[08.10.2021]

Bulky mediastinal lymphoma classification with ML-techniques

Activity report

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Meeting ML_INFN @ Firenze
[8 October 2021]

Objective

Classification of *bulky mediastinal lymphoma* using **Machine Learning** techniques applied to PET and CT images.

Lymphoma types:

1. *Hodgkin* (HL)
2. *Gray Zone* (GZ)
3. *Primary Mediastinal Lymphoma* (PML)

PLANNED

From low-level data

- Data: PET and CT images
- Technique: Image classification
- Algorithm: *Convolutional Neural Nets*

IN PROGRESS

From high-level data

- Data: features drawn by LIFEx from images
- Technique: Binary and multiclass classification
- Algorithm: *Logistic regression + Random Forest*

First attempts: *high-level dataset*

Database of 119 rows x 101 columns

- **different data types** → need for homogeneous dataset
  - numbers
  - dates
  - texts
  - intervals
- **dim[*instance space*] ~ dim[*feature space*]** → need for reducing the feature space

Public repository on GitHub to **prepare**, **clean** and **study** the high-level dataset through Jupyter Notebooks:

- `data_preparation` -- data format correction
- `data_visualization` -- correlated features removal
- `binary_classification` -- classification in HL and non-HL
- `multiclass_classification` -- classification in HL, GZ and PML

Feature list

ID
Lymphoma typer (HL =1, GZ = 2, PML =3)
Data nascita
dPET staging
SUVmin (SUV)
SUVmean (SUV)
SUVstd (SUV)
SUVmax (SUV)
MTV (# vx)
MTV (mL)
SMTV (mL/Kg)
TLG (SUV*mL)
STLG (SUV*mL/Kg)
MTV (# vx) TOT
MTV (mL) TOT
SMTV (mL/Kg) TOT
TLG (SUV*mL) TOT
STLG (SUV*mL/Kg) TOT

SHAPE_Volume(mL)
SHAPE_Volume(vx)
SHAPE_Sphericity[onlyFor3DROI])
SHAPE_Surface(mm2)[onlyFor3DROI]
SHAPE_Compacity[onlyFor3DROI]
PARAMS_DistanceOfNeighbours
PARAMS_NumberOfGreyLevels
PARAMS_BinSize
PARAMS_IntensityResampling
PARAMS_BoundsRangeOfValueAfterDiscre
PARAMS_ZSpatialResampling
PARAMS_YSpatialResampling
PARAMS_XSpatialResampling

NGLDM_Coarseness
NGLDM_Contrast
NGLDM_Busyness
GLZLM_SZE
GLZLM_LZE
GLZLM_LGZE
GLZLM_HGZE
GLZLM_SZLGE
GLZLM_SZHGE
GLZLM_LZ
GLZLM_LZ
GLZLM_GL
GLZLM_ZL
GLZLM_ZP
TimePosi
zLocatio

CHECK_Cluster(s)ToSmall
GLCM_Homogeneity[=InverseDifference]
GLCM_Energy[=AngularSecondMoment]
GLCM_Contrast[=Variance]
GLCM_Correlation
GLCM_Entropy_log10
GLCM_Entropy_log2[=JointEntropy]
GLCM_Dissimilarity
GLRLM_SRE
GLRLM_LRE
GLRLM_LGRE
GLRLM_HGRE
GLRLM_SRLGE
GLRLM_SRHGE
GLRLM_LRLGE
GLRLM_LRHGE
GLRLM_GLNU
GLRLM_RLNU
GLRLM_RP

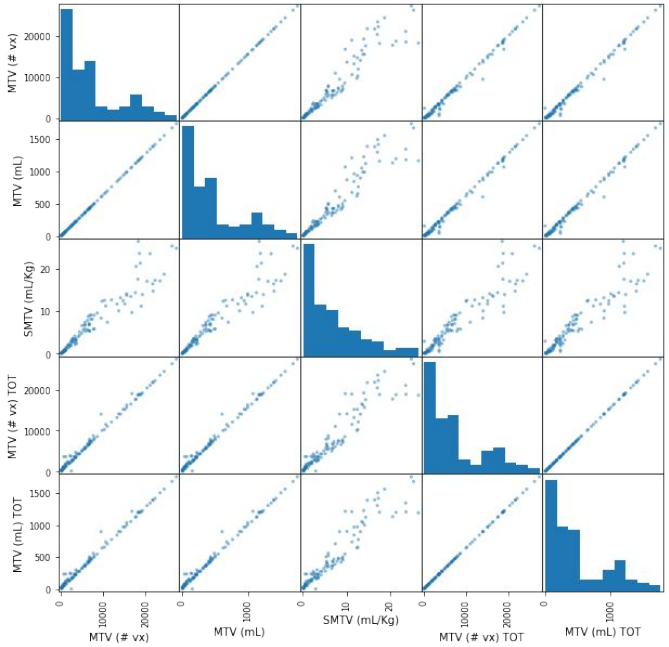
- number
- date
- text
- interval

ue only for PET or NM)
tized volume sought
DISCRETIZED_SUVbwpeakSphere1mL(value only for PET or NM)
DISCRETIZED_TLG(mL)[onlyForPETorNM]
DISCRETIZED_HISTO_Skewness
DISCRETIZED_HISTO_Kurtosis
DISCRETIZED_HISTO_ExcessKurtosis
DISCRETIZED_HISTO_Entropy_log10
DISCRETIZED_HISTO_Entropy_log2
DISCRETIZED_HISTO_Energy[=Uniformity]

CONVENTIONAL_SUVbwm
CONVENTIONAL_SUVbwm
CONVENTIONAL_SUVbws
CONVENTIONAL_SUVbwm
CONVENTIONAL_SUVbwC
CONVENTIONAL_SUVbwC
CONVENTIONAL_SUVbwC
CONVENTIONAL_SUVbwS
CONVENTIONAL_SUVbwK
CONVENTIONAL_SUVbwE
CONVENTIONAL_SUVbwpeakSphere0,5mL:discretized volume sought
CONVENTIONAL_SUVbwpeakSphere0,5mL(value only for PET or NM)
CONVENTIONAL_SUVbwpeakSphere1mL:discretized volume sought
CONVENTIONAL_SUVbwpeakSphere1mL(value only for PET or NM)
CONVENTIONAL_TLG(mL)[onlyForPETorNM]

Dataset cleaning

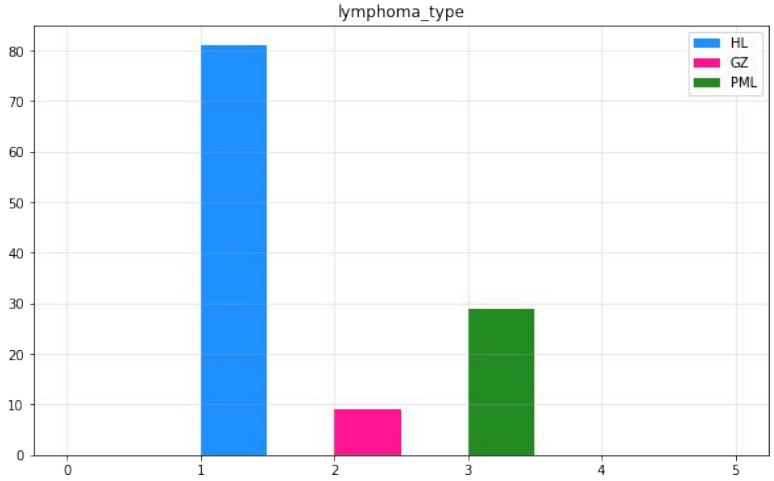
- Features with no clear contents **dropped**
  - text data
  - intervals
- Variables with strong correlations **dropped**
  - $\rho_{X,Y} \geq |0.75| \rightarrow$ *strong correlation*
- **New feature added**
  - **age**, from dates subtraction (then dropped)



99 → 17 FEATURES

`binary_classification`

Instance space

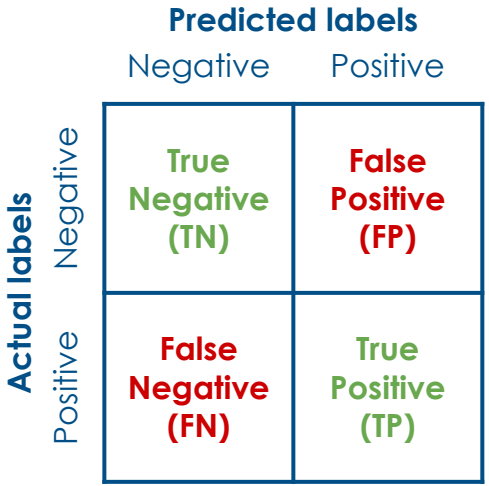


- Missing information
  - some features not available for all the instances
  - instances **dropped** to keep homogeneity
  - 119 → 101 rows (*instances*)
- Dataset strongly **unbalanced**
  - HL-class is over-represented w.r.t. the other two ones
  - classification suffers from unbalancing
- **Binary classification**
  - HL and non-HL classification
  - dataset a bit more balanced
  - NHL-HL ratio : 55.4%
- Train/Test split : **80%/20%**
- k-Folds Cross Validation with **k=3**

Performance measures: *accuracy, precision & recall*

The ***accuracy*** is generally not the preferred performance measure for classifiers, especially when one are dealing with **unbalanced datasets**. In fact, classifiers succeed in recognizing instances belonging to most frequent label, resulting in high accuracy even if the other instances are mis-classified.

In order to ensure a model evaluation robust against unbalanced datasets, one can use ***precision*** or ***recall*** scores.



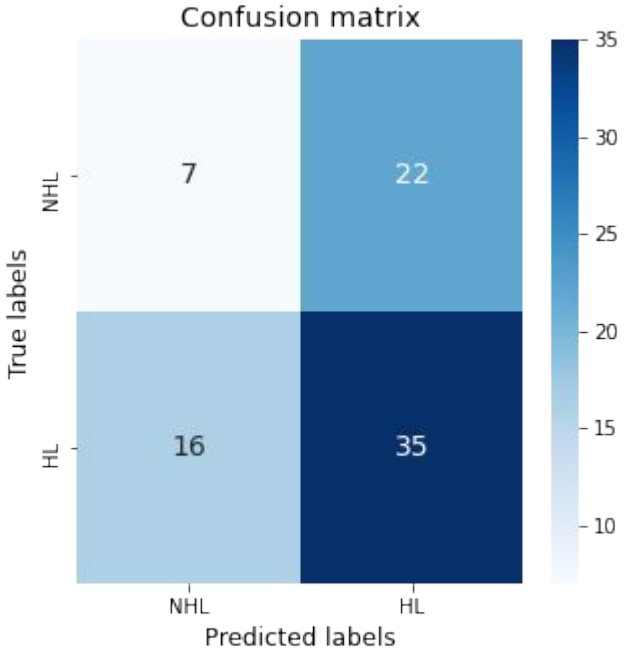
In the Jupyter Notebook we have used RECALL!

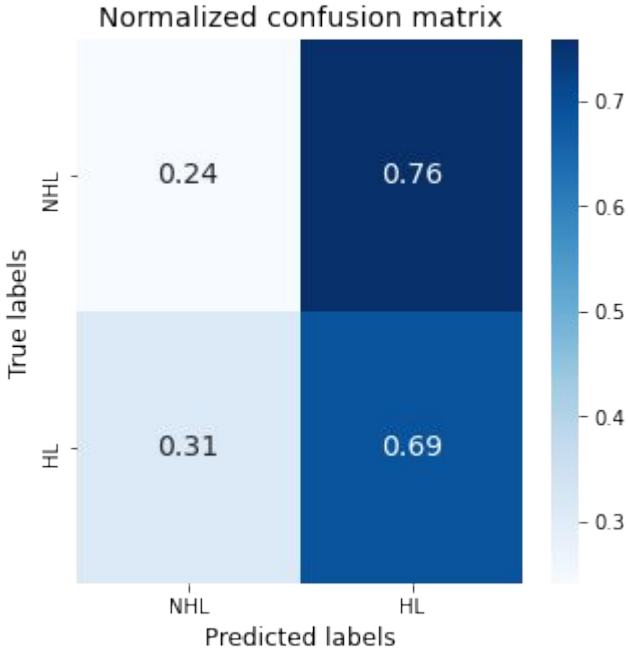
$$\text{accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}$$

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

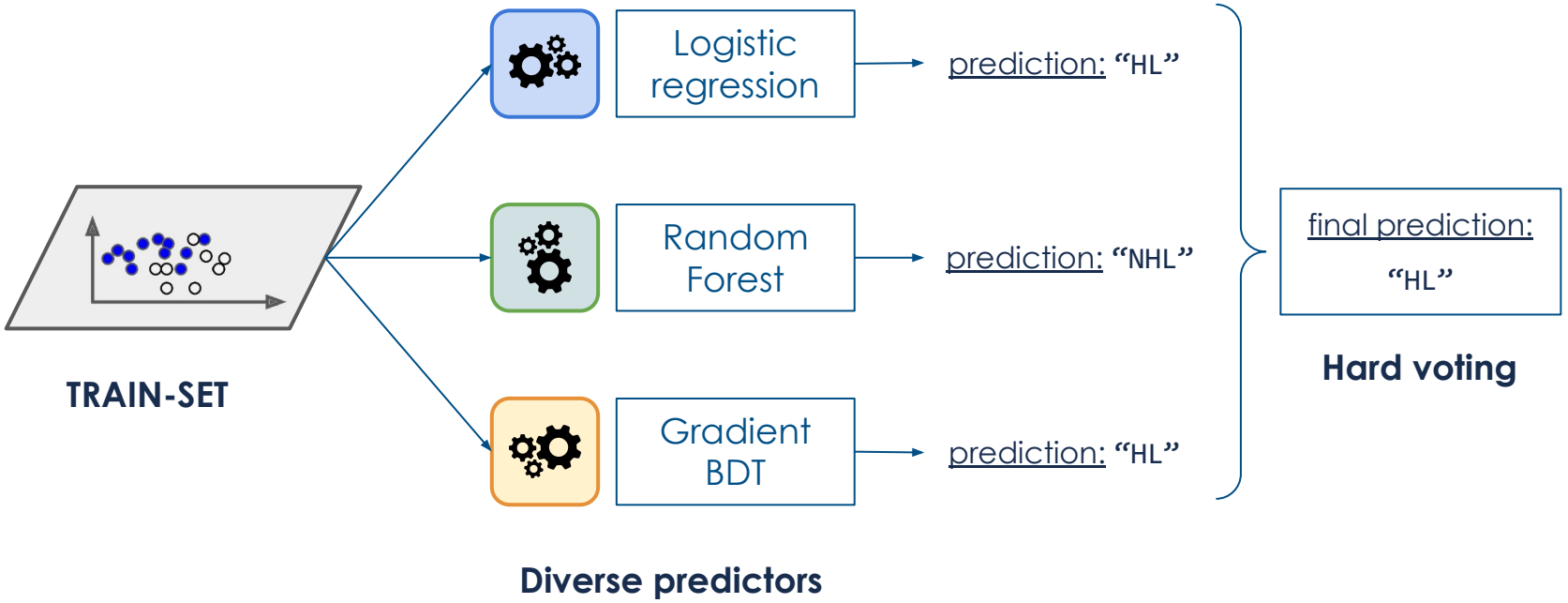
$$\text{recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Dummy Classifier: *performance*

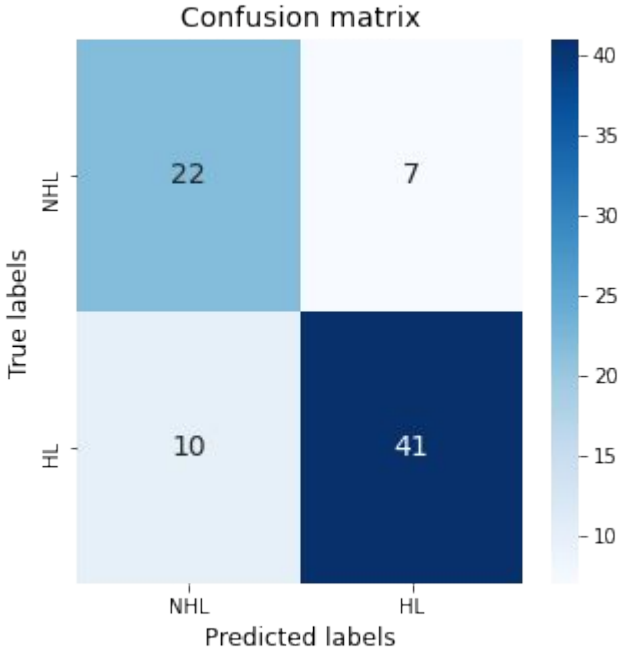


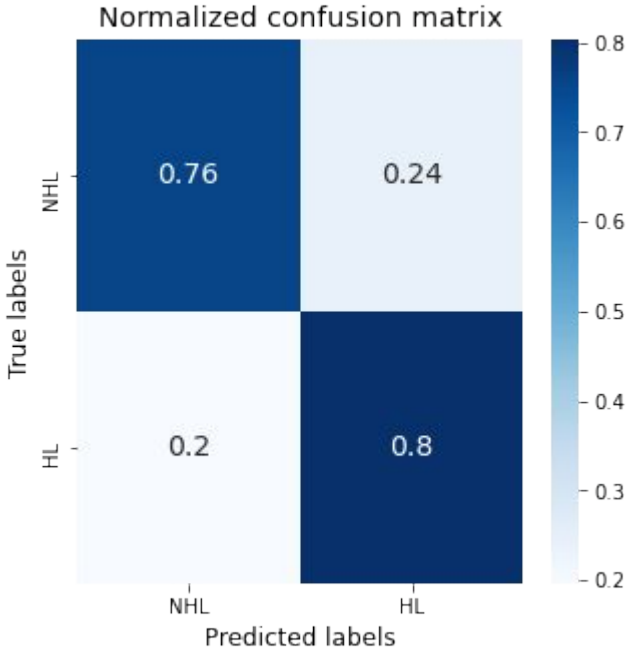


Model combination

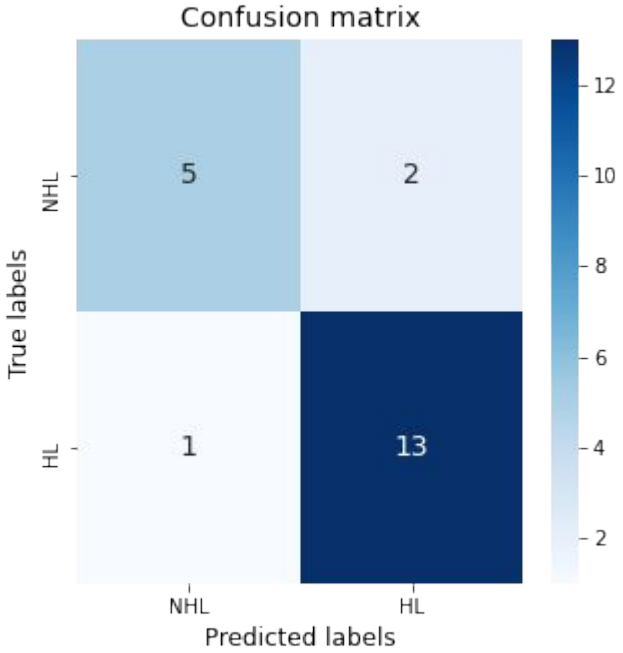


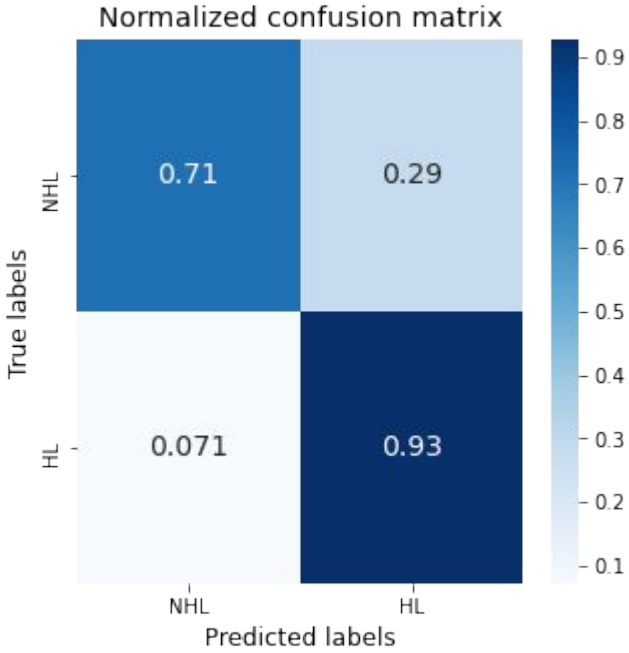
Model combination: *performance*





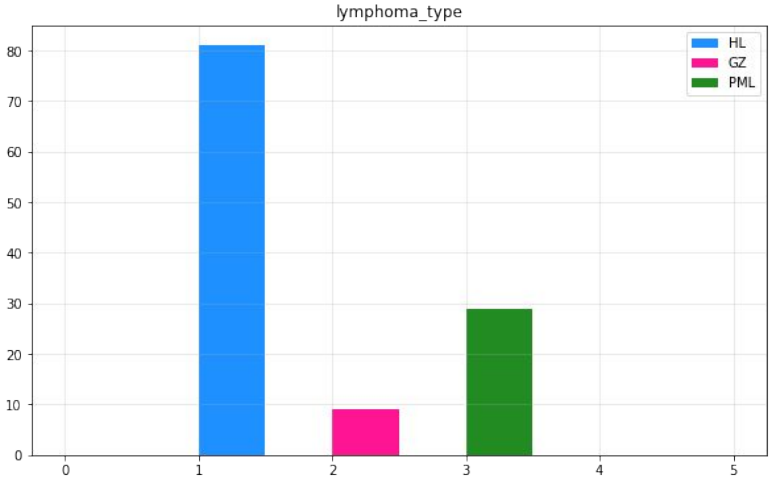
Results on the test-set





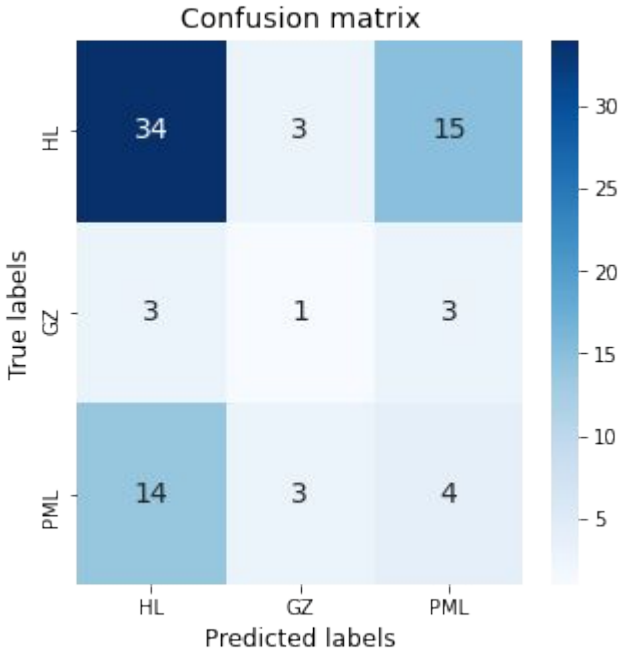
`multiclass_classification`

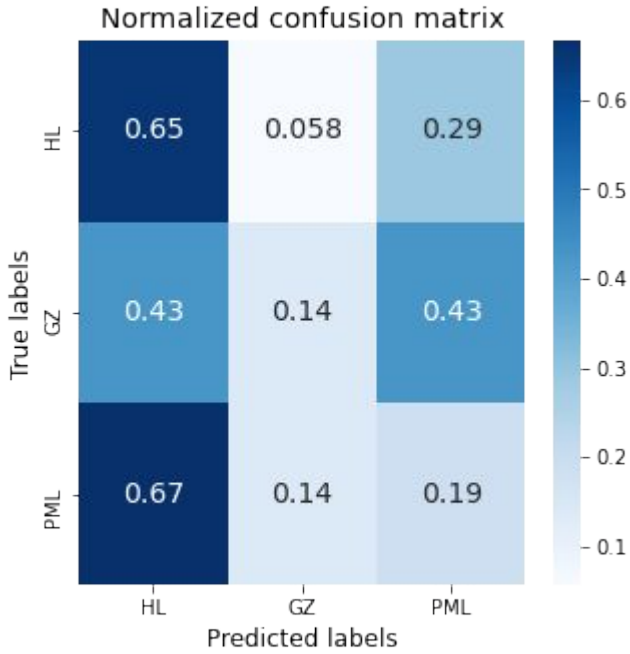
Instance space



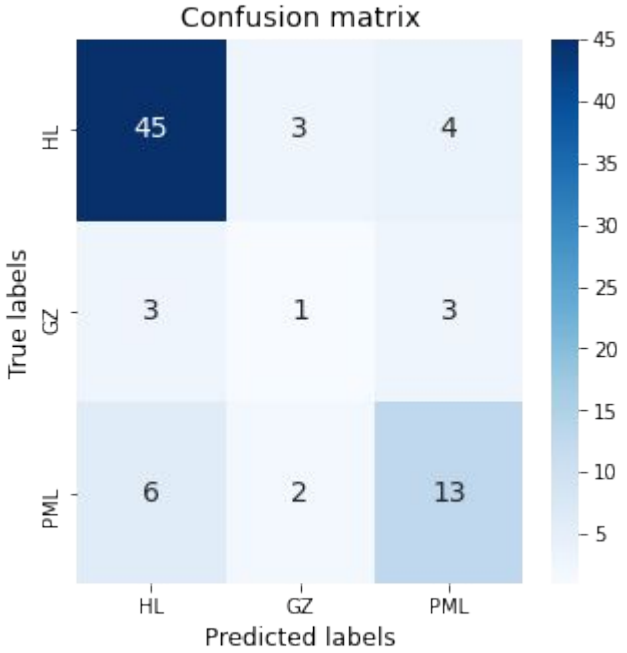
- Missing information
  - some features not available for all the instances
  - instances **dropped** to keep homogeneity
  - 119 → 101 rows (*instances*)
- Dataset strongly **unbalanced**
  - HL-class is over-represented w.r.t. the other two ones
  - classification suffers from unbalancing
- **Multiclass classification**
  - HL, GZ and PML classification
  - GZ-HL ratio : 13.8%
  - PML-HL ratio : 41.5%
- Train/Test split : **80%/20%**
- k-Folds Cross Validation with **k=3**

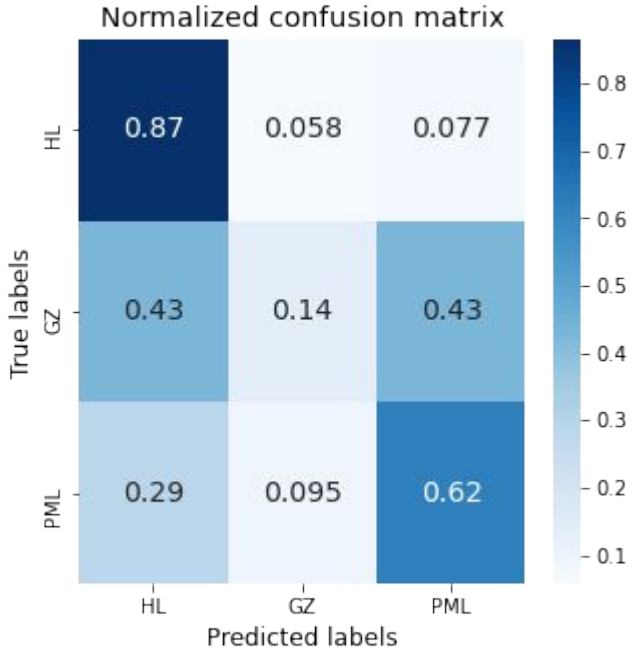
Dummy Classifier: *performance*



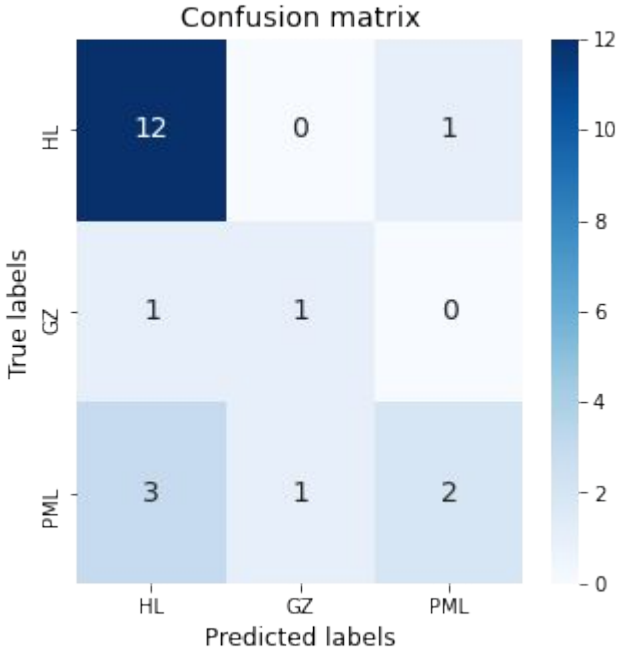


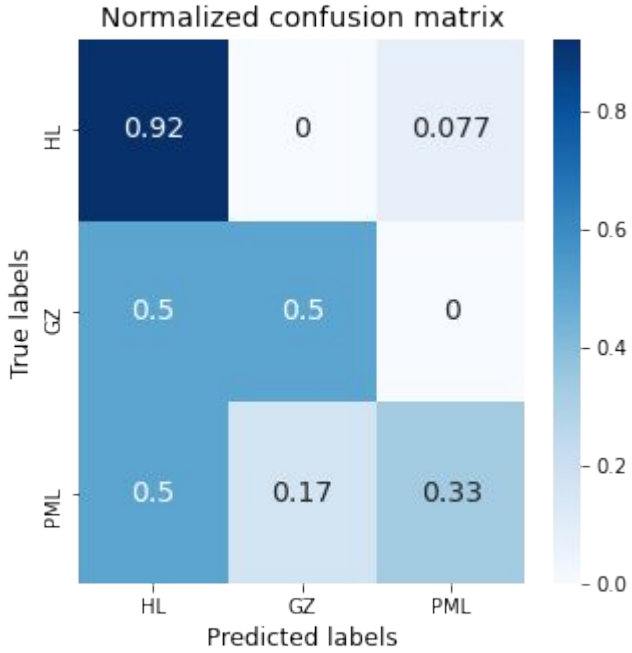
Model combination: *performance*





Results on the test-set





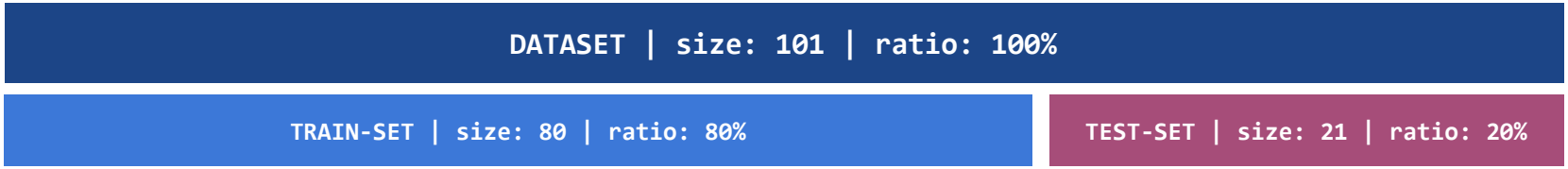
Conclusion

- Preliminary studies
- There is room for improvements
  - **increasing** the dataset → more data
  - **balancing** the dataset → expanding *low-represented* classes
  - working with **low-level data** → *image classification* techniques
- **Binary classification** looks promising
  - GZ-class should be treated as a *classification uncertainty*
  - custom probability thresholds → multiclass classification

Open to any kind of suggestions!

Backup

Train/Test split



To ensure that our Machine Learning model will be able to **generalize** well to new cases, namely to behave like a *true predictor*, we should avoid to use all the dataset to train our model. A better option is to **split the data into two sets**:

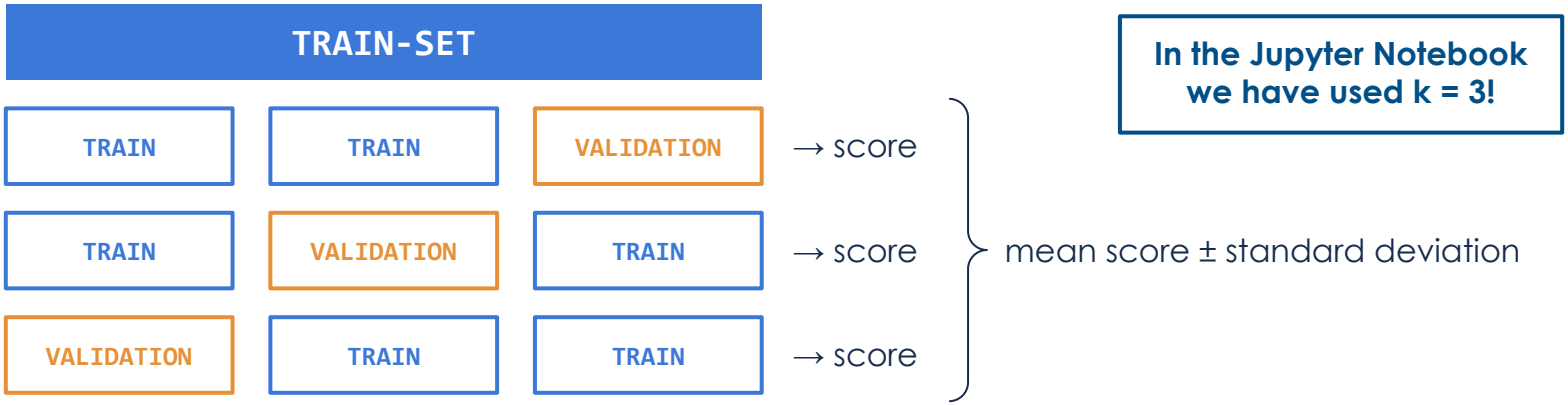
- ***training set*** to train the model
- ***test set*** to test the model

The error rate on new cases is called the ***generalization error***, and we can estimate it evaluating the trained model on the test set.

Model optimization: *k-Folds Cross Validation*

In the search of the best possible predictor, we should avoid that our model learns by heart the training instances, because it will result in a **greater generalization error**.

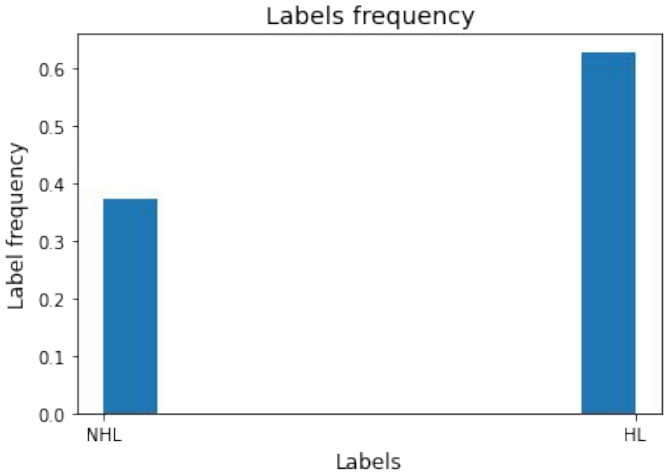
A possible solution is to use ***k-Folds Cross Validation***, an algorithm based on the splitting of the training set into k different subsets. We will use k-1 subsets to train the model and leave the last subset to validate it. Then, the average performance of our model against each of the folds can be used as a robust score to build an **optimization problem**, namely to find the best possible model.



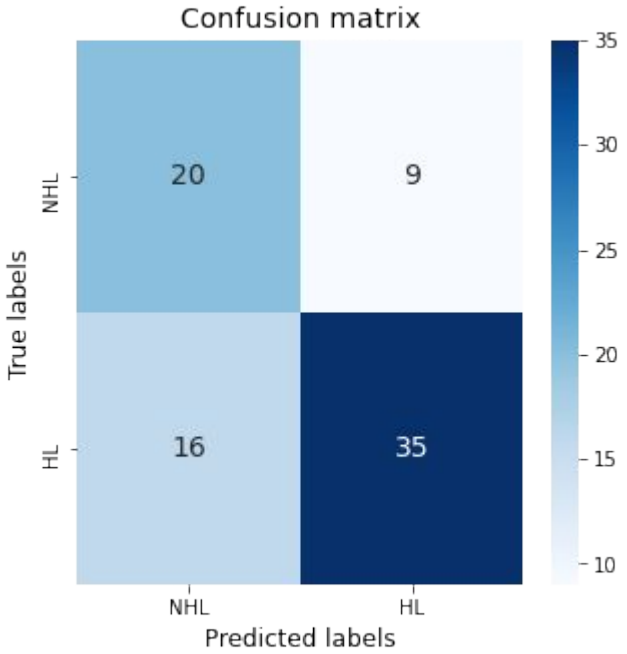
In the Jupyter Notebook we have used k = 3!

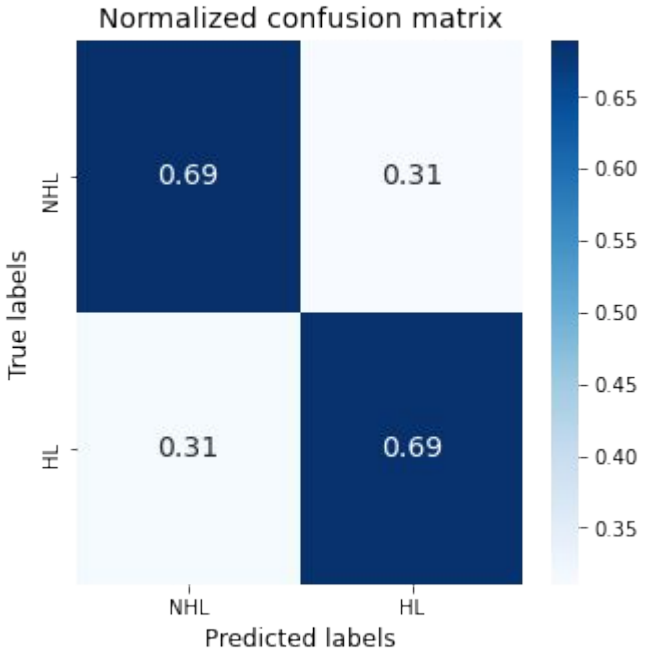
Dummy Classifier: *model baseline*

- The ***Dummy Classifier*** is a simple classifier that makes predictions using simple rules:
  - computes the frequency of each label
  - interprets such frequencies as probabilities
  - predicts new instances label on the basis of computed probabilities
- This classifier is useful as a simple baseline to compare with other (real) classifiers

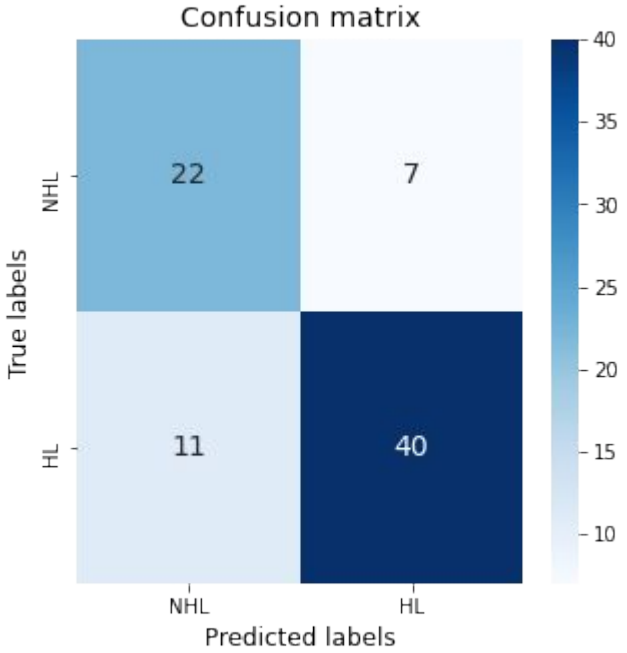


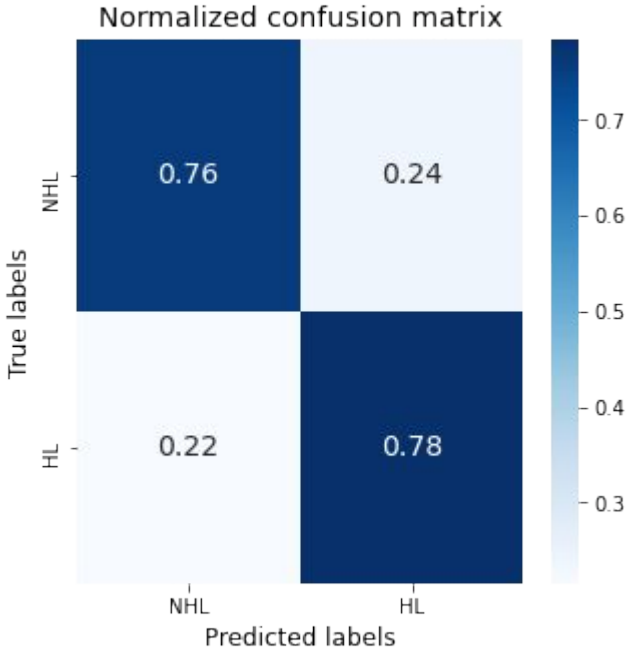
Logistic regression: *performance*



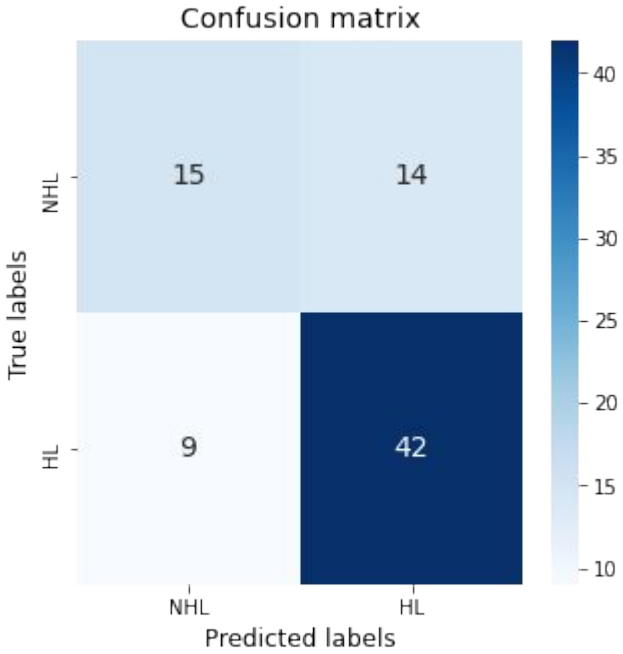


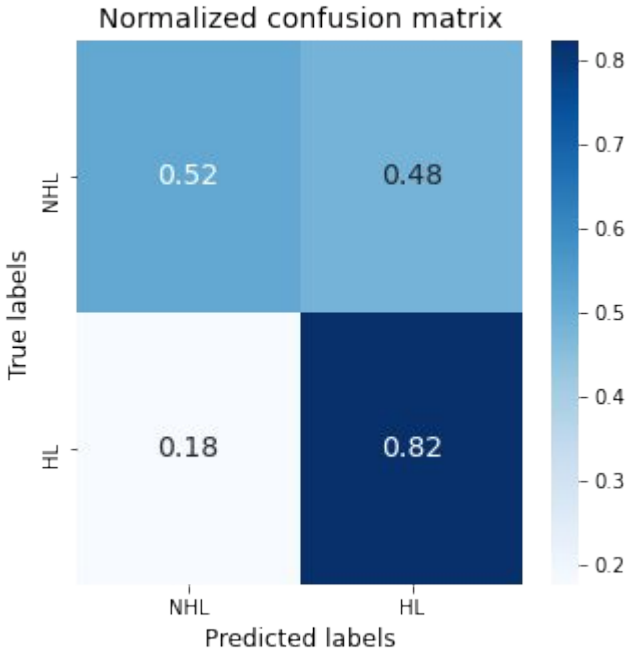
Random Forest classifier: *performance*



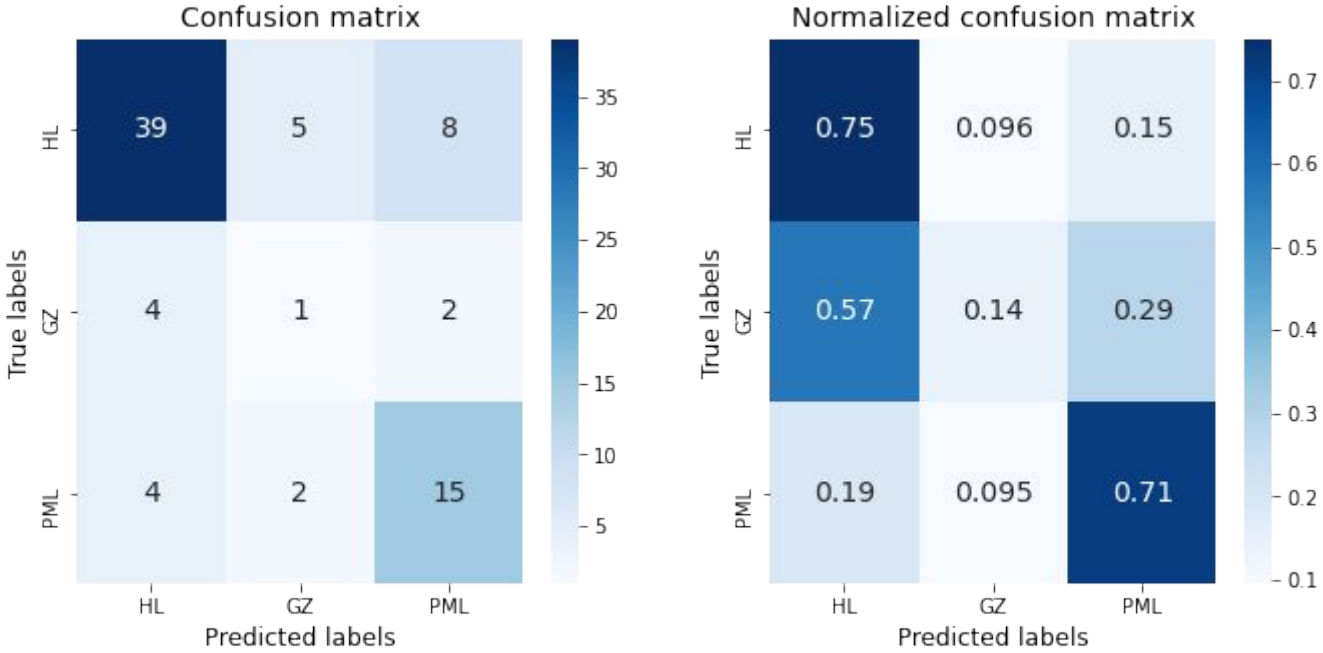


Gradient BDT classifier: *performance*

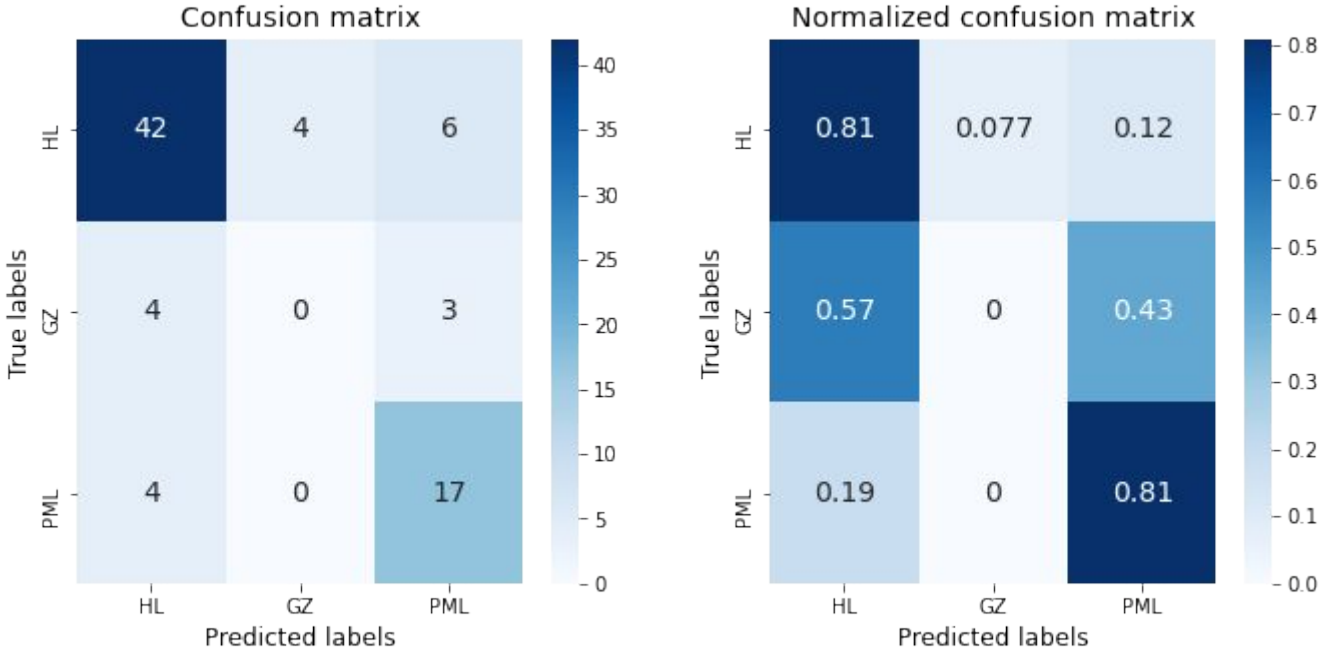




Logistic regression: *performance*



Random Forest classifier: *performance*



Gradient BDT classifier: *performance*