Catching your breath

Calculating the breathing rate from a wearable ECG /PPG device

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Take a deep

breath

Using a selection of supervised machine learning techniques, we are able to predict any user's respiratory rate in real time with data readily accessible with any smart device health monitor.

Training on solely the BIDMC Dataset consisting of 53 patients, our algorithm is able to predict respiratory rates with an R^2 accuracy of 0.9 .

150,000 people die each year in the US from chronic respiratory disease

CDC 2016

By monitoring breathing rate, doctors can make diagnostic insights about major diseases including pneumonia

Patients currently have their respiratory rate measured when they visit their doctor.

This is an infrequent occurrence and often only happens ***after*** something has gone wrong.

Smart watches can record electrocardiogram and pulmonary data all day every day.

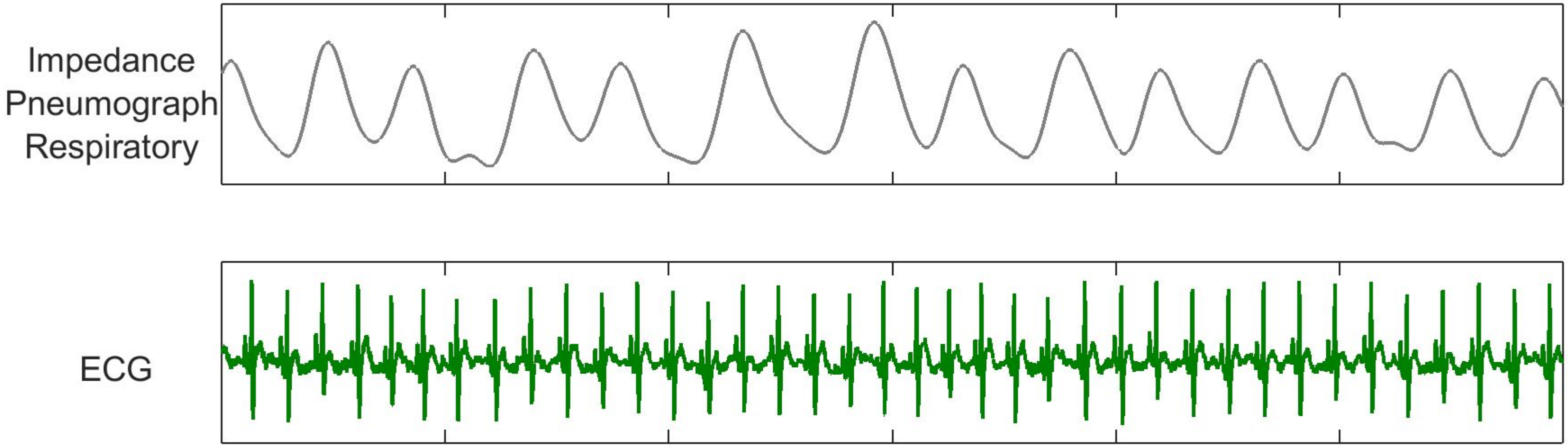
Apple watch sales increased 30% with the introduction of Apple Watch Health

FDA clears prescription smart-watches

3 in 4 people in the US use a smartphone

Source: forbes.com, theverge.com, Global Mobile Market Report

Respiratory Rate and ECG



Method for modelling

- Random Forest Regressor
- K-nearest neighbors
- Ada Boost
- XGBoost
- Ordinary Least Squares..

Best Model Selection

Random Forest

90% R^2 for real time breathing rate prediction at 125Hz

Extrapolatory Data Analysis

Assumptions

1. Resp. rate, ECG, PPG, etc are stationary
2. Resp. rate is measured (vs estimated) and has a mean of 12 breaths per minute (σ=2)

Feature Engineering

1. Created summary statistic representation for each predictor (mean, min, max, standard deviation, skew, kurtosis)
2. Extrapolated 1Hz signals to 125Hz
3. Stripped patient identifiers

Source: [Cleveland Clinic]

Detailed Model Performance

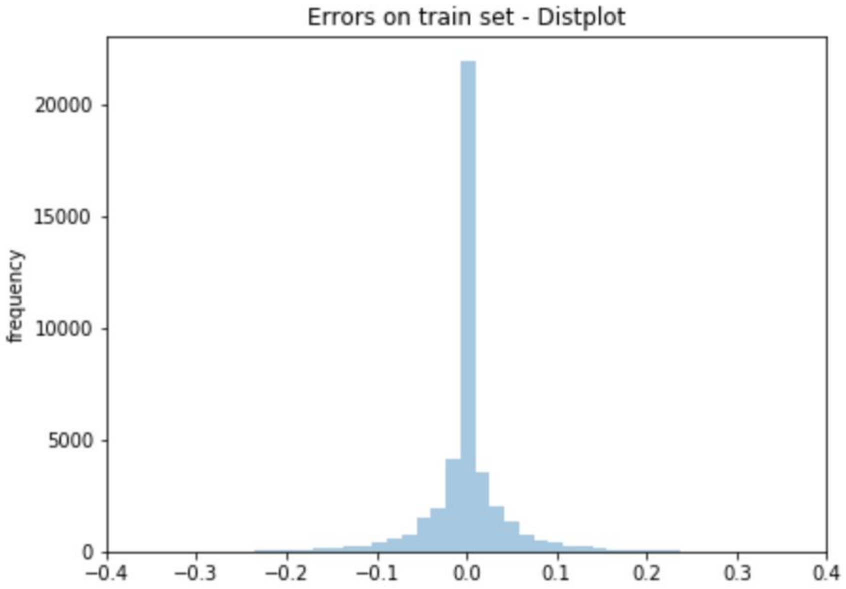
(trained on 45 patients/2.7million rows)

Benchmark: Pimentel et. al MAE 3.5 rpm (σ=1)

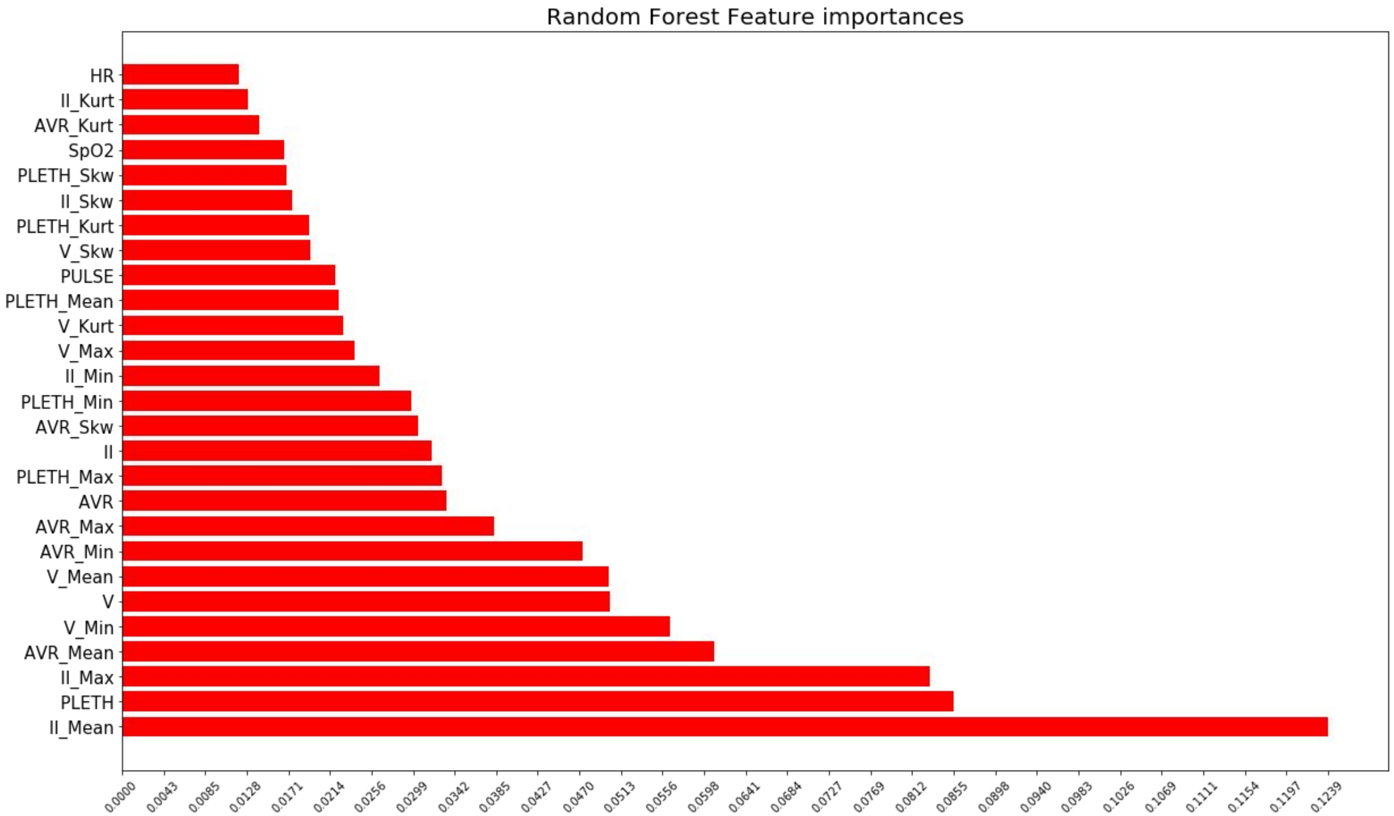
Model	R^2	MAE (norm. breaths/min)	Time (s)
Random Forest regressor	0.9	0.061	342
KNN regressor	0.85	0.078	199
Adaboost	0.10	0.312	372
XGboost	0.4	0.240	222

Detailed Model Performance

(trained on 45 patients/2.7million rows)



RFF Feature Importance



Deployment

Chronically Ill and at-risk

Doctors are prescribing at-home health monitors to evaluate patients

Rural Patients

Patients without easy access to a well-equipped care facility require easy to use tools for diagnosis

Impoverished

People without the financial means of visiting a hospital require tools which can prevent expensive visits

Milestones

March 2019

Derive RESP

Mid

Auto-detect anomalies

Predict resp. rate across activities

Now

Future

Near

Improved Model Performance

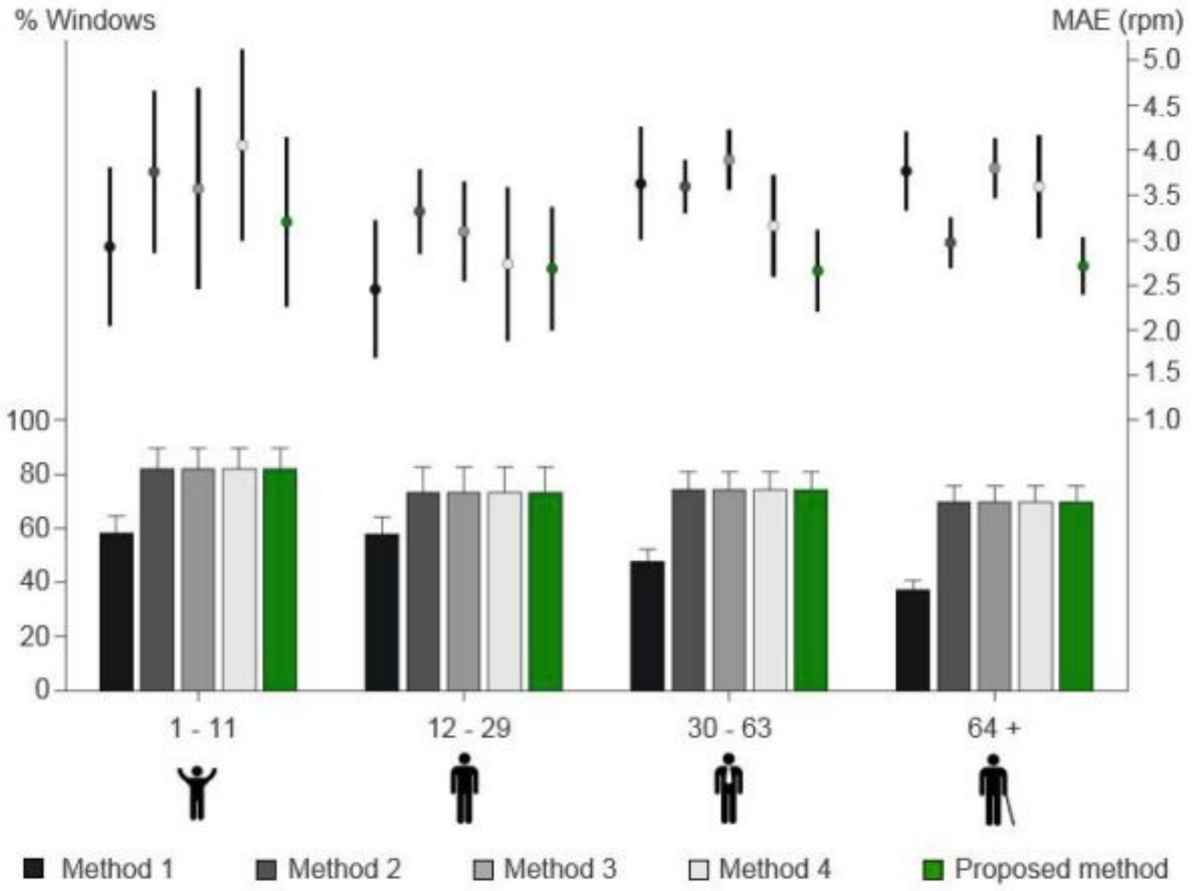
Personalized resp. rate calculation

Long

Predict current and future patient pulmonary health

Fig. 9.

Results obtained for the different methods: bars denote the average percentage of windows considered in each method (refer to axes on the left) and points denote the mean absolute error (refer to axes on the right). Error bars denote one standard error of the mean.



	MAE	R2 score	RMSE	model	time
0	0.293627	1.187999e-01	0.359239	OLS	1.279344
1	0.310653	-1.331680e-09	0.382689	ElasticNet	1.032249
2	0.293627	1.188001e-01	0.359239	BayesianRidge	2.062691
3	0.310653	-1.331680e-09	0.382689	Lasso	0.987775
4	0.293627	1.187999e-01	0.359239	Ridge	0.613171
5	0.097136	8.014152e-01	0.170537	KNN	162.766203
6	0.087372	8.205810e-01	0.162099	RFF	253.116708
7	0.320699	8.913112e-02	0.365236	Ada	328.040219
8	0.245525	3.747992e-01	0.302591	XGB	196.523845

Models’ performance without PPG information https://www.ecnmag.com/videos/2018/10/smartwatch-monitors-health-heart-and-physical-wellness