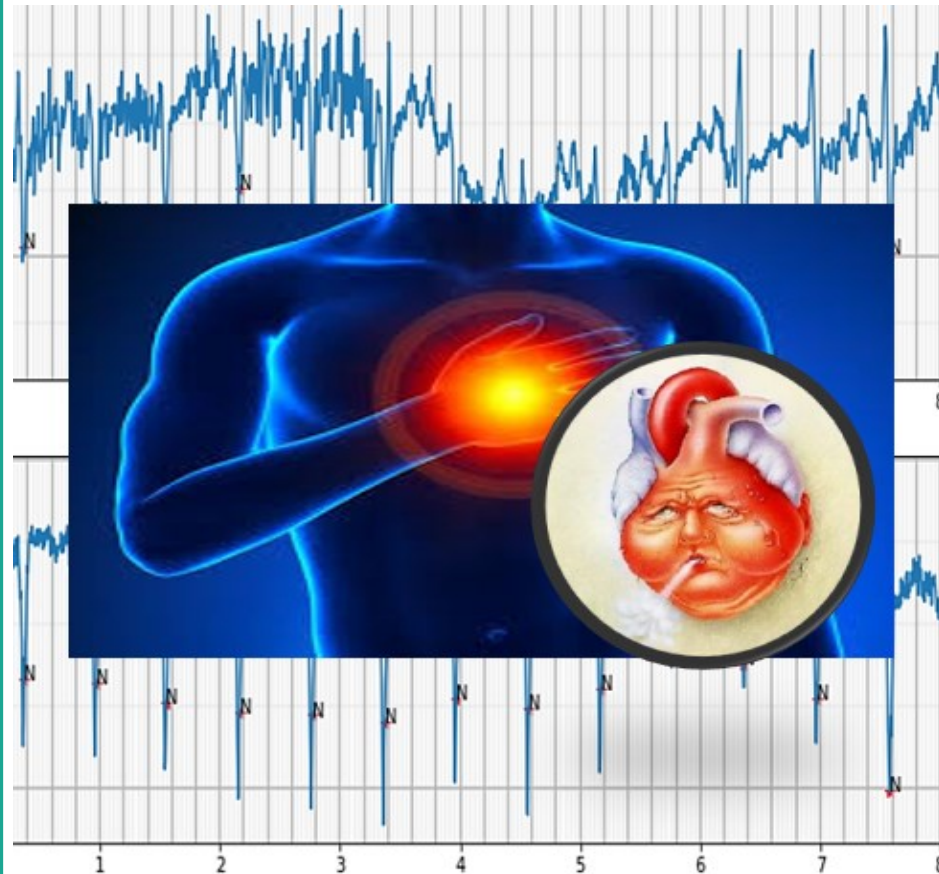
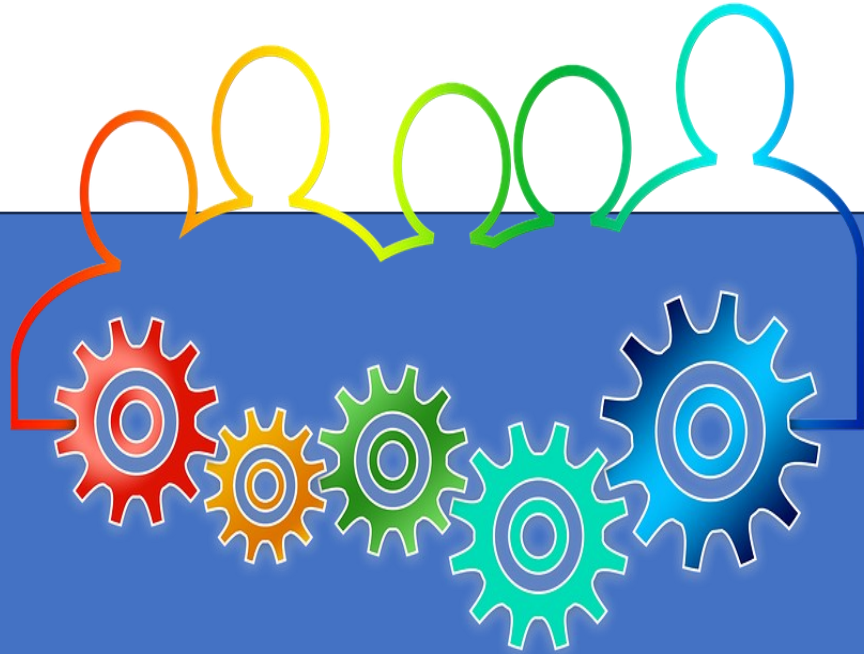


University of Warwick



OPTIMISING CLASSIFICATION OF CONGESTIVE HEART FAILURE USING FEATURE WEIGHT IMPORTANCE CORRELATION





The Team

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Description

Feature engineering pipeline

Selection of 10 most important features according to 14 different classifiers.

Pooling of selected features and importance score for further analysis.

Weight appropriation to features based on frequency of occurrence and mean importance score.

Features subjected to correlation analysis in an iterative manner and values examined using heat maps.

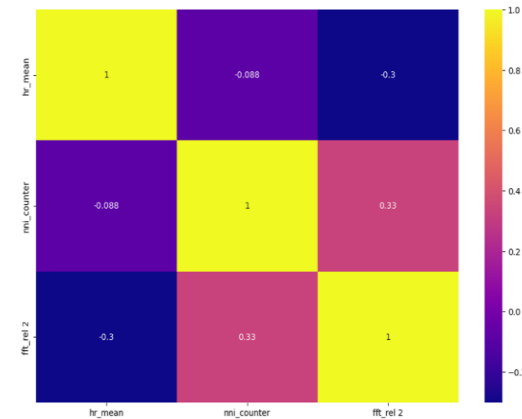
Features with correlation values greater than the selected CIT knocked off.

Frequency table of selected classifiers

SUMMARY REPORT

S/N	Feature name	Frequency of occurrence	Average importance score across classifiers	S/N	Feature name	Frequency of occurrence	Average importance score across classifiers
1.	hr_mean	8	4.0542	17.	nmi_min	1	0.037009
2.	nmi_mean	7	1.6348	18.	hr_std	1	0.048487
3.	nmi_counter	5	2.8315	19.	pnn20	1	0.013626
4.	nmi_max	4	0.0389	20.	fft_peak 0	1	9
5.	fft_rel 2	3	2.3525	21.	lomb abs 0	1	7
6.	hr_max	3	1.4047	22.	ar_rel 1	1	2
7.	tri_index	3	1.0068	23.	sd_ratio	1	0.032949
8.	lomb_total	3	0.6920	24.	sdnn	1	0.066783
9.	lomb_log 1	3	0.0476	25.	ar_abs 2	1	0.033391
10.	fft_norm 0	3	0.0428	26.	lomb_norm 1	1	0.011130
11.	fft_rel 0	3	0.0376	27.	pnn50	1	0.010881
12.	hr_min	2	0.0479	28.	lomb abs 1	1	0.005974
13.	fft_norm 1	2	0.1159	29.	nmi_diff_max	1	0.005093
14.	fft_peak 1	2	0.0372	30.	ar_rel 2	1	0.04
15.	sdann	2	0.0153	31.	sdsd	1	0.028307
16.	ar_norm 0	2	0.0264	32.	dfa alpha	1	0.026311

Resultant heat map for correlation values $\leq \pm 0.40$

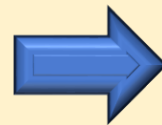


Resultant heatmap after applying correlation iteration threshold (CIT) of ≤ 0.40

Objectives and recipients of the work

Objectives:

- To develop a novel method for selecting the optimal set of input features for classifying the presence of congestive heart failure (CHF) using long-term ECG data.
- To ensure model transparency and trustworthiness by building interpretability and explainability into the model .



Is the
diagnosis
reliable?

Patients

Healthcare
Professionals

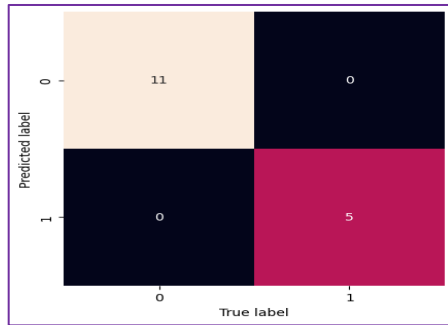
Healthcare
Regulatory
bodies

Which features
have the greatest
influence on the
predicted results?

How do different
features impact
the model's
prediction?

Can the model
performance
metrics be
trusted?

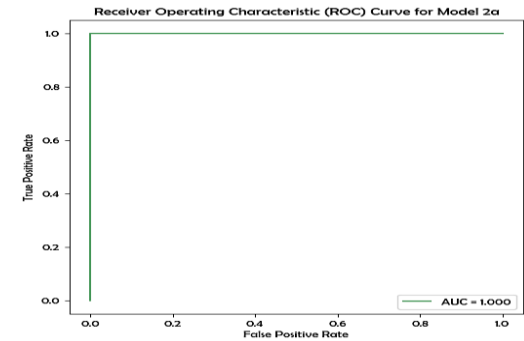
Results



RMS: 0.0

	precision	recall	f1-score	support
0	1.00	1.00	1.00	11
1	1.00	1.00	1.00	5
accuracy			1.00	16
macro avg	1.00	1.00	1.00	16
weighted avg	1.00	1.00	1.00	16

Accuracy: 1.0

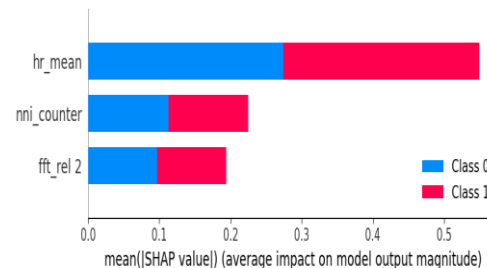
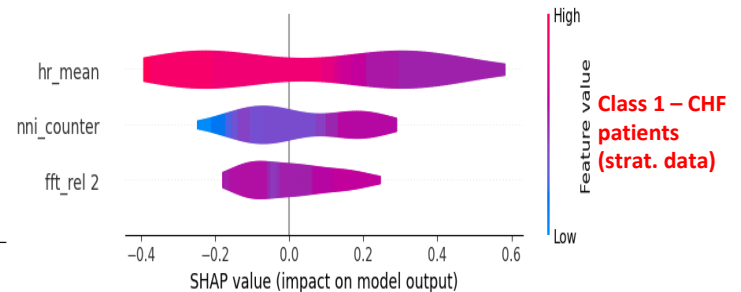
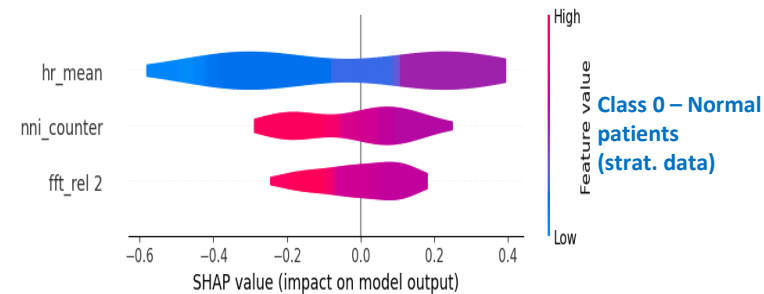


Best performing model – implemented with feature weight importance correlation (FWIC): (a) Confusion matrix; (b) performance metrics; (c) ROC AUC

Accuracy: 1.00
Accuracy: 1.00
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Accuracy: 1.00
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Accuracy: 1.00

	precision	recall	f1-score	support
Normal	1.00	1.00	1.00	8
CHF	1.00	1.00	1.00	8
accuracy			1.00	16
macro avg	1.00	1.00	1.00	16
weighted avg	1.00	1.00	1.00	16

Accuracy: 0.94
Accuracy: 1.00
Accuracy: 0.88
Accuracy: 1.00
Accuracy: 1.00
Accuracy: 1.00
Accuracy: 1.00
Accuracy: 0.94
Accuracy: 1.00



Bar plot of global feature importances.

Violin plots: Positive SHAP values in a plot indicate that the input feature has a positive impact on the prediction and vice versa.



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