful and precise model. It usually works well on a wide range of issues, including those with non-linear relationships.

K-Nearest Neighbor(KNN)- The K-Nearest Neighbour algorithm is based on the Supervised Learning technique and is one of the most basic Machine Learning algorithms. The K-NN algorithm assumes that the new case/data and existing cases are similar and places the new case in the category that is most similar to the existing categories. The K-NN method stores all available data and classifies a new data point based on its similarity to the existing data. This means that new data can be quickly sorted into a well-defined category using the K-NN method. The K-NN algorithm can be used for both regression and classification, but it is more commonly used for classification tasks. The K-NN algorithm is a non-parametric algorithm, which means it makes no assumptions about the underlying data.

II. Proposed solution

A. Data Acquisition and Pre-processing

In order to obtain the dataset required for this , we used a python program to doenload the BIDMC dataset from the Physionet website. A total of 53 subjects were included in the study. Sensor readings of ECG and PPG electrocardiograms were included in the dataset. The measurements were taken for an 8-minute period. The patient was in a resting state at the time. The data that was downloaded can be seen in the diagram below.

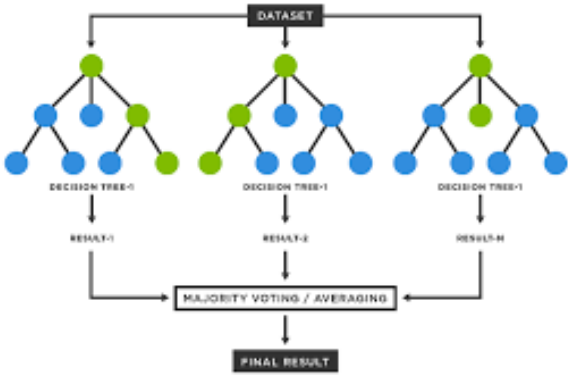
	RESP	PLETH	V	AVR	II	HR	PULSE	SpO2
0	0.35386	0.43597	0.52549	0.30392	0.72549	94.0	93.0	97.0
1	0.35679	0.43206	0.51961	0.33529	0.67059	94.0	93.0	97.0
2	0.35875	0.42815	0.51569	0.37451	0.60980	94.0	93.0	97.0
3	0.36168	0.42424	0.50588	0.41961	0.55098	94.0	93.0	97.0
4	0.36364	0.42131	0.50980	0.44902	0.50000	94.0	93.0	97.0

We then attempted to plot the graph of this data to see if the data had been downloaded correctly. We chose topic 12 to see if the dataset had been downloaded successfully. The data was displayed using Python tools.

B. Feature Extraction And Implementation

To use the Machine Learning model, we need to select the features that will assist us in properly forecasting the target variable (Respiratory Rate). Summary statistics of 125 values collected every second will be used as features for this. Max value, Min value, Mean value, Kurtosis Value, and Skew value are a few examples. The Random Forest Regression model was then fitted to our dataset. For this, we divided the data into a 30-70 split, with 70 percent of the data going to training and 30 percent going to testing.

1) Random Forest Regression: Random Forest Regression is a supervised learning method that uses the ensemble learning technique to do regression, which means it combines the predictions from several machine learning algorithms to generate much more accurate predictions. The random forest regression model is highly accurate and dynamic. It is capable of solving a wide range of problems, including characteristics of non-linear interactions (source: https://levelup.gitconnected.com). The drawbacks, on the other hand, are as follows: We must pick the amount of trees that will be included in the model because there is no interpretation and overfitting is a possibility.



Using the model importance function, we attempted to determine the relevance of each feature that we utilised in creating the model after receiving the results. When we look at the graph, we can see that the II Mean is the feature that has the biggest influence on the outcome prediction.

2) XGBoost: XGBoost is a gradient boosting-based decision-tree-based ensemble Machine Learning technique. Artificial neural networks surpass all other algorithms or frameworks in prediction issues involving unstructured data (pictures, text, etc.). However, decision tree-based algorithms are now considered best-in-class for small-to-medium structured/tabular data.

XGBoost and Gradient Boosting Machines (GBMs) are both ensemble tree approaches that use the gradient descent architecture to boost weak learners (CARTs in general). XGBoost, on the other hand, enhances the fundamental GBM framework through system optimization and algorithmic improvements.

XGBoost is a scalable and highly accurate version of gradient boosting that pushes the limits of computing power for boosted tree algorithms. It was designed primarily to increase machine learning model performance and computational speed. Unlike GBDT, XGBoost builds trees in parallel rather than sequentially. It employs a level-wise technique, scanning over gradient values and evaluating the quality of splits at each feasible split in the training set using partial sums.

3) Elastic Net: The conventional regression algorithm assumes a linear relationship between the inputs and the target variable, which is known as linear regression. Adding penalties to the loss function during training encourages simpler models with smaller coefficient values, which is an extension of linear regression. Regularized linear regression and penalised linear regression are terms used to describe these expansions.

Elastic net is a sort of regularised linear regression that combines two well-known penalties, the L1 and L2 penalty functions.

The term "linear regression" refers to a model in which the input variables and the target variable are assumed to have a linear relationship. This connection is a line with a single input variable, and it can be thought of as a hyperplane with greater dimensions that connects the input variables to the destination variable. The model's coefficients are determined by an optimization procedure that aims to reduce the total squared error between the predicted (yhat) and expected goal values (y).

loss = sum i=0 to n $(\mathrm{y}_i - yhat_i)^2$

The concern with linear regression is that the model's predicted coefficients might grow enormous, making it sensitive to inputs and potentially unstable. This is especially true for issues where the number of observations (samples) or samples (n) is greater than the number of input predictors (p) or variables (so-called p ¿¿ n problems).

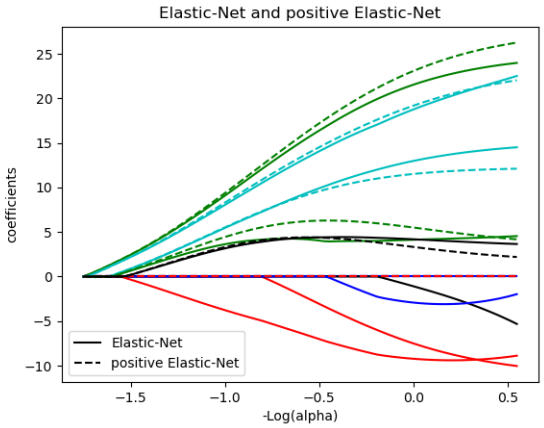
Changing the loss function to include additional costs for a model with big coefficients is one way to address regression model stability. Penalized linear regression refers to all linear regression models that apply these adjusted loss functions during training.

The sum of the squared coefficient values is a common penalty. This is referred to as an L2 penalty. Although an L2 penalty reduces the amount of all coefficients, it prohibits any of them from being eliminated from the model.

$l2_penalty = sumj = 0topbeta_j^2$

The sum of the squared coefficient values is a common penalty. This is referred to as an L2 penalty. Although an L2 penalty reduces the amount of all coefficients, it prohibits any of them from being eliminated from the model.

$l1_penalty = sumj = 0topabs(beta_j)$



During training, the elastic net is a penalised linear regression model that contains both the L1 and L2 penalties. A hyperparameter "alpha" is supplied to allocate how much weight is given to each of the L1 and L2 penalties, using terminology from "The Elements of Statistical Learning." The L1 penalty's contribution is weighted by one minus the alpha value, while the L2 penalty is weighted by one minus the alpha value.

$\mathrm{elastic}_net_penalty = (alpha * l1_penalty) + ((1 - alpha) * l2_penalty)$

The advantage is that elastic net permits a balance of both penalties, which might result in greater performance on particular tasks than a model with only one penalty.

Another hyperparameter called "lambda" regulates how the sum of both penalties is weighted in the loss function. The fully weighted penalty is applied by default with a value of

1.0; the penalty is not applied with a value of 0. Lambada values as low as 1e-3 or even below are rather typical.

elastic$_net_loss = loss + (lambda * elastic_net_penalty)$

4) KNN

The algorithm makes its predictions based on the nearest neighbors, we need to tell the algorithm the exact number of neighbors we want to consider. Hence, "k" represents the number of neighbors and is simply a hyperparameter that we can tune. Once the neighbors are found, one of the two things will happen depending on whether you are performing classification or regression analysis. Classification: the algorithm uses simple majority voting to assign the label to the new data point. Regression: the algorithm calculates the average value of all the neighbors.

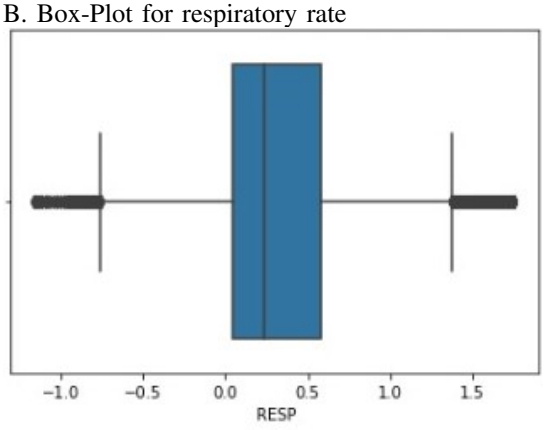
kNN is a very intuitive algorithm, making it easy to explain how the predictions were made. Thus, it is in contrast to other classification and regression algorithms such as RandomForest or XGBoost.

C. Results

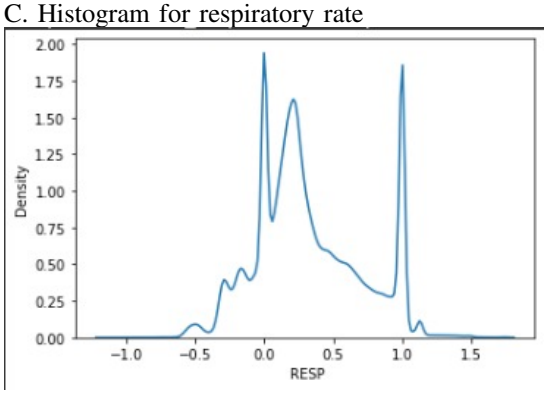
A. Metrics Table

Metric	Value
Skewness	4.192024e-01
Kurtosis	-0.450148
Variance	0.144377
Mean	0.322684
Median	0.240470
Std	0.382592

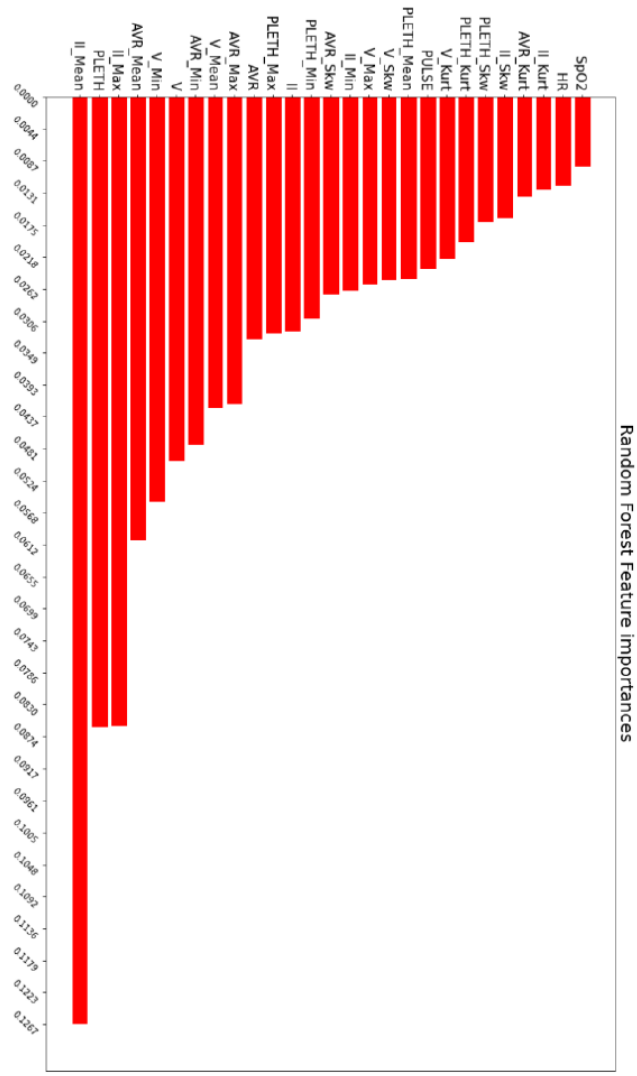
B. Box-Plot for respiratory rate



C. Histogram for respiratory rate



D. Feature Ranking

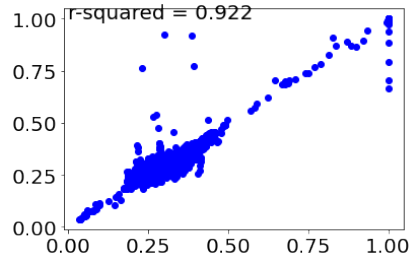


E. Comparison Table

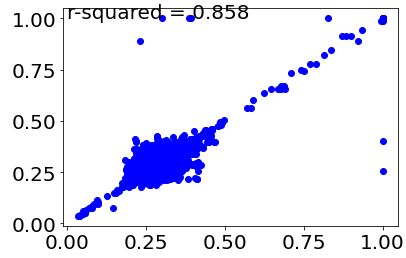
Model	RMSE	MAE	R2 Score
DT	0.0202	0.006	0.858006
ElasticNet	0.0574	0.038	0.000078
KNN	0.0222	0.011	0.849709
RF	0.0143	0.006	0.992261
XGB	0.0306	0.023	0.714864
CB	0.0180	0.011	0.895001

From the above table, we can see that Decision tree, CatBoost and Random Forest have the highest R2 values, therefore the are the best models fit for this task. The following are the scatter plots between their actual vs predicted values.

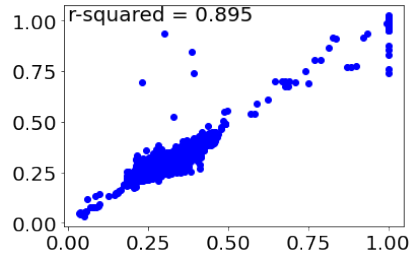
DecisionTree Regression



CatBoost Regression



RandomForest Regression



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