

Stacked ensemble classifier for predicting disease onset using temporal and non-temporal data

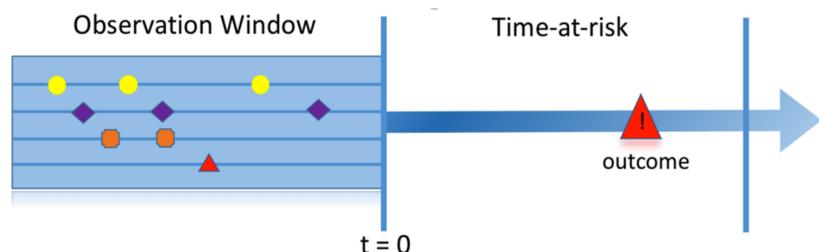
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We present a stacked ensemble classifier to predict disease onset using temporal measurement data fed into a deep convolutional neural network, and non-temporal data fed into a random forest. We compare the hybrid method with other algorithms on two clinical tasks: hypertensive disorder in pharmaceutically treated depression (PTD) patients and heart failure in type 2 diabetes mellitus (T2DM) patients. In both tasks, our ensemble classifier shows higher discriminative performance. We also investigate different ensemble strategies and the results show that the stacked ensemble is superior to others. The developed pipeline can easily be expanded to cover more advanced network structures and hybrids.

Problem definition

Among a target patients, we aim to predict which patients at a defined moment in time ($t=0$) will experience outcome disease during a time-at-risk. Prediction is done using only information about patients in an observation window prior to that moment in time.



Two clinical tasks:

1. 28,526 PTD patients, 587 develop hypertensive disorder.

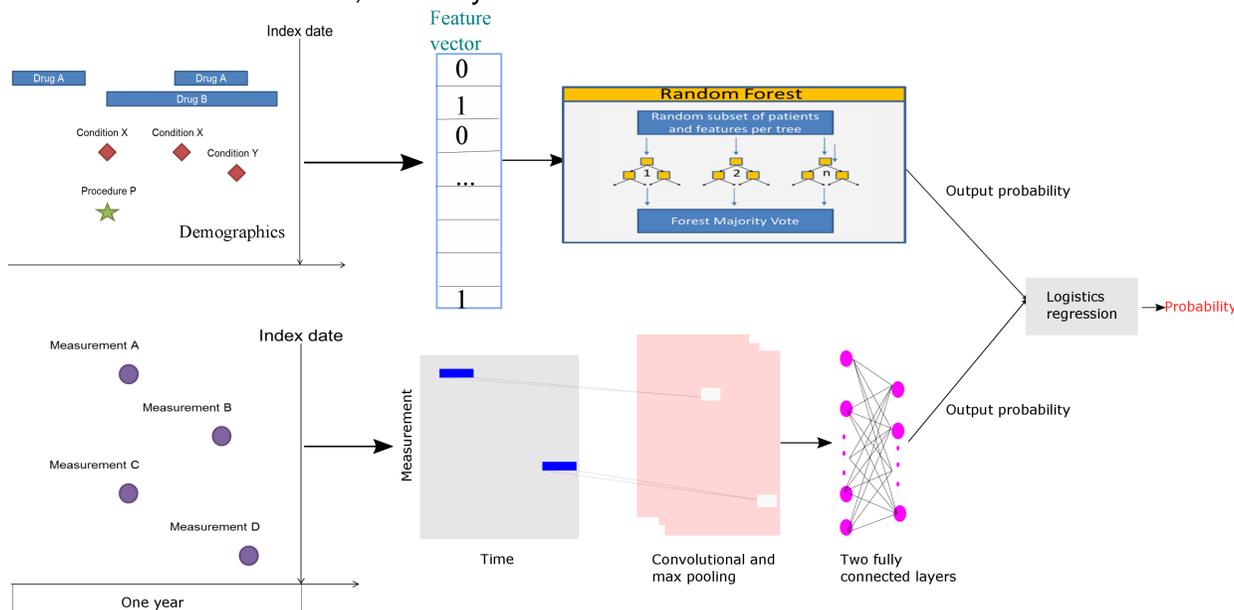
2. 29,034 T2DM patients, 364 develop heart failure.

Observation window: 365 days

Time-at-risk window: 365 days

Methods

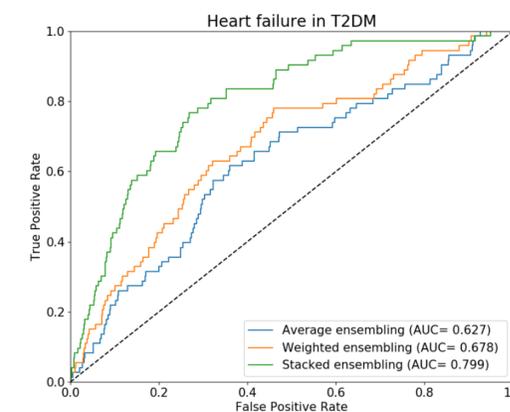
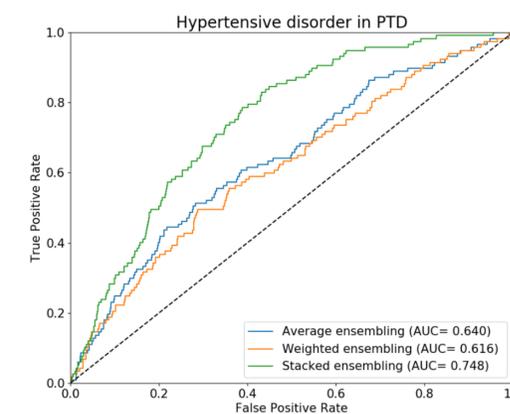
The temporal data (the measurements), are fed into the CNN with a similar architecture as used by Razavian et al. [1]. The non-temporal data (all except for the measurements), are fed into the a random forest (RF) model. We use a weighted loss function to overcome the class imbalance problem when training the model using Adam with regularization [2]. We compared the performance with Lasso and RF as implemented in R (Cyclops [3]) using only measurements and Lasso, RF, Gradient Boosting Machine (GBM), Self-Normalizing Neural Networks (SNN) using the full feature set, CNN using only measurements, logistics regression (LR) and MLP as implemented in PyTorch on the full feature set, and a hybrid of CNN and MLP/LR /Lasso/SNN/RF.



Results

Algorithm	Features	Hypertensive disorder in PTD		Heart failure in T2DM	
		Train AUC	Test AUC	Train AUC	Test AUC
Lasso	Measurements	0.60	0.59	0.73	0.61
RF	Measurements	0.66	0.61	0.93	0.66
CNN	Measurements	0.72	0.63	0.77	0.62
Lasso	All	0.71	0.67	0.86	0.78
GBM	All	0.79	0.68	0.88	0.78
AdaBoost	All	0.79	0.60	0.90	0.73
RF	All	0.95	0.70	0.95	0.79
LR Torch	All	0.69	0.63	0.84	0.75
MLP Torch	All	0.71	0.63	0.87	0.75
SNN	All	0.76	0.55	0.86	0.72
CNN-LR Torch	Measurements / other	0.77	0.70	0.88	0.70
CNN-MLP Torch	Measurements / other	0.86	0.65	0.90	0.74
CNN-SNN	Measurements / other	0.80	0.62	0.88	0.76
CNN-Lasso	Measurements / other	0.76	0.67	0.84	0.69
Lasso-RF	Measurements / other	0.94	0.69	0.93	0.76
CNN-RF	Measurements / other	0.94	0.75	0.96	0.80

When using only measurements, CNN and RF perform better than Lasso. When using the full feature set, CNN-RF outperform other individual algorithms and ensemble algorithms on both clinical tasks.



Compared to other ensemble strategies, the stacked ensemble classifier CNN-RF achieves better performance, and always outperform any individual algorithm.

Conclusions

We extended the PatientLevelPrediction package with deep learning methods using the PyTorch framework and implemented several ensemble classifiers. A stacked ensemble of CNN and RF showed promising performance on two clinical prediction tasks. The next step is to expand this to more prediction problems and assess the external validity of these findings.

References

- [1] Razavian N, Sontag D (2016) Temporal Convolutional Neural Networks for Diagnosis from Lab Tests. 2016 ICLR.
- [2] Diederik K, Jimmy B (2014) Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980: 339-344
- [3] Cyclic coordinate descent for logistic, Poisson and survival analysis. <https://github.com/OHDSI/Cyclops>