## Predictive Modeling

Ma ChengYuan

#### detasets intro

#### datasets:

Based on epiz\_inform\_stationary\_risks\_10\_events.csv

- 1.final\_obj\_hospitalization.txt
  - personal info
- 2.from all\_epizodes\_risks\_strat.pkl -
  - operation code
  - diagnosis
- 3.all\_analisis\_risk\_stratif.txt
  - test result

#### target disease :

- 1) Желудочковая тахикардия
- 2) Острый коронарный синдром
- 3) Медиастинит
- 4) OHMK

#### feature info

feature info :

patients number by target:

Клинический диагноз рубрика: 723

желудочковая\_тахикардия: 1723

Код МЭС: 611

острый коронарный синдром :712

Код теста: 2469

медиастинит: 46

онмк: 437

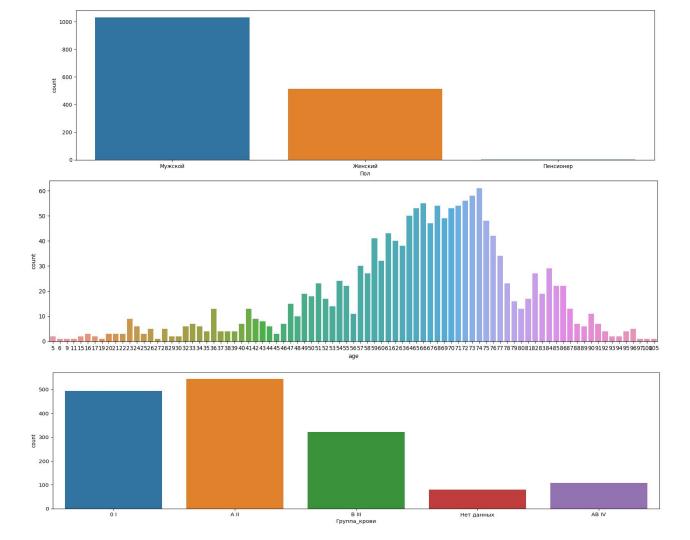
#### basic data distribution

#### order by target as below:

- желудочковая\_тахикардия
- острый\_коронарный\_синдром
- медиастинит
- ОНМК

#### graph showed from top to bottom:

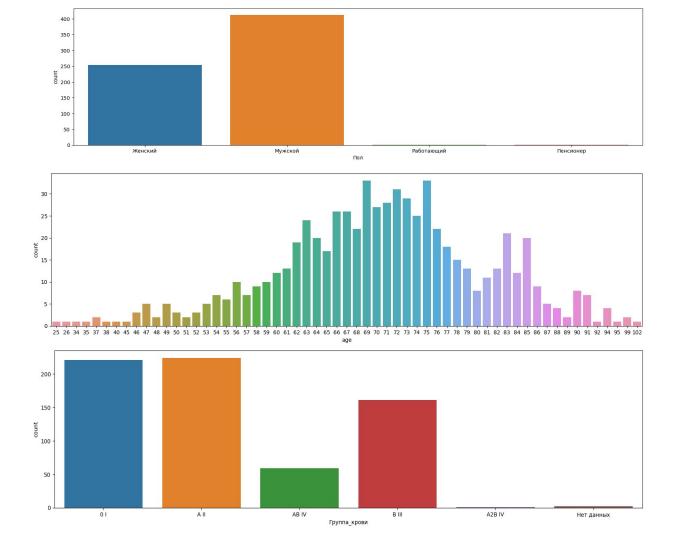
- gender
- age
- blood type



here we can see that obviously this disease concentrates on group of people whose age is around 70 years old .

Male shows nearly 2 times of possibility to get this disease

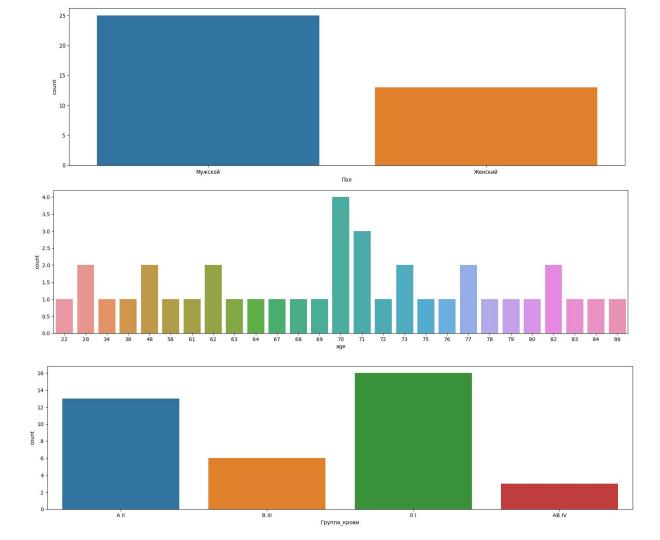
From the blood type , we can conclude that from higher proportion to lower , it is A2 , O1 , B3



here we can see that obviously this disease concentrates on group of people whose age is around 70 years old .

Male shows nearly 2 times of possibility to get this disease

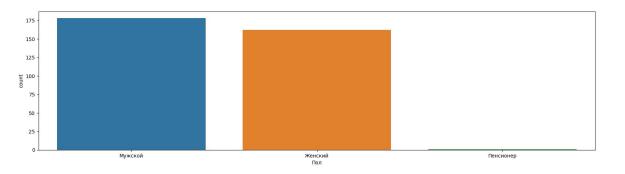
From the blood type , we can conclude that O1 , B3 , A2 shows higher proportion

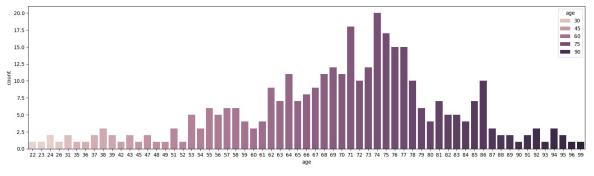


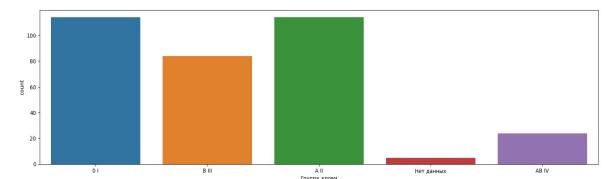
here we can see that obviously this disease concentrates on group of senior people

Male shows nearly 2 times of possibility to get this disease

From the blood type , we can conclude that O1 , A2 shows higher proportion







here we can see that obviously this disease concentrates on group of people whose age is around 70 years old .

From the blood type , we can conclude that O1 , B3 , A2 shows higher proportion

pipeline tune accuracy datasets problem preprocessin feature analyze g train model engineering prediction change tune model model

### preprocessing

- select potential columns from each df (feature engineering)
- convert categorization value to numerical value using one-hot encoding (preprocessing)

```
*** main datasets ***
all analisis risk_stratif:
```

- - Код теста
- fill null cell in col('Значение число') with average value from criteria ((lower + upper) / 2)

```
clinical diag 293 strat risk:
```

- Код МЭС
- Клинический диагноз рубрика

### model training

- all\_analisis\_risk\_stratif:
- Код\_теста

#### test sets:

- 1) numerical value using col('Значение\_число') with average value in null cell
- 2) classified into lower & higher of criteria
- 3) without value in null cell
- 4) numerical columns of echo data included, without value in null cell + test sets (1)

- 2. clinical\_diag\_293\_strat\_risk:
  - Код\_МЭС
  - Клинический\_диагноз\_рубрика

## test result(1)

1)

row x column: 4909x3121

original

желудочковая тахикардия: Neural Net: f1: 0.567878

xgb: f1: 0.693428

острый коронарный синдром:

Neural Net: f1: 0.592496

xgb: f1: 0.759434

медиастинит:

Neural Net: f1: 0.498126

xgb: f1: 0.498126

онмк:

Neural Net: f1: 0.510228

xgb: f1: 0.599690

oversample

желудочковая тахикардия: Neural Net: f1: 0.566822

xgb: f1: 0.679563

cross validation желудочковая\_тахикардия:

xgb: f1: 0.684981

острый коронарный синдром:

острый коронарный синдром: xgb: f1: 0.742531

Neural Net: f1: 0.574827

xgb: f1: 0.754864

медиастинит:

медиастинит:

Neural Net: f1: 0.483158

xgb: f1: 0.498126

xgb: f1: 0.52202

OHMK:

OHMK:

Neural Net: f1: 0.420461

xqb: f1: 0.618609

## test result(2)

2)

row x column : 4909x3435

2) original

желудочковая\_тахикардия : Neural Net : f1 :0.671587

xgb: f1: 0.688900

острый\_коронарный\_синдром:

Neural Net: f1: 0.725524

xgb: f1: 0.691100

медиастинит:

Neural Net: f1: 0.497954

xgb: f1: 0.497954

онмк:

Neural Net: f1: 0.589569

xgb: f1: 0.602336

2) oversample

желудочковая\_тахикардия : Neural Net : f1 : 0.636534

xgb: f1: 0.694334

ole 2) cross validation желудочковая\_тахикардия:

xgb: f1: 0.693104

острый\_коронарный\_синдром:

острый\_коронарный\_синдром:

Neural Net: f1: 0.702459

xgb: f1: 0.684404

xgb: f1: 0.69856

медиастинит:

медиастинит :

Neural Net : f1 :0.544369

xgb: f1: 0.569381

онмк :

ОНМК:

Neural Net : f1 : 0.602206

xgb: f1: 0.589569

xgb: f1: 0.610675

## test result(3)

желудочковая\_тахикардия : xgb : f1 : 0.693428 decsiontree : f1 : 0.640268 LGB : f1 : 0.686466 catboost :

острый\_коронарный\_синдром: xgb: f1:0.754944 decsiontree: f1:0.652398 LGB: f1:0.768578 catboost: f1:0.743238

острый коронарный синдром:

f1: 0.498126 xgb: f1: 0.498297 decsiontree: f1: 0.497784 LGB: f1: 0.498297 catboost: f1: 0.498297

медиастинит:

Neural Net:

catboost : f1 : 0.536594

OHMK:

онмк:

f1: 0.619066

decsiontree:

f1: 0.659900

f1: 0.614116

xgb:

LGB:

original from (1):

f1: 0.667132

желудочковая\_тахикардия

:

xgb : f1 : 0.759434

xgb: f1: 0.693428

xgb: f1: 0.498126

## test result(4)

желудочковая\_тахикардия:

острый\_коронарный\_синдром:

онмк:

xgb:

xgb:

медиастинит : Neural Net :

xgb :

f1:0.708828

f1: 0.752493

f1: 0.498297

f1: 0.626451

original from (1):

желудочковая\_тахикардия

медиастинит:

ОНМК:

:

xgb: f1: 0.759434

острый\_коронарный\_синдром:

xgb: f1: 0.498126

xgb: f1: 0.599690

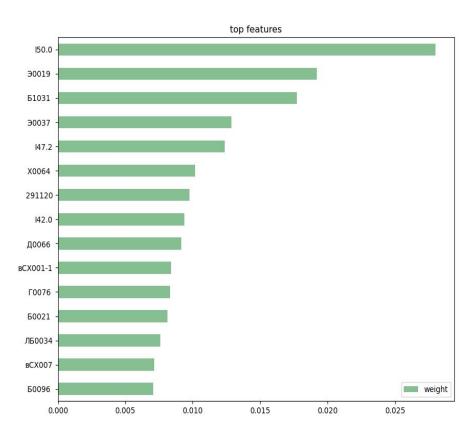
#### conclusion

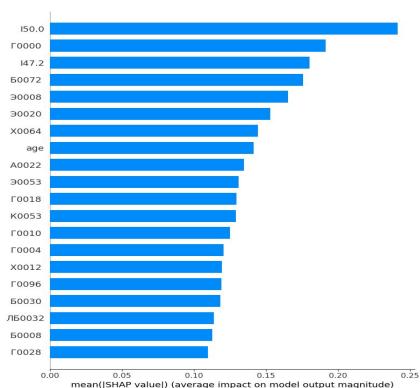
after tests, test set 1 is considered as baseline to compare with other test sets, test set 3 and 4 shows better accuracy on **OHMK** 

therefore, it can be considered that numerical value in echo data is clarifying the classification of **OHMK** 

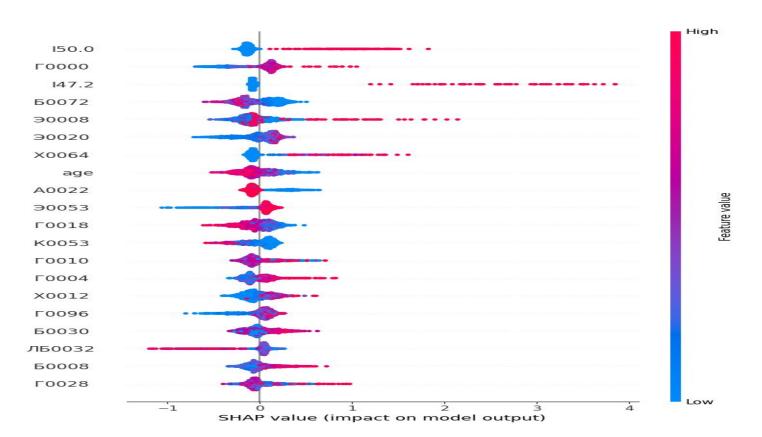
further investigation was processed with test set 1

#### feature importance (left xgb , right shap)

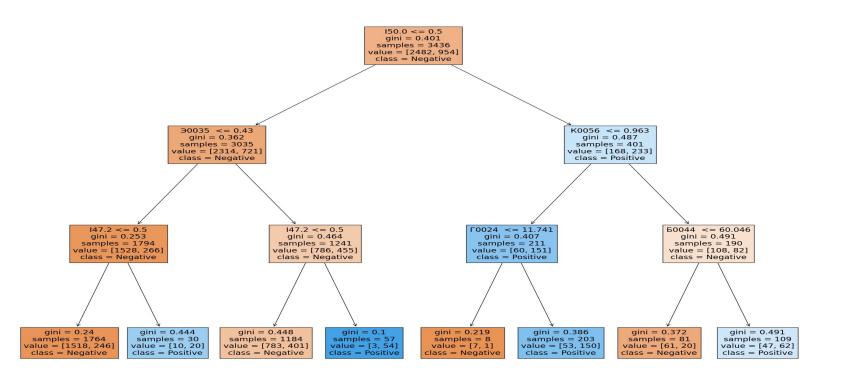




#### feature importance (shap)(black box model)



#### feature importance (decision tree)



#### feature selection(pearson)

X : correlation rate used to remove features (higher rates means less feature removed)

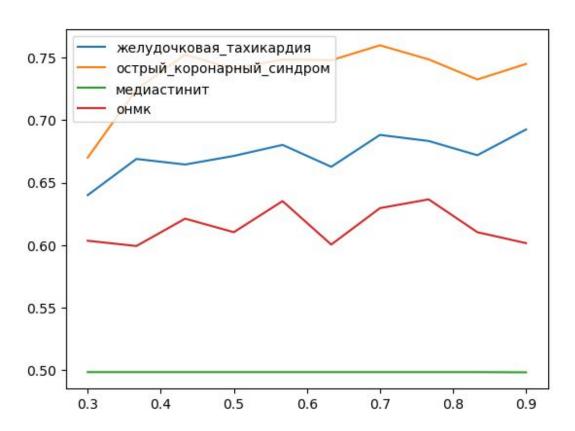
Y: F1 score

желудочковая\_тахикардия best at: 0.9

острый\_коронарный\_синдром best at 0.7

медиастинит best at 0.3

онмк best at 0.75



# feature selection(L2 regularization after removal correlated columns)

желудочковая\_тахикардия:

острый\_коронарный\_синдром:

OHMK:

total features: 2415

total features: 1870

total features: 802

медиастинит:

total features: 2148

selected features: 776

selected features: 580

selected features: 226

selected features: 671

f1: 0.678326

f1: 0.739063

f1: 0.498126

f1: 0.599242

original from (1):

желудочковая\_тахикардия:

острый\_коронарный\_синдром:

медиастинит:

онмк:

xgb: f1: 0.693428

xgb: f1: 0.759434

xgb: f1: 0.498126

#### feature selection(L2 regularization with original data)

желудочковая\_тахикардия:

total features: 3117

selected features: 958

f1: 0.678892

test feature is 606 operations feature is 153 diagnosis feature is 196 ['Ποπ', 'age', '0 I']

compared with original from

test(1):

желудочковая\_тахикардия:

xgb: f1: 0.693428

острый\_коронарный\_синдром:

total features: 3117

selected features: 813

f1: 0.737259

test feature is 530 operations feature is 125 diagnosis feature is 154 ['age', 'A II', 'AB IV', 'B III']

острый коронарный синдром:

xgb: f1: 0.759434

онмк :

total features: 3117

selected features: 853

f1: 0.617764

test feature is 495 operations feature is 98 diagnosis feature is 99 ['Ποπ', '0 I', 'A II', 'B III']

онмк:

#### shapley extraction

желудочковая\_тахикардия:

total features: 958

selected features: 236

f1: 0.689613

['age', 'Пол', '0 I']

test feature is 210

operations feature is 8

diagnosis feature is 15

original from previous result желудочковая тахикардия:

xgb: f1: 0.678892

roc auc score: 0.7758469115345669

острый\_коронарный\_синдром: total features: 814

selected features: 207

f1: 0.737874

['B III', 'age', 'A II']

test feature is 189 operations feature is 9 diagnosis feature is 6

острый\_коронарный\_синдром:

xgb: f1: 0.737259

онмк:

total features: 853

selected features: 218

f1: 0.633716

['Пол', 'age', '0 I', 'A II']

test feature is 204

operations feature is 7

diagnosis feature is 3

онмк:

#### metrics (желудочковая\_тахикардия)

0.78

0.69

0.76

1473

1473

1473

11 1 01005015	precision	recall	f1-score	support
0	0.81	0.90	0.85	1065
1	0.64	0.45	0.53	408

0.72

0.76

0.67

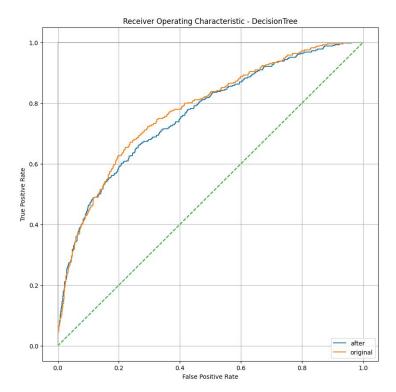
0.78

f1 • 0 689613

accuracy

macro avg weighted avg

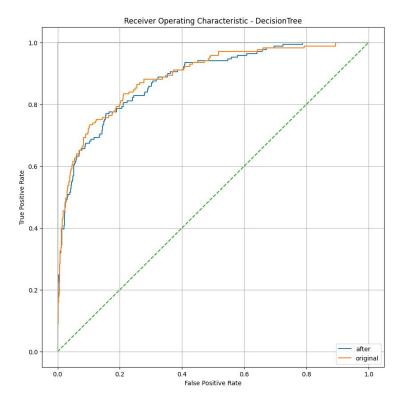
#### roc auc score is: 0.7625172604252969



#### metrics (острый\_коронарный\_синдром)

f1 : 0.737874			£1		
	precision	recall	f1-score	support	
0	0.93	0.98	0.95	1304	
1	0.73	0.41	0.52	169	
accuracy			0.91	1473	
macro avq	0.83	0.69	0.74	1473	
_					
weighted avg	0.90	0.91	0.90	1473	

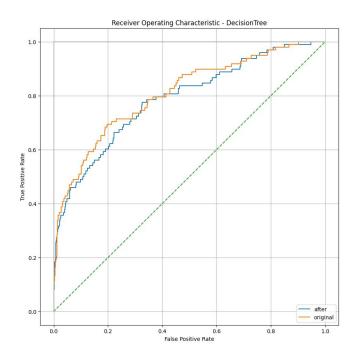
#### roc auc score is: 0.8834628090173159



#### metrics (онмк)

f1: 0.633716	precision	recall	f1-score	support
0 1	0.94 0.78	1.00 0.18	0.97 0.30	1375 98
accuracy macro avg weighted avg	0.86 0.93	0.59 0.94	0.94 0.63 0.93	1473 1473 1473

#### roc auc score is: 0.7870278293135435



#### feedback

After feature extraction, features were trimmed to around 200, and f1 score still can maintain with good quality.

It is obvious to see that **test feature** can influence the result of prediction more than other features

#### related previous work

желудочковая тахикардия:

острый коронарный синдром:

медиастинит:

OHMK:

A machine learning-based risk stratification model for ventricular tachycardia and heart failure in hypertrophic cardiomyopathy

A Machine Learning-Based Approach for the Prediction of **Acute Coronary Syndrome Requiring Revascularization** 

Performance of a Machine Learning Algorithm in **Predicting Outcomes of Aortic Valve Replacement** 

**Performance Analysis of Machine Learning Approaches in Stroke** Prediction

link:

https://www.sciencedirect.com/ science/article/pii/S0010482521 00442X

link:

https://link.springer.com/article/ 10.1007/s10916-019-1359-5

link:

https://www.sciencedirect.com/ science/article/abs/pii/S000349 7520311565

link:

https://ieeexplore.ieee.org/abstrac t/document/9297525?casa token =TfM OTIj2BEAAAAA:vV39vNcK MpzQc9iI oopWu0eggmUj9CRo METefwiKE7d3W07qChFVqS8H mEnghtRvggkcX0FChDokA

#### related previous work

желудочковая\_тахикардия:

A machine learning-based risk stratification model for ventricular tachycardia and heart failure in hypertrophic cardiomyopathy

#### link:

https://www.sciencedirect.com/ science/article/pii/S0010482521 00442X

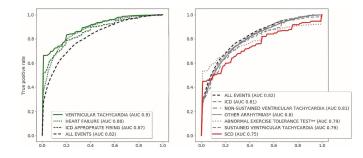
**Table 1**Patient demographic, physical and clinical characteristics. The upper part of the table shows patient overview characteristics and the lower part shows the statistics in terms of baseline and follow-up measurements.

Characteristics	Patients	Total (N = 2302)
Male         1448 (62.9%)           Female         854 (37.1%)           Family history of HCM         983 (42.7%)           Family history of SCD         426 (18.5%)           Family history of CAD         104 (4.5%)           Diabetes         82 (3.6%)           Type 2 diabetes         73 (3.2%)           Hypertension         214 (9.3%)           Hypercholesterolemia         478 (20.8%)           Genetic mutations         100 (18.5%)           MYBPC3         455 (34.4%)           MYH7         254 (19.2%)           MYL2         13 (1.0%)           MYL3         7 (0.5%)           TNN13         42 (3.2%)           TNN172         45 (3.4%)           TPM1         8 (0.6%)	Characteristics	no. (%)
Female         854 (37.1%)           Family history of HCM         983 (42.7%)           Family history of SCD         426 (18.5%)           Family history of CAD         104 (4.5%)           Diabetes         82 (3.6%)           Type 2 diabetes         73 (3.2%)           Hypertension         214 (9.3%)           Hypercholesterolemia         478 (20.8%)           Genetic mutations         Total tests performed (N           = 1321)         455 (34.4%)           MYH7         254 (19.2%)           MYL2         13 (1.0%)           MYL3         7 (0.5%)           TNNI3         42 (3.2%)           TNNT2         45 (3.4%)           TPM1         8 (0.6%)	Sex	
Family history of HCM	Male	1448 (62.9%)
Family history of SCD         426 (18.5%)           Family history of CAD         104 (4.5%)           Diabetes         82 (3.6%)           Type 2 diabetes         73 (3.2%)           Hyperrcholesterolemia         478 (20.8%)           Genetic mutations         Total tests performed (N           = 1321)         455 (34.4%)           MYH7         254 (19.2%)           MYL2         13 (1.0%)           MYL3         7 (0.5%)           TNNI3         42 (3.2%)           TNNT2         45 (3.4%)           TPM1         8 (0.6%)	Female	854 (37.1%)
Family history of CAD         104 (4.5%)           Diabetes         82 (3.6%)           Type 2 diabetes         73 (3.2%)           Hypertension         214 (9.3%)           Hypercholesterolemia         478 (20.8%)           Genetic mutations         Total tests performed (N = 1321)           MYBPC3         455 (34.4%)           MYH7         254 (19.2%)           MYL2         13 (1.0%)           MYL3         7 (0.5%)           TNNI3         42 (3.2%)           TNNT2         45 (3.4%)           TPM1         8 (0.6%)	Family history of HCM	983 (42.7%)
Diabetes         22 (3.6%)           Type 2 diabetes         73 (3.2%)           Hypertension         214 (9.3%)           Hypercholesterolemia         478 (20.8%)           Genetic mutations         10tal tests performed (N           = 1321)         455 (34.4%)           MYH7         254 (19.2%)           MYL2         13 (1.0%)           MYL3         7 (0.5%)           TNN13         42 (3.2%)           TNNT2         45 (3.4%)           TPM1         8 (0.6%)	Family history of SCD	426 (18.5%)
Type 2 diabetes 73 (3.2%) Hypertension 214 (9.3%) Hyperrholesterolemia 478 (20.8%) Genetic mutations = 1321) MYBPC3 455 (34.4%) MYH7 254 (19.2%) MYL2 13 (1.0%) MYL3 7 (0.5%) TNNI3 42 (3.2%) TNNT2 45 (3.4%) TPM1 8 (0.6%)	Family history of CAD	104 (4.5%)
Hypertension         214 (9.3%)           Hypercholesterolemia         478 (20.8%)           Genetic mutations         Total tests performed (N = 1321)           MYBPC3         455 (34.4%)           MYH7         254 (19.2%)           MYL2         13 (1.0%)           MYL3         7 (0.5%)           TNNI3         42 (3.2%)           TNNT2         45 (3.4%)           TPM1         8 (0.6%)	Diabetes	82 (3.6%)
Hypercholesterolemia Genetic mutations Total tests performed (N = 1321)  MYBPC3 455 (34.4%)  MYH7 254 (19.2%)  MYL2 13 (1.0%)  MYL3 7 (0.5%)  TINNI3 42 (3.2%)  TINNT2 45 (3.4%)  TPM1 8 (0.6%)	Type 2 diabetes	73 (3.2%)
Genetic mutations         Total tests performed (N = 1321)           MYBPC3         455 (34.4%)           MYH7         254 (19.2%)           MYL2         13 (1.0%)           MYL3         7 (0.5%)           TNNI3         42 (3.2%)           TNNT2         45 (3.4%)           TPM1         8 (0.6%)	Hypertension	214 (9.3%)
= 1321) MYBPC3	Hypercholesterolemia	478 (20.8%)
MYBPC3 455 (34.4%) MYH7 254 (19.2%) MYL2 13 (1.0%) MYL3 7 (0.5%) TNN13 42 (3.2%) TNN172 45 (3.4%) TPM1 8 (0.6%)	Genetic mutations	Total tests performed (N
MYH7 254 (19.2%) MYL2 13 (1.0%) MYL3 7 (0.5%) TNN13 42 (3.2%) TNNT2 45 (3.4%) TPM1 8 (0.6%)		= 1321)
MYL2 13 (1.0%) MYL3 7 (0.5%) TNN13 42 (3.2%) TNN12 45 (3.4%) TPM1 8 (0.6%)	MYBPC3	455 (34.4%)
MYL3 7 (0.5%) TNN13 42 (3.2%) TNNT2 45 (3.4%) TPM1 8 (0.6%)	MYH7	254 (19.2%)
TNNI3 42 (3.2%) TNNT2 45 (3.4%) TPM1 8 (0.6%)	MYL2	13 (1.0%)
TNNT2 45 (3.4%) TPM1 8 (0.6%)	MYL3	7 (0.5%)
TPM1 8 (0.6%)	TNNI3	42 (3.2%)
	TNNT2	45 (3.4%)
TTN 3 (0.2%)	TPM1	8 (0.6%)
	TTN	3 (0.2%)

Performance of the machine learning algorithms on the task of risk stratification of HCM patients. The results of the 10-fold cross-validation for predicting high-risk patients five years ahead are shown. The reported values are mean values and standard deviation between cross-validation folds. The best results for each metric are in bold.

Model	Accuracy	AUC	Specificity	Sensitivity	Precision	F <sub>1</sub> score
Random forest	$0.72 \pm 0.03$	$0.79 \pm 0.03$	$0.81 \pm 0.05$	$0.62 \pm 0.03$	$0.74 \pm 0.05$	$0.68 \pm 0.03$
SVM (linear)	$0.69 \pm 0.05$	$0.74 \pm 0.04$	$0.69 \pm 0.05$	$0.69 \pm 0.08$	$0.59 \pm 0.08$	$0.63 \pm 0.07$
SVM (RBF)	$0.67 \pm 0.02$	$0.73 \pm 0.03$	$0.68 \pm 0.03$	$0.64 \pm 0.05$	$0.62 \pm 0.04$	$0.63 \pm 0.04$
Boosted trees	$0.75 \pm 0.02$	$0.82 \pm 0.02$	$0.81 \pm 0.03$	$0.67 \pm 0.04$	$0.78 \pm 0.02$	$0.72 \pm 0.02$
Neural-Networks	$0.74 \pm 0.03$	$0.80\pm0.04$	$0.86 \pm 0.05$	$0.61 \pm 0.07$	$0.79 \pm 0.05$	$0.68\pm0.05$

AUC - Area Under Curve, SVM - support vector machine, RBF - radial basis kernel.



## comparison(желудочковая\_тахикардия)

my	(желудочковая_тахикардия)
removed rows when there is missing value	copying past/known values of the last result (in the range of five years)
filled missing value with average value from range of criteria	missing numerical values were replaced by random samples from the normal distributions
	combining all possible pairs of patient measurements as features
4909 (1723:3186)	2302 (undefined)
XGB	XGB
AUC 0.76, F1 0.69	AUC 0.82, F1 0.71

#### related previous work

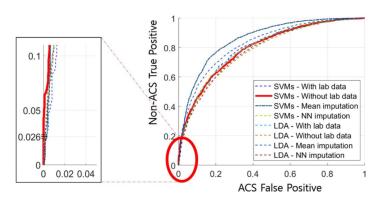
острый\_коронарный\_синдром:

A Machine Learning-Based Approach for the Prediction of Acute Coronary Syndrome Requiring Revascularization

#### link:

https://link.springer.com/article/ 10.1007/s10916-019-1359-5

		Features
Epidemiological data	1	Gender
	2	Age
Clinical data at emergency department or outpatient clinic	3	Systolic BP
	4	Diastolic BP
	5	HR
Past medical history before presenting chest pain	6	CAD
	7	MI
	8	CABG
	9	PCI
	10	Hypertension
	11	DM
	12	Hyperlipidemia
	13	CVA
	14	PCI
	15	History of Smokin
	16	Current smoking
Laboratory data before presenting chest pain	17	TC
	18	LDL- cholesterol
	19	HDL-cholesterol
	20	TG



## comparison(острый\_коронарный\_синдром)

my	(острый_коронарный_синдром)
filled missing value with average value from range of criteria	Nearest neighbor imputation to fill missing value
4909 (712:4197)	5838 (2311 : 3527)
XGB	SVM
AUC 0.88, F1 0.74	AUC 0.86

#### CCDS

interface : telegram

language: python

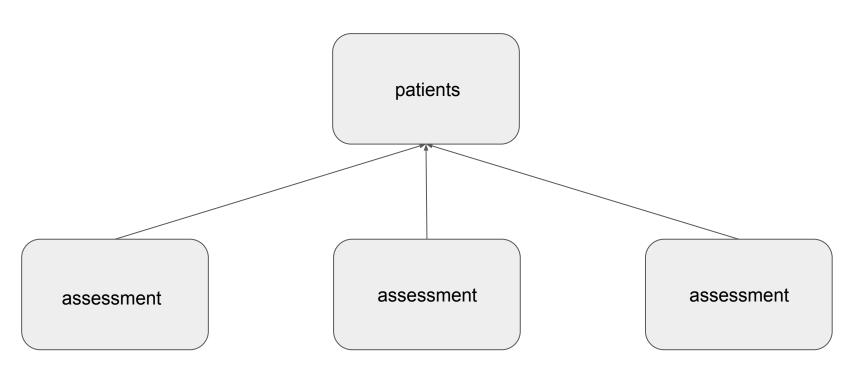
database : mongodb

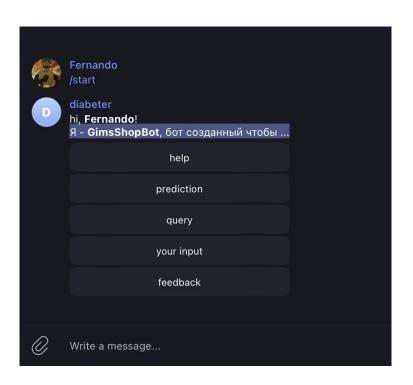
motivation: To support doctor by prediction and possible factors

goal: To reduce the diagnosis time in order to offer faster and more accurate treatment and relieve labourious workload for medical staffs

pipeline accuracy new datas problem preprocessin feature analyze train model g engineering prediction tune model

#### database design





/help - to offer instruction

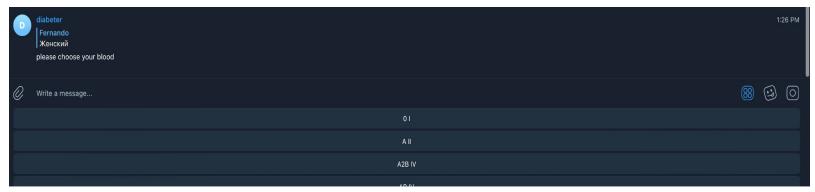
/prediction - main functionality to predict

/query - to offer the name of code

/your input - to showcase the current input

/feedback - to assess the prediction in order to trace the accuracy

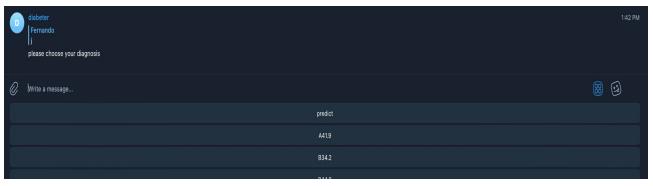


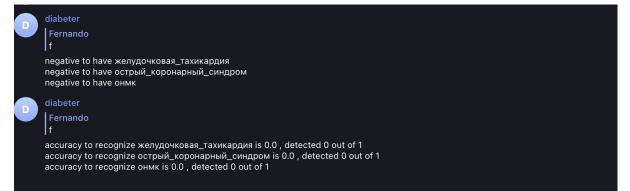


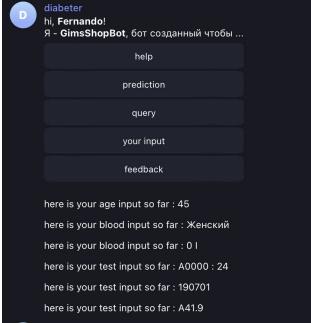












```
diabeter
Fernando
negative to have желудочковая_тахикардия
T09.1 <= 0.00
Д0072 <= 5.50
108.2 <= 0.00
D37.7 <= 0.00
K57.2 <= 0.00
K83.1 <= 0.00
00073 <= 43.50
T82.8 <= 0.00
ЛБ0046 <= 5.41
st15.018 <= 0.00
Ц0022 <= 0.00
ПЭ0083 <= 40.83
00080 <= 19.62
Б0060 <= 0.00
M33.2 <= 0.00
```

### furthre improvement

- 1) advice of treatment
- 2) implement CDS hooks
- 3) implement censorship to input in order to prevent abnormal input
- 4) implement more clear explanation instead of code

# End (thank you very much)

Ma ChengYuan