Kunisch Recognition through Multi-Label Classification Algorithms

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Prof. Iván Sipirán

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1. Introduction

Ornamente Geometrischer Vasen: Ein Kompendium[1] is a collection of patterns present on archaeological objects, each of which is labeled with a set of labels.

This work seeks to apply multi-label classification algorithms on them, in order to develop a tool that serves for the labeling of new entries in the future.

[1]Norbert Kunisch, 1998

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For the labels:

- We decided to use the English version of labels, due to some good properties of the language (such as gender neutrality).
- Labels were extracted manually.

7b Opposed diagonals, separated by solid triangles, horizontal panel
Traits obliques affrontés, séparés par des triangles noirs, panneau horizontal
Triangoli di vernice, fra tratti intrecciati diagonalemente, campo orizzontale
Εναλλασσόμενες λοξές γραμμές, ενδιάμεσα μελαμβαφή τρίγωνα, οριζόντια ζώνη

7c Gegenständige Diagonalen, dazwischen Firnisdreiecke, Senkrechtfeld
Opposed diagonals, separated by solid triangles, vertical panel
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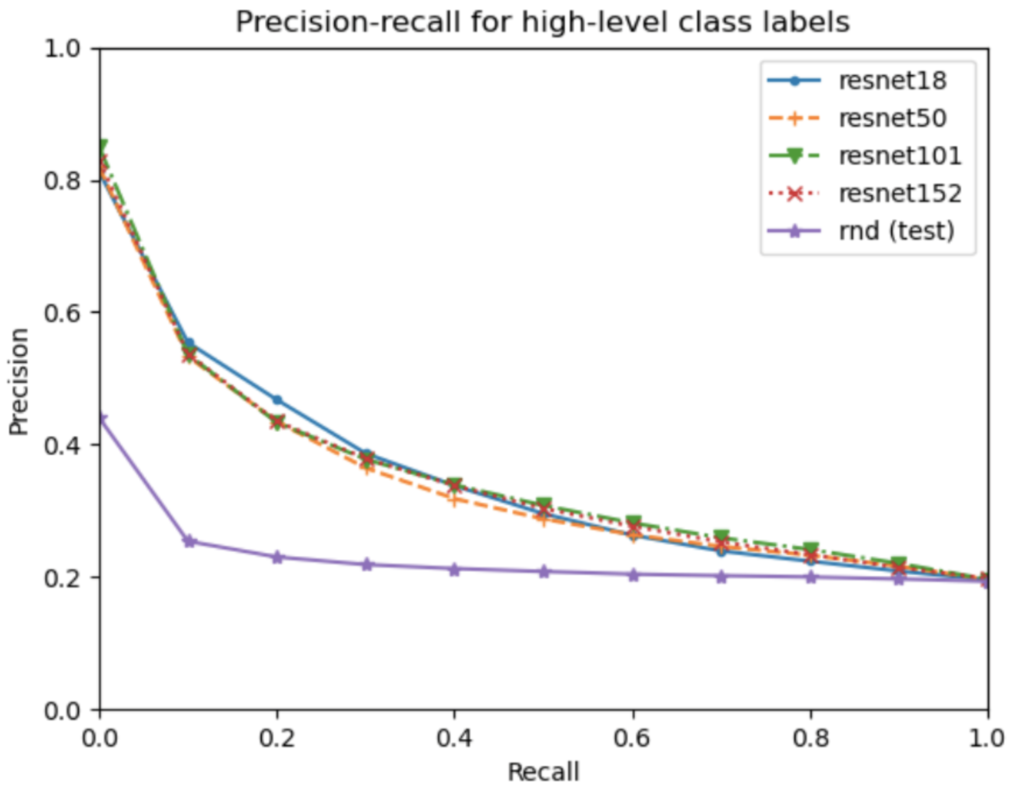
For the descriptors:

- We conducted experiments testing ResNet architectures and a Random Neural Network in the task of classifying patterns in their high-level classes (chapter of the book).

- We decided to use ResNet18 features as descriptors for the patterns, and we also took the ones from ResNet50 in order to have an option to compare with.



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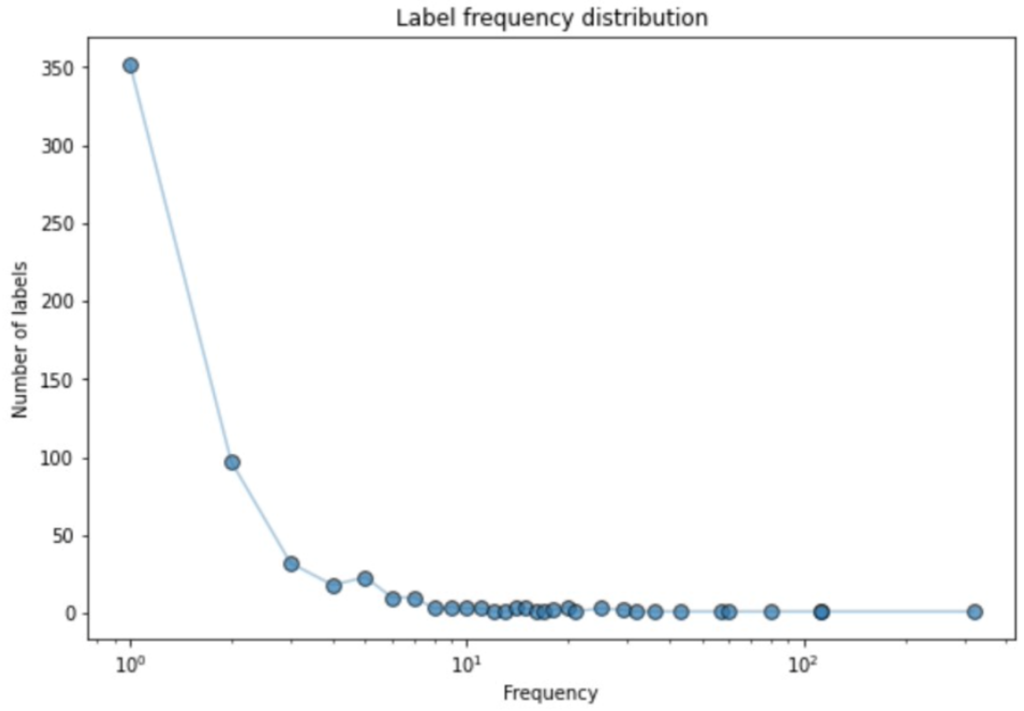
Too many labels with low number of events in the data:

- For low numbers of events there are many labels, while for high occurrences there are very few labels.
- As example, there are 352 labels with a single event in the data, and only 3 with more than 100.
- Zipf-like distribution?



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Consequently, an extremely low *label density*[2]:

- Relation between the number of samples and labels related to each of them (which could be seen as how multi-label is the data).
- In our case, this measure takes a value of 0.005, extremely low.
- This is not surprising, however, since label cardinality (average number of labels per example) is very low relative to the total of labels (4 vs 586).

$$LD(D) = \frac{1}{|D|} \sum_{i=1}^{|D|} \frac{|Y_i|}{|L|}$$

[2]Tsoumakas G., Katakis I., V. I., "A review of multi-label classification methods," International Journal of Data Warehousing and Mining, vol. 3, pp. 1–13, 2007.

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For Problem Transformation, we tried with SVM and Logistic Regression as base classifiers.

For Algorithm Adaptation, we did a grid search to find best hyperparameters.

Experiments were conducted through the BSD-licensed **scikit-multilearn** library.

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We decided to use 3 metrics:

- **Exact Match Ratio**
- **Hamming Loss**
- **Hamming Score** (also knew as label-based accuracy).

$$\text{Hamming-Loss} = \frac{1}{m}\sum_{i=1}^{m}\left|\frac{Y_i \Delta Z_i}{M}\right|$$

$$\text{Hamming-Score} = \frac{1}{m}\sum_{i=1}^{m}\left|\frac{Y_i \cap Z_i}{Y_i \cup Z_i}\right|$$

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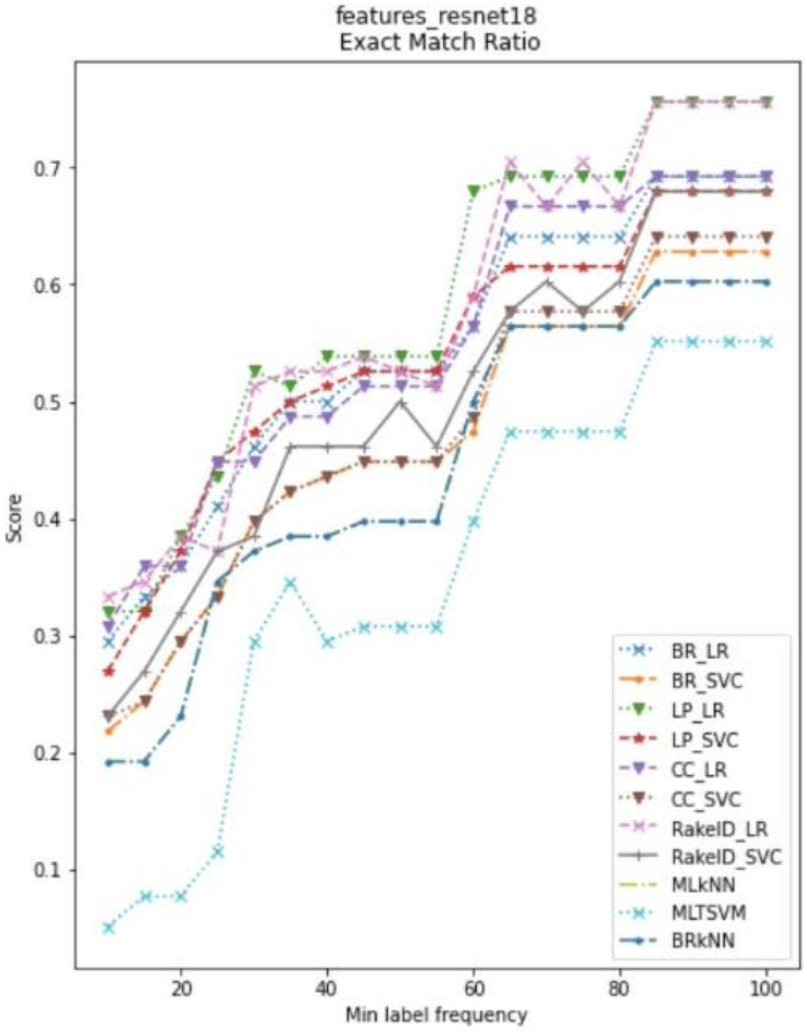
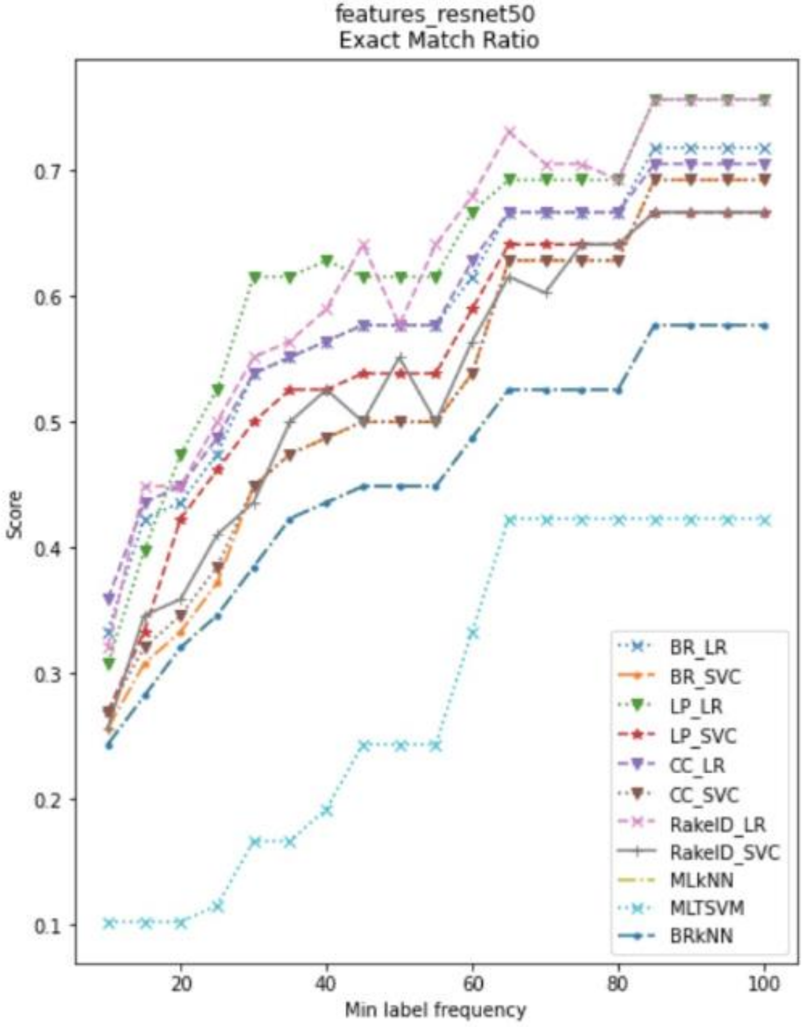
The more we prune, the easier the problem… But it also becomes less interesting.

7. Results



(a) Features from ResNet18



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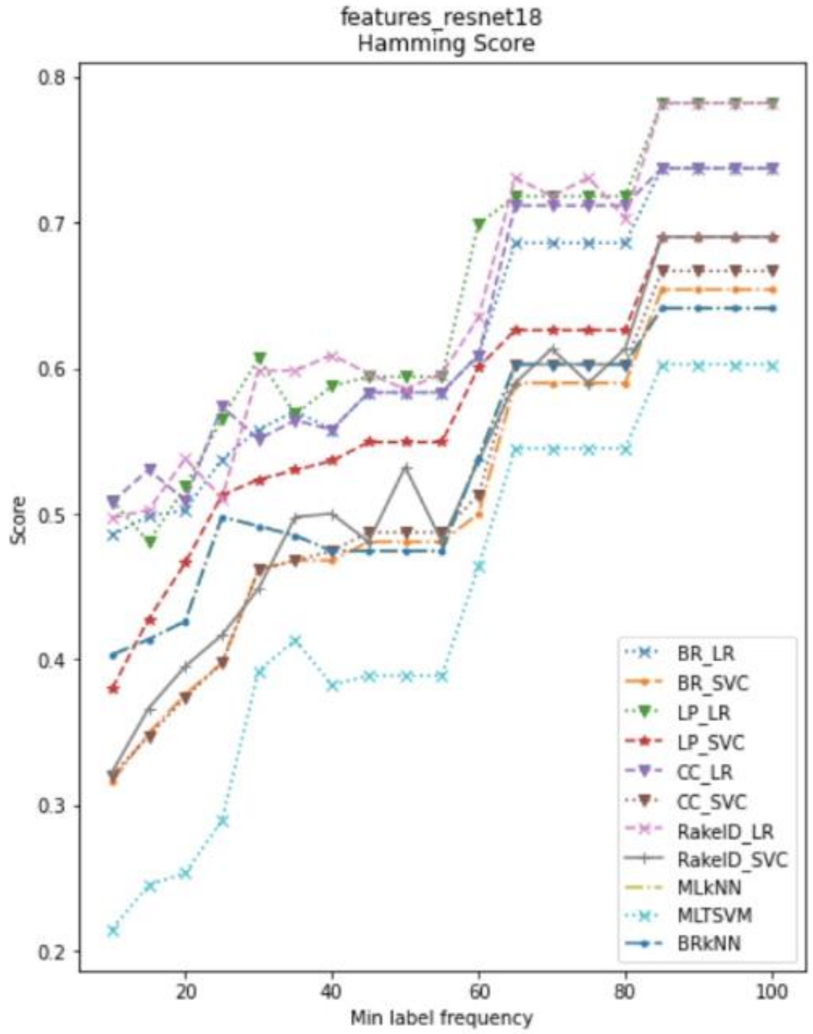

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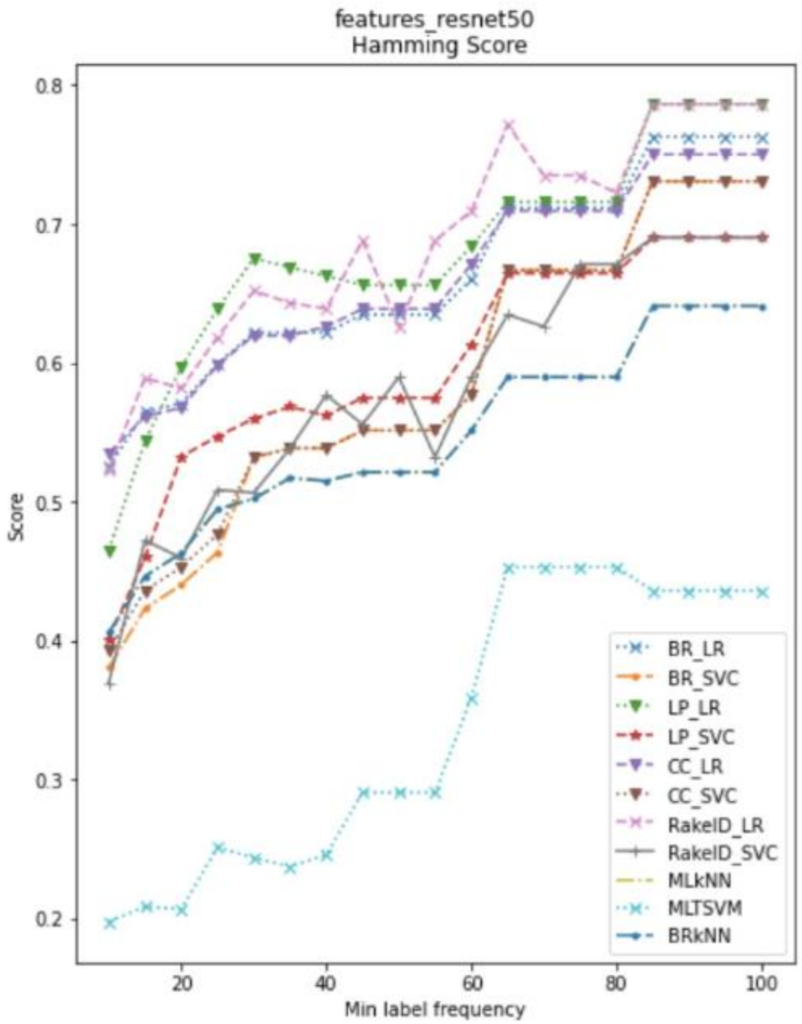
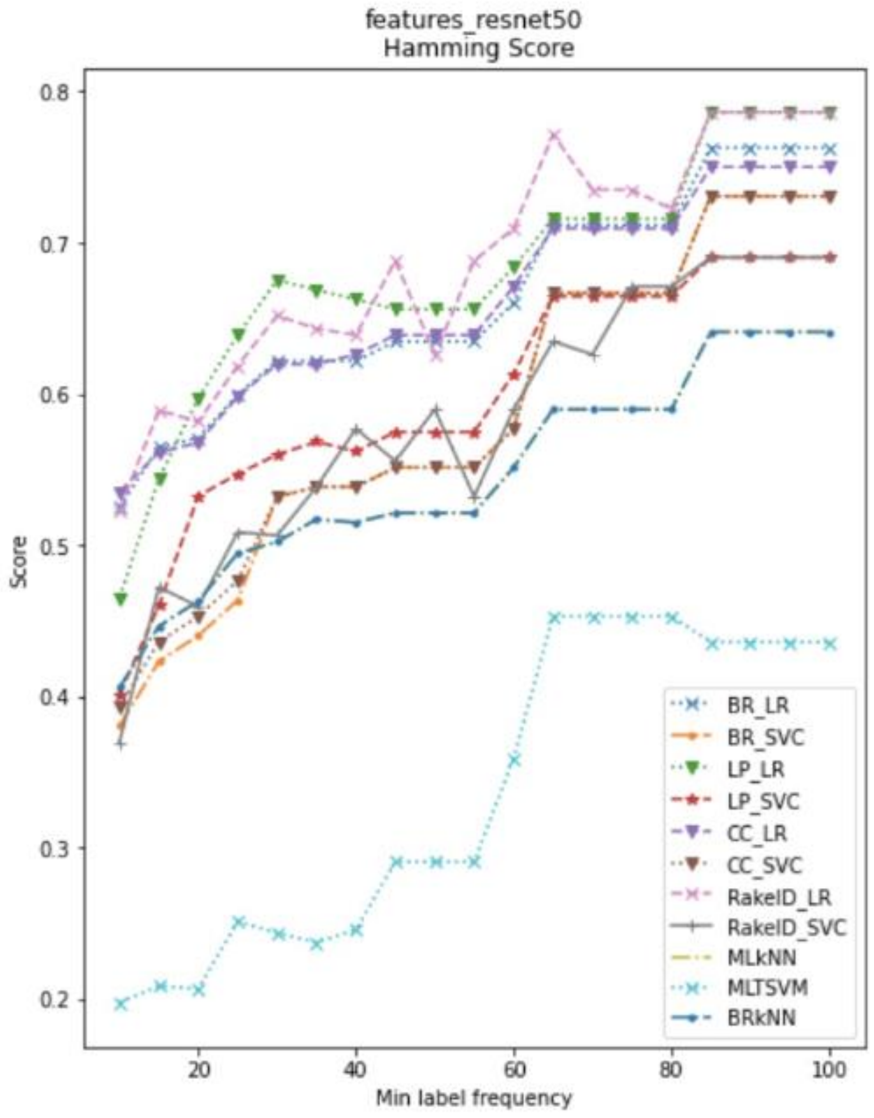


(b) Features from ResNet50

8. Discussion

- Firstly, we note that as we move along the abscissa, the methods tend to give better results.



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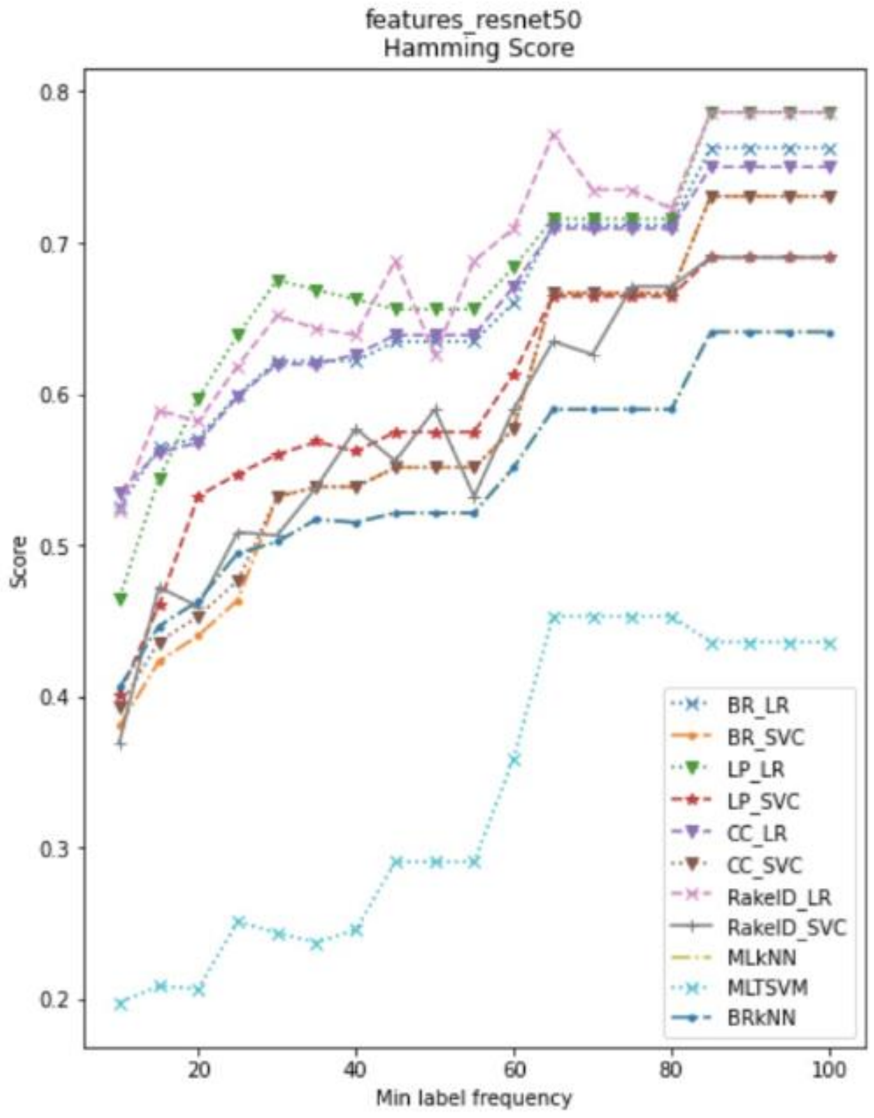

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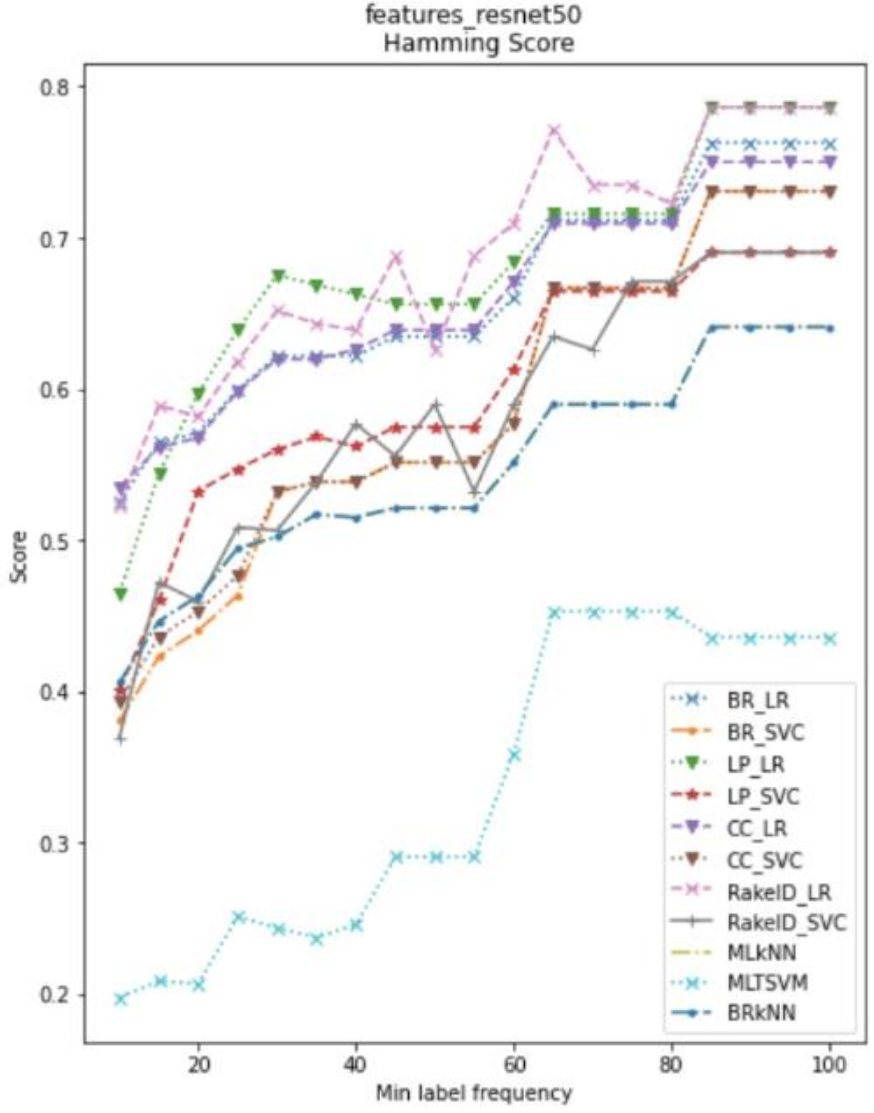
- We also note that the Problem Transformation Methods give better results than Algorithm Adaptation ones.



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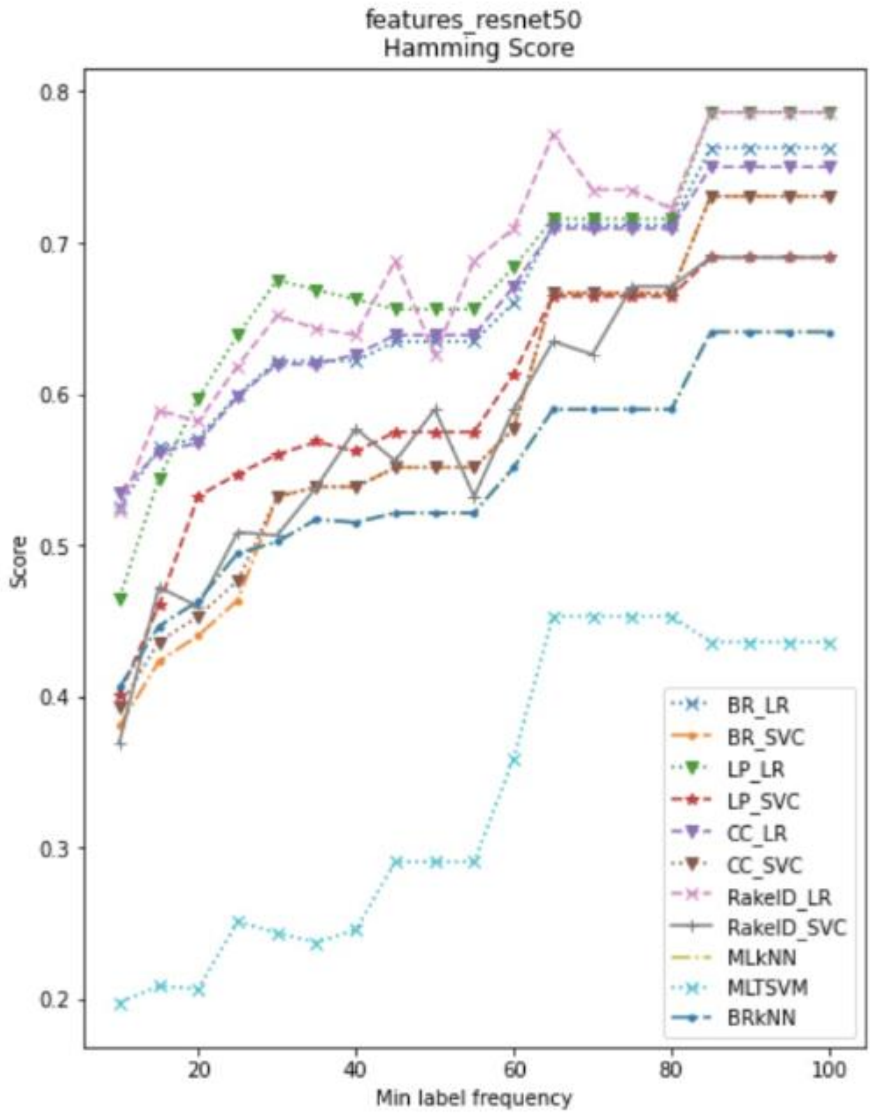

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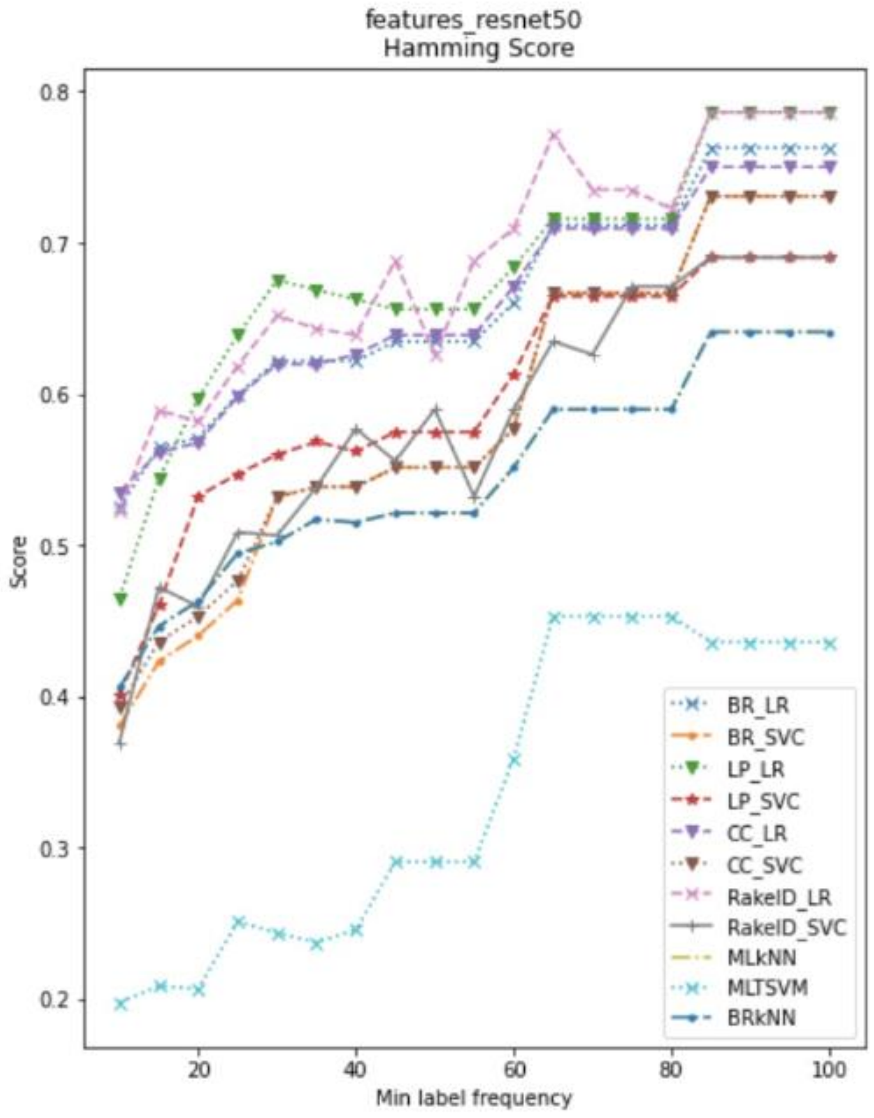

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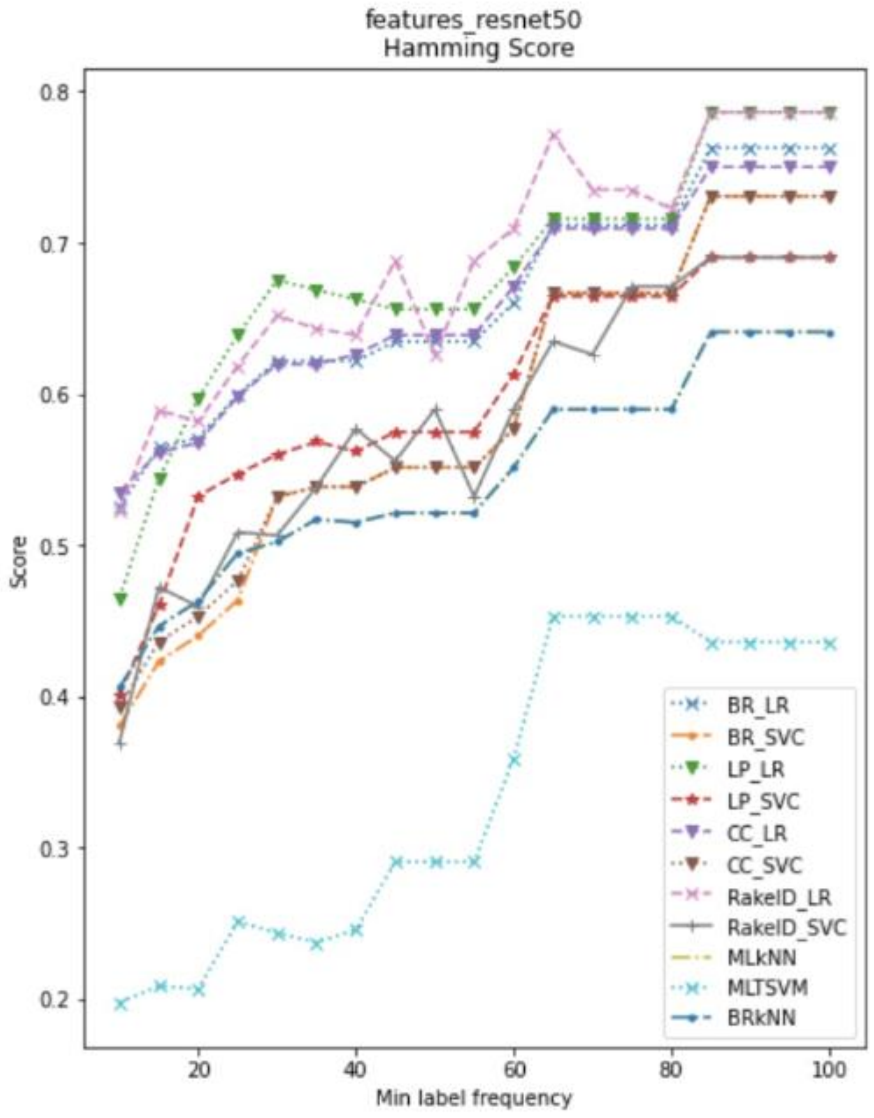

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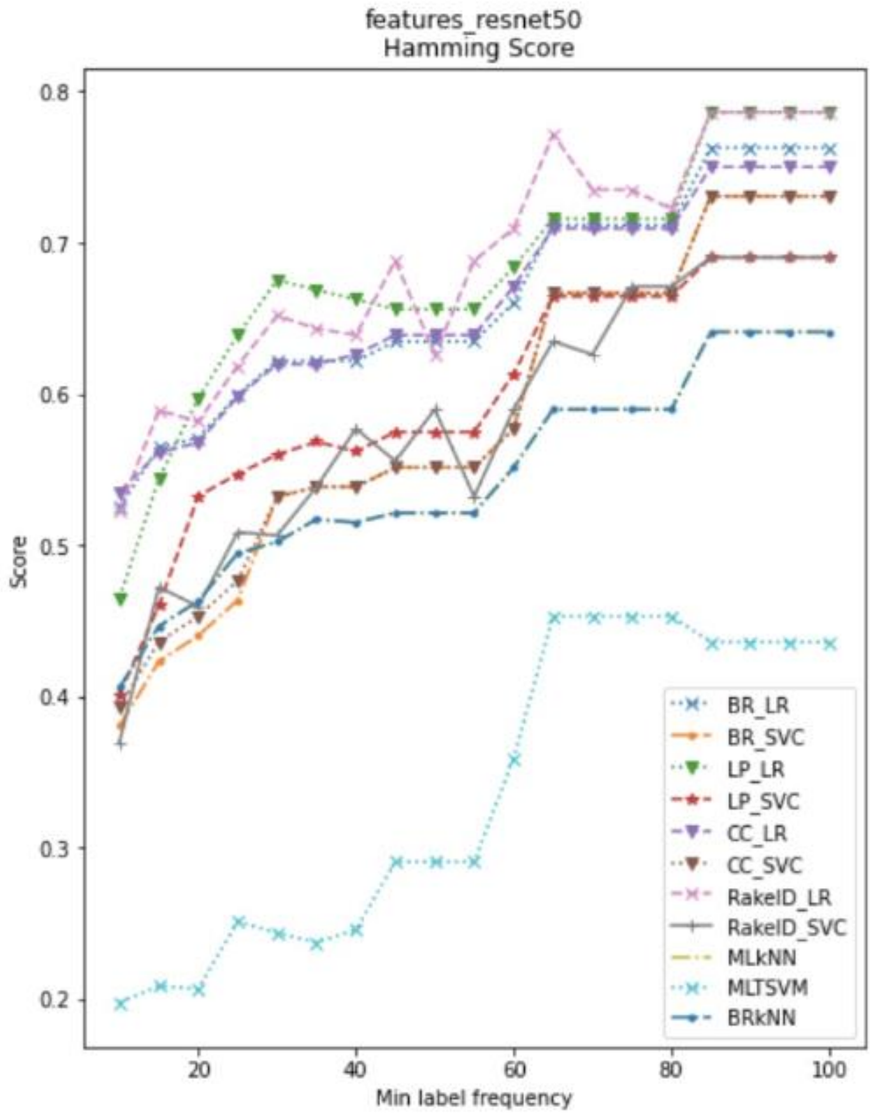
- We want to keep the problem as interesting as possible, i.e., use the lowest threshold possible.
- Let's assume that $t = 15$ is enough. This left us with the 26 most frequent labels (4.43% of total labels)



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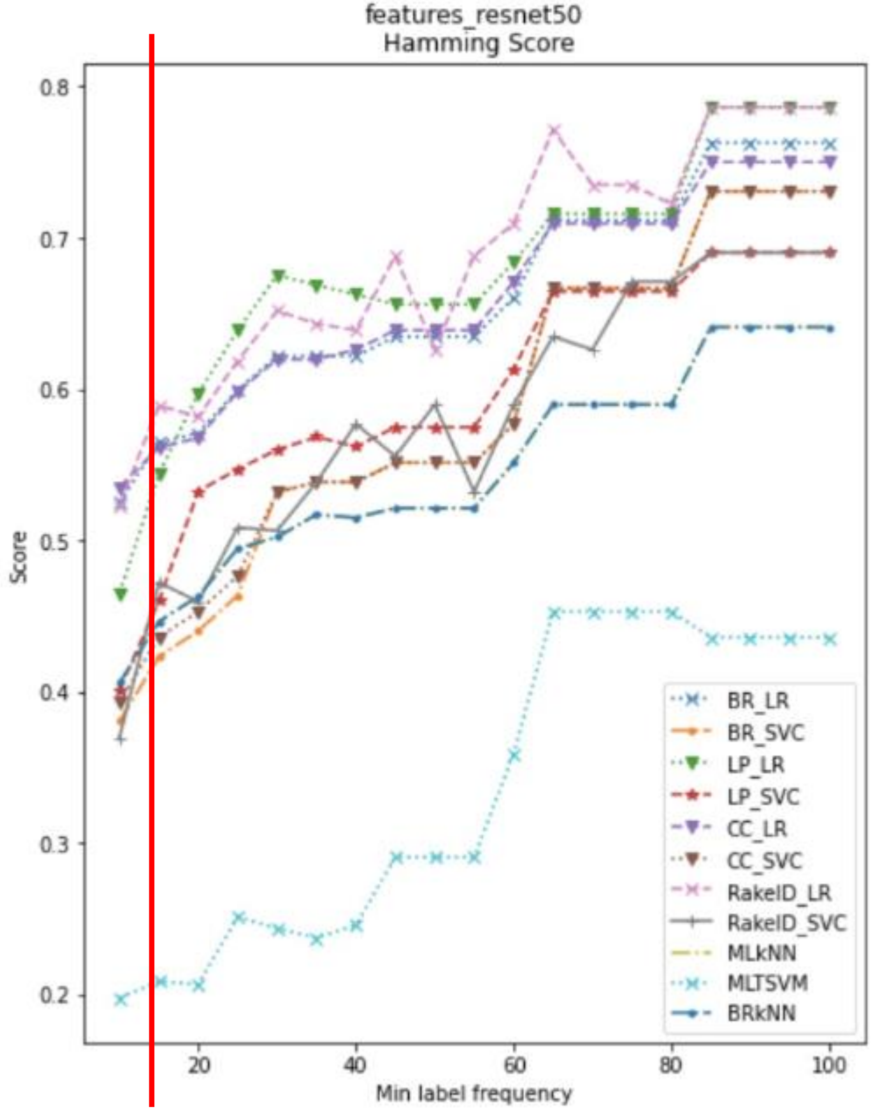

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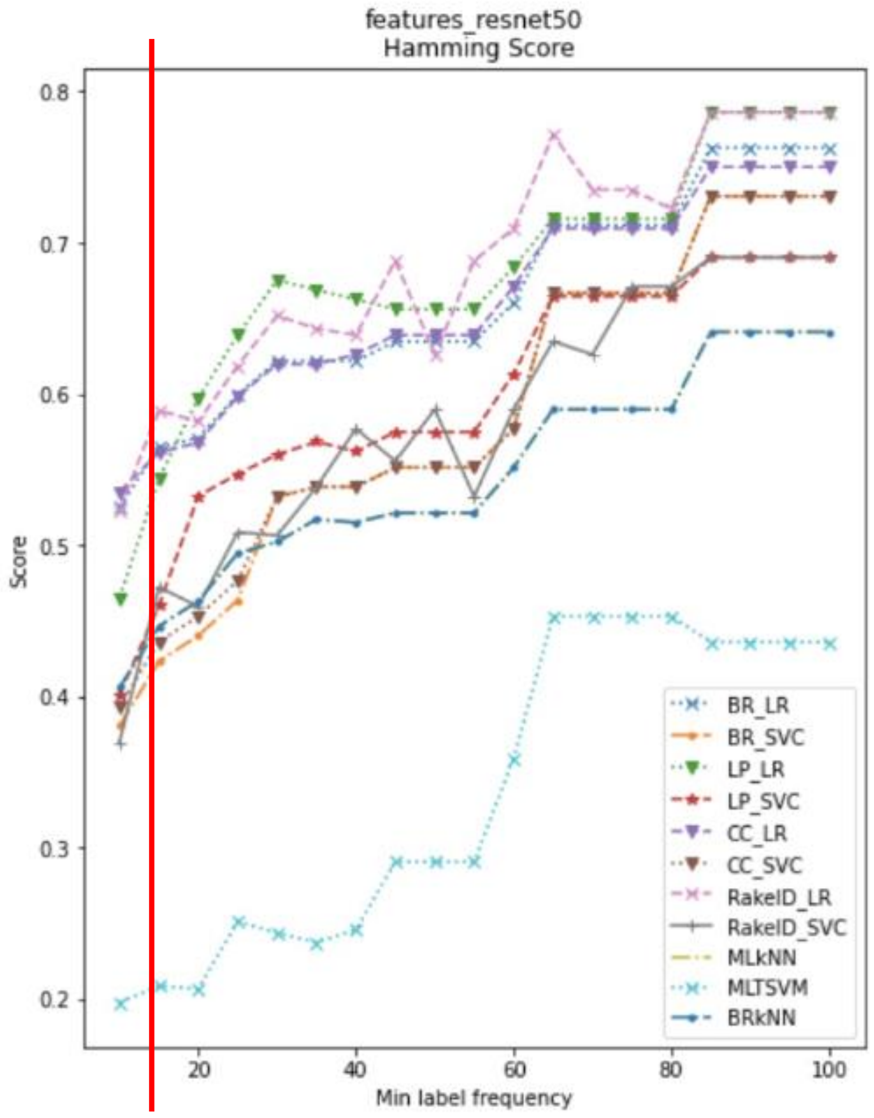
- These are, in decreasing order, RakelD_LR, CC_LR, BR_LR and LP_LR.



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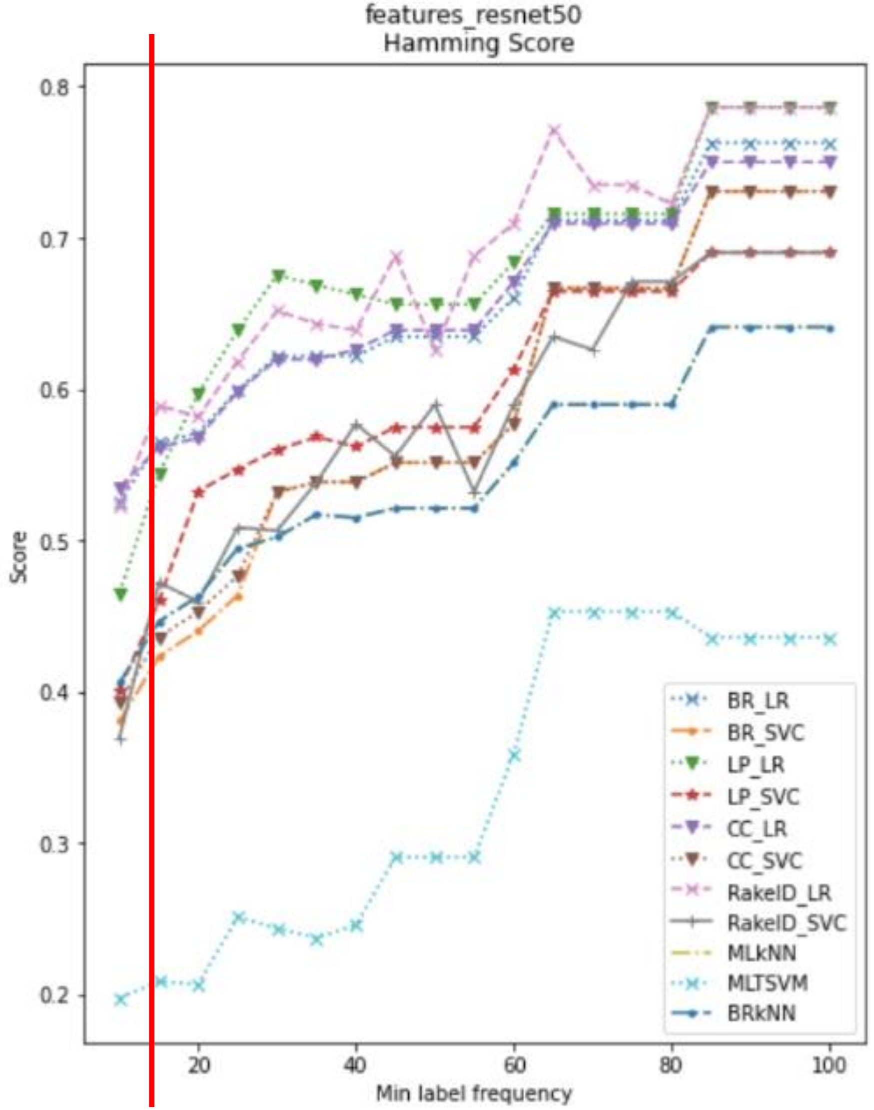

Method	Exact Match Ratio	Hamming Loss	Hamming Score
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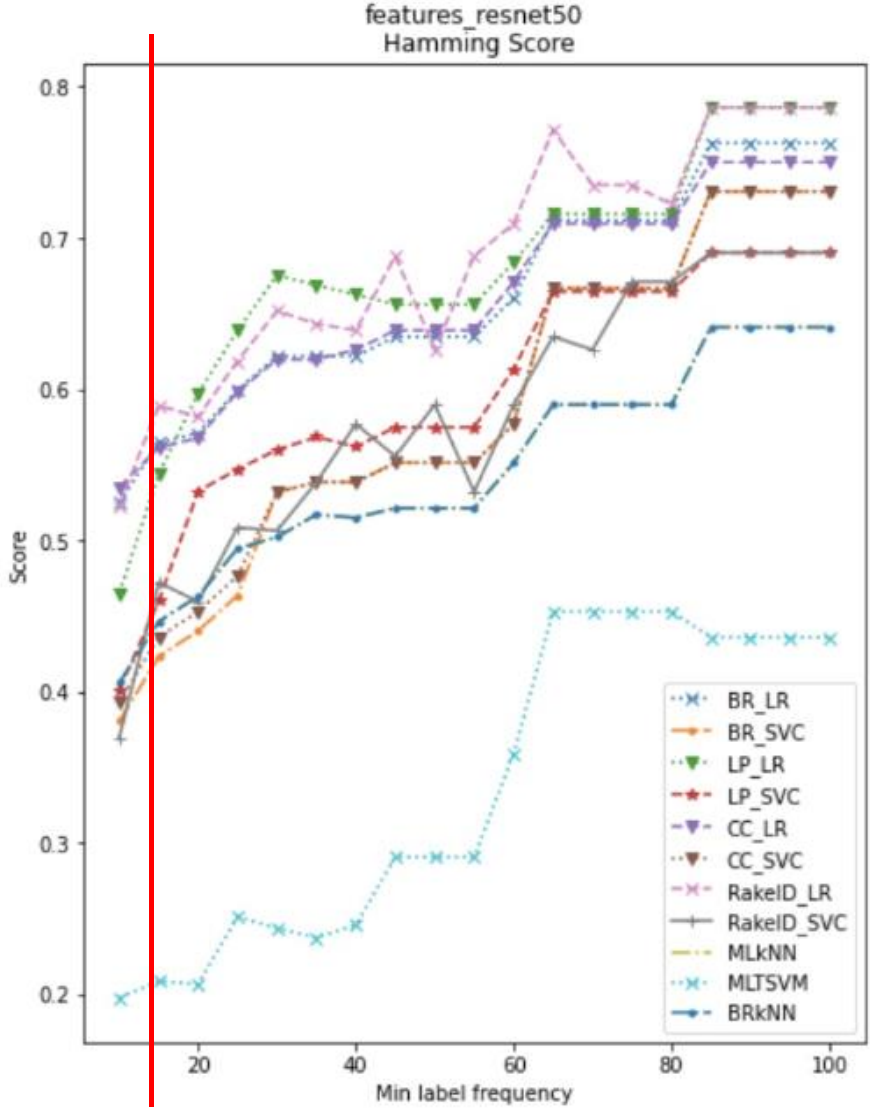

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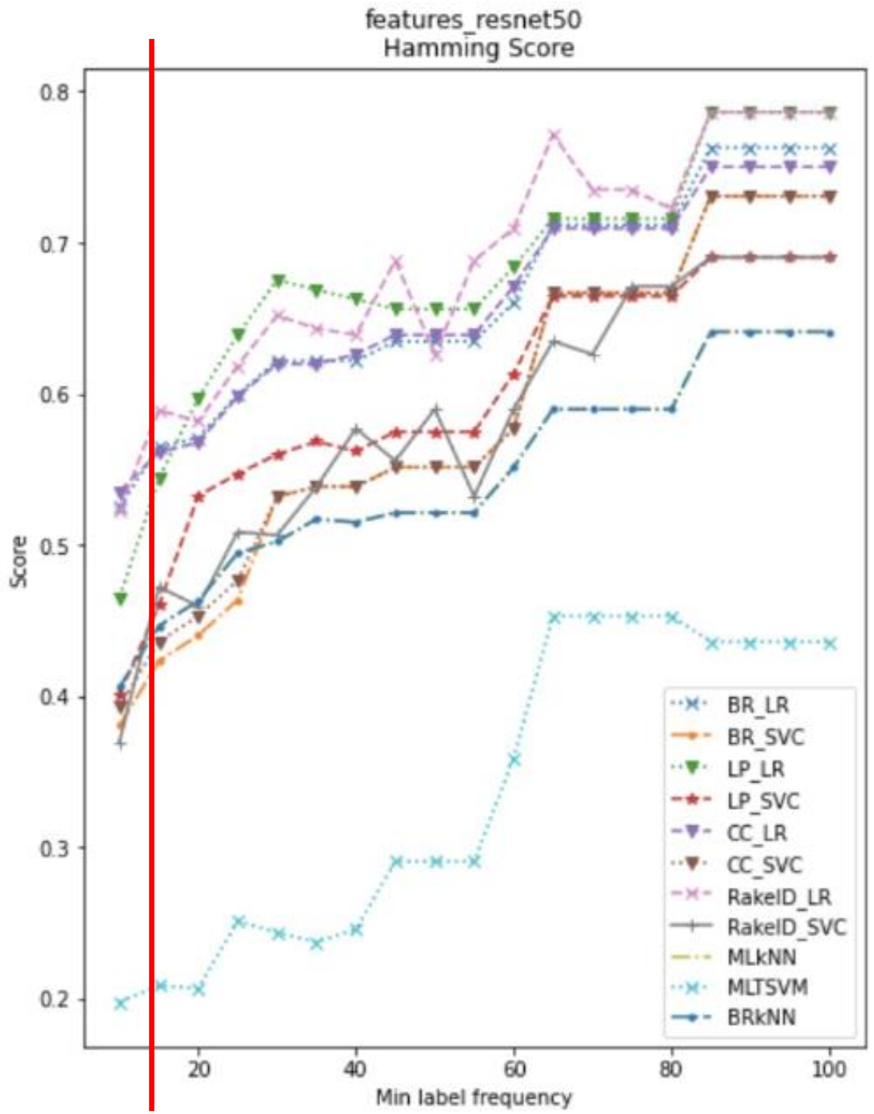
- It is then reasonable to study it's results in depth.



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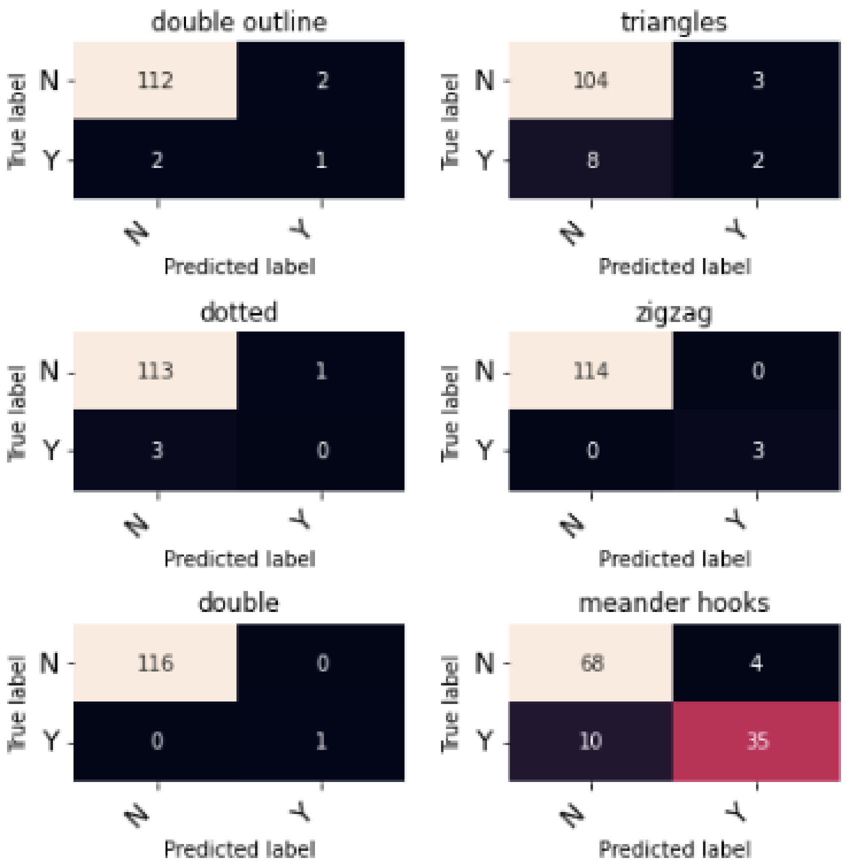

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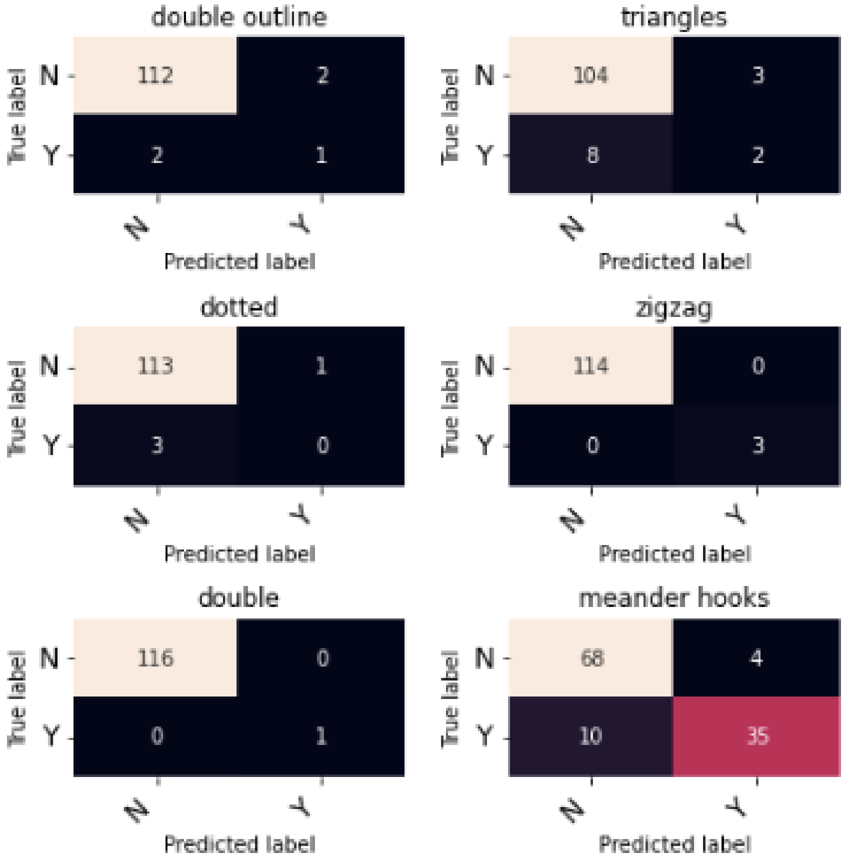

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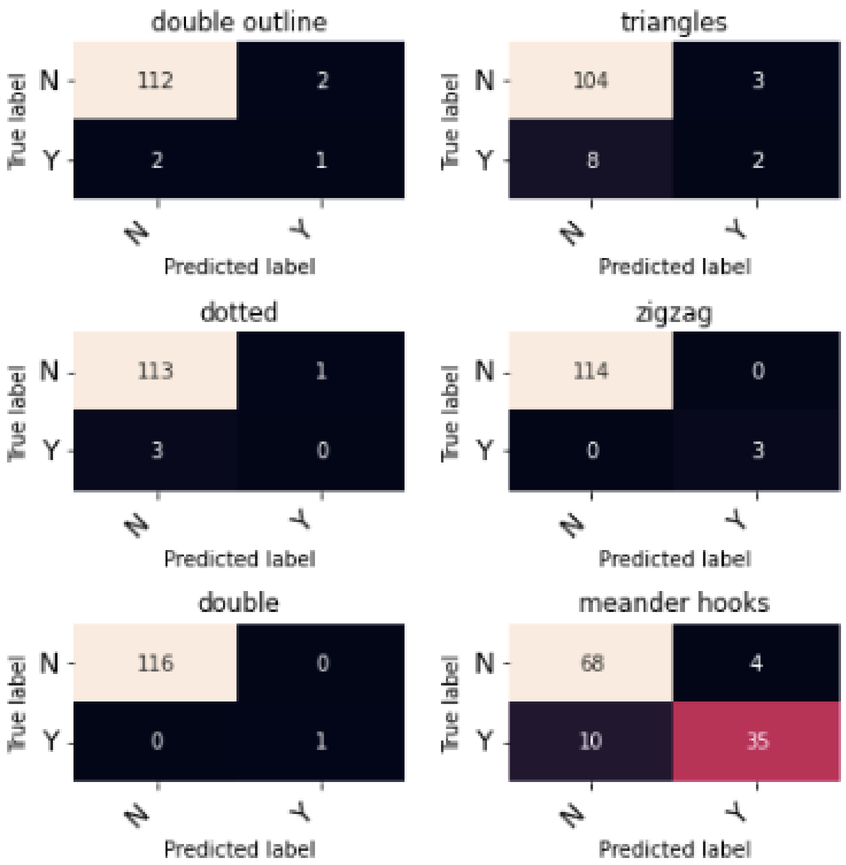

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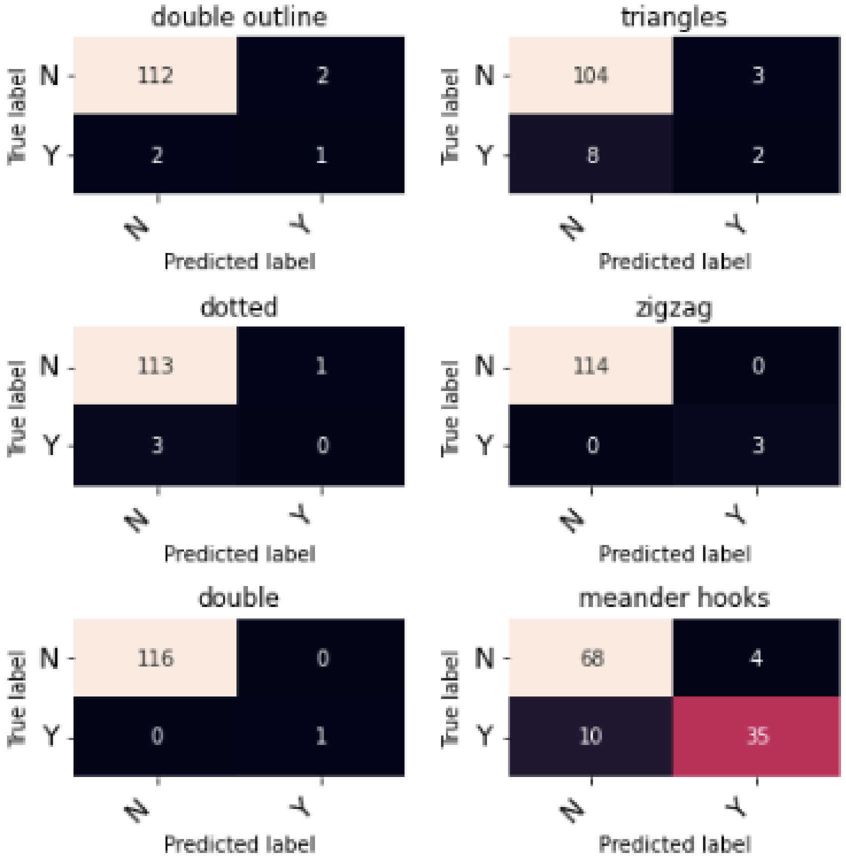
- We note that approximately 95% of classifications fall into true negatives.
- This shows an exaggerated disproportion between negative and positive cases for each label. We assume this happens both in test and training.
- As consequence, the algorithm is managing to **learn correctly when a pattern should not be tagged with a certain label,** but **not in the opposite case**: when the label correspond to that pattern.



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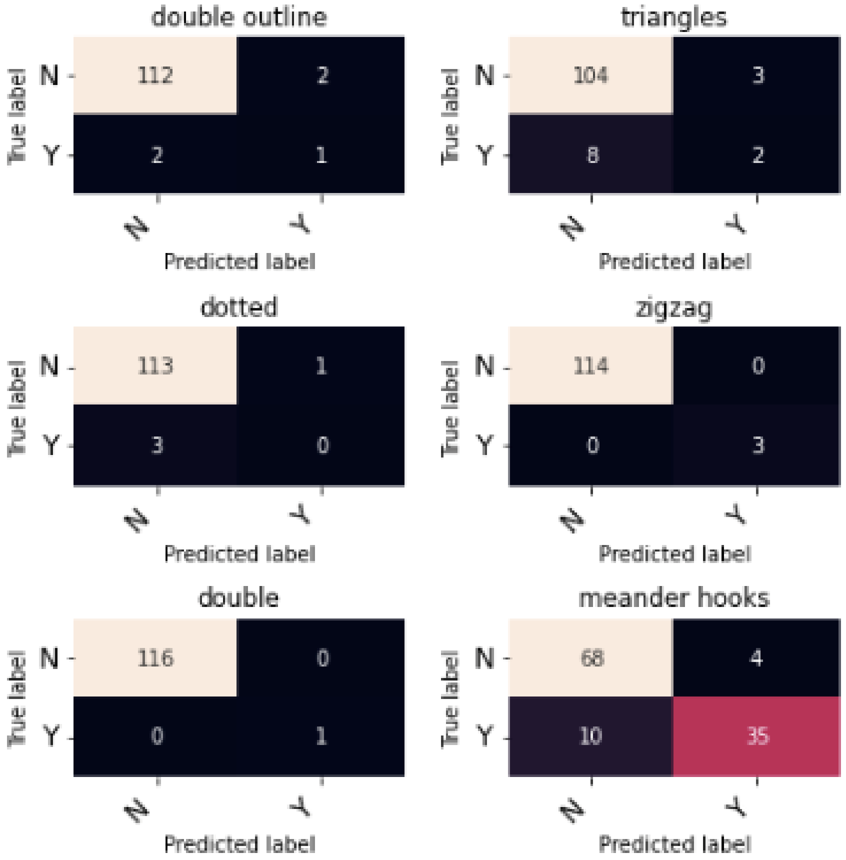
- The already mentioned low label density,
- A poor construction of training and test set.



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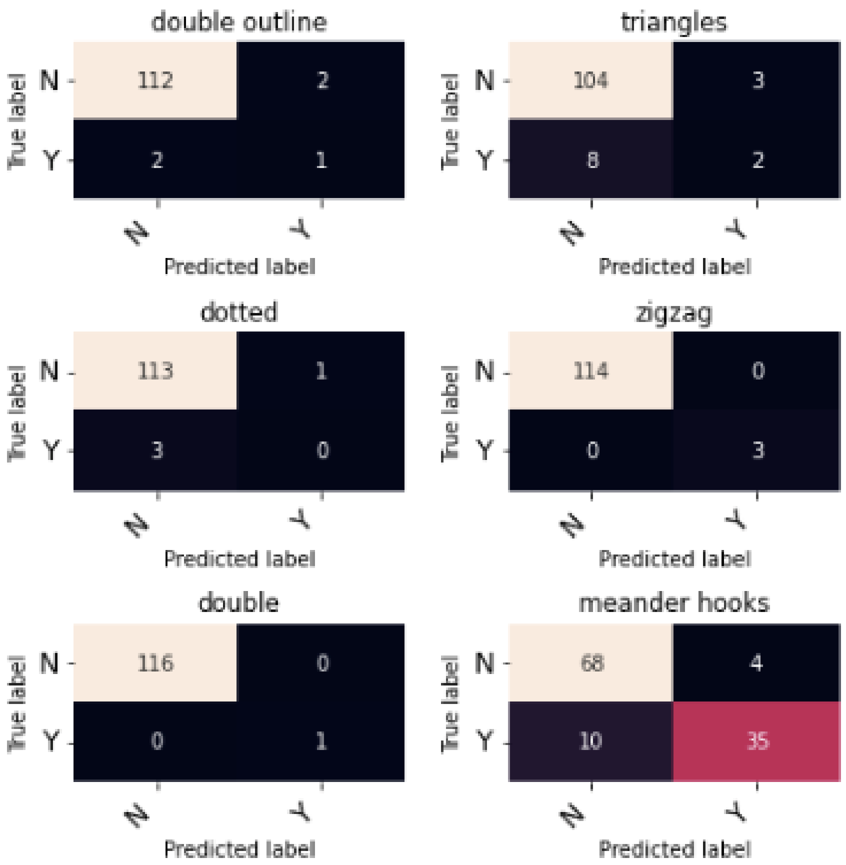
However, since we know that label density is extremely low, we can assume that the difficult lies there. This way, the problem is in the data set itself.



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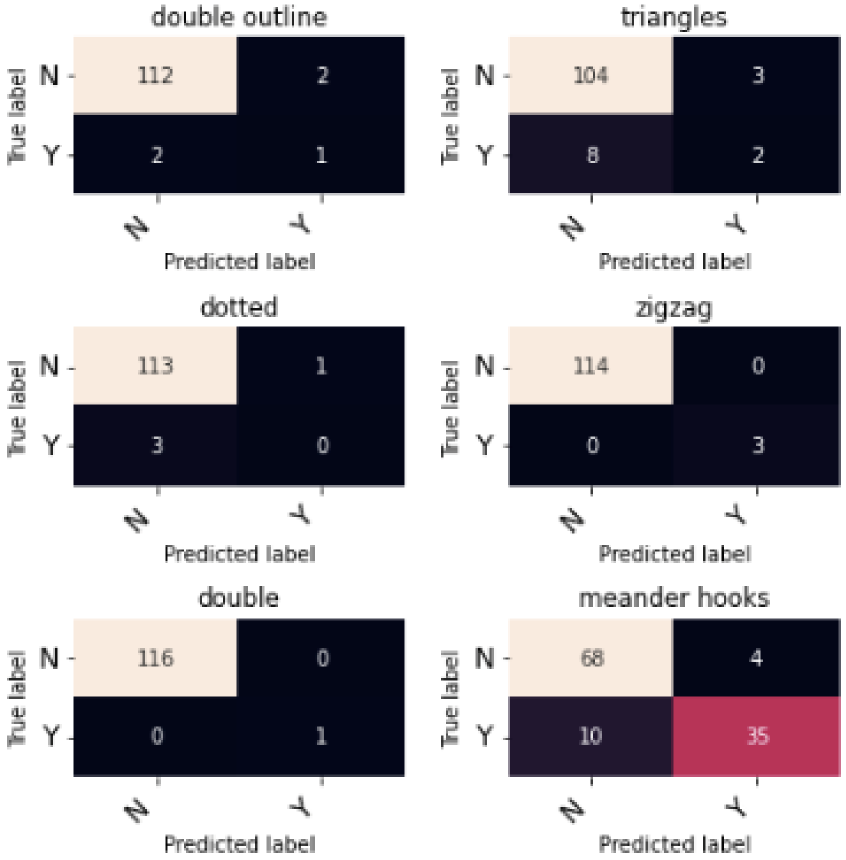

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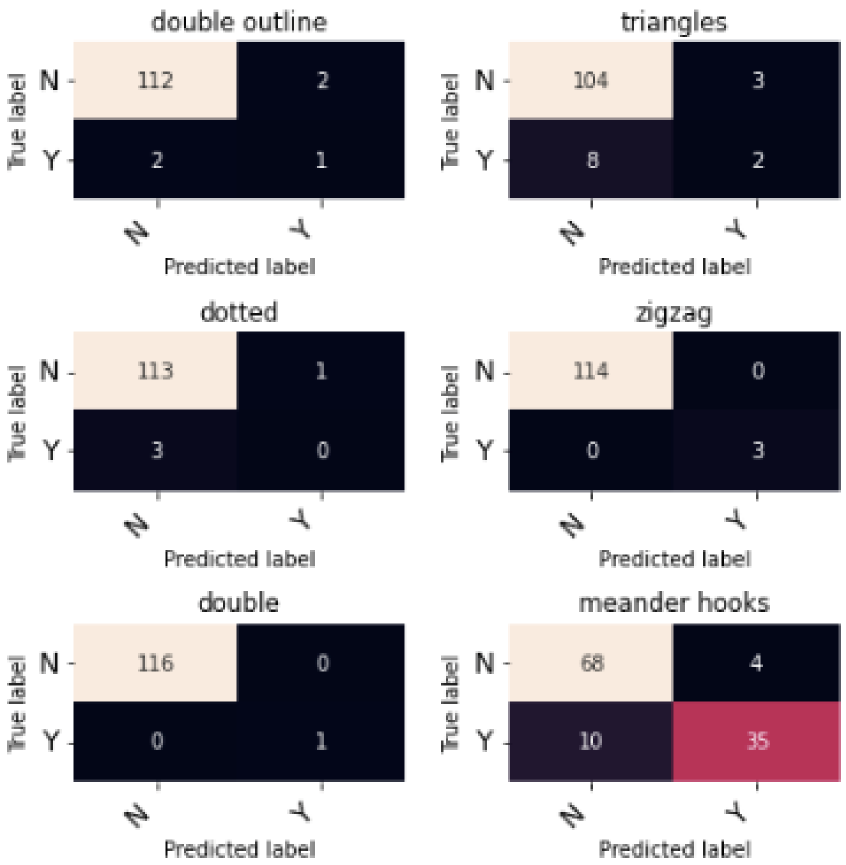

9. Future work

We detected that one way to improve the data set is by **homogenizing the labels**. This to treat some undesirable cases:

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This way we could reduce the number of single-event labels, as well as increasing the number of labels per pattern.

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- **The need to define to what level we will prune the problem.**
  - Bearing in mind that the more we can, the easier the problem is… But less interesting as well.
- **Investigate techniques and apply them to labels in order to improve the data set.**
  - We need to increase the label density to get better results.

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