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Pattern Recognition and Artificial Intelligence Group

Can patch selection heuristics enhance layout analysis of music scores?

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- **Preservation** and **accessibility** of music scores are possible by means of **Optical Music Recognition (OMR) systems**.
- This paper focuses on **Layout Analysis (LA)**, a process in OMR that **classifies each pixel** in different layers of information.
- The trend is to use neural networks at the expense of the **high cost of manual labeling**.
- **Objective**: reducing the amount of labeled data.
- **Proposal**: labeling a portion of an image, selected according to a **specific criterion**.

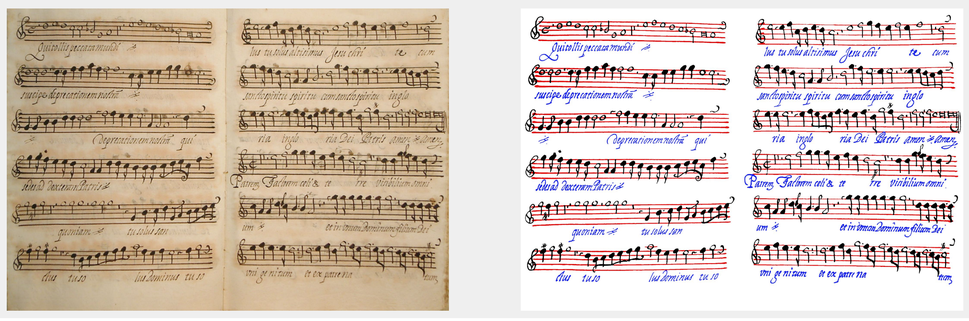


Fig. 1: Example of LA for an input image to detect staff lines, text, music symbols and background.

Methodology

We use an existing few-shot method for LA as our basis, called **Few-shot Selectional Auto-encoder (FSAE)**:[1]

1. Manual partial annotations.
2. Extracting random patch samples.
3. Training the model with the random samples.

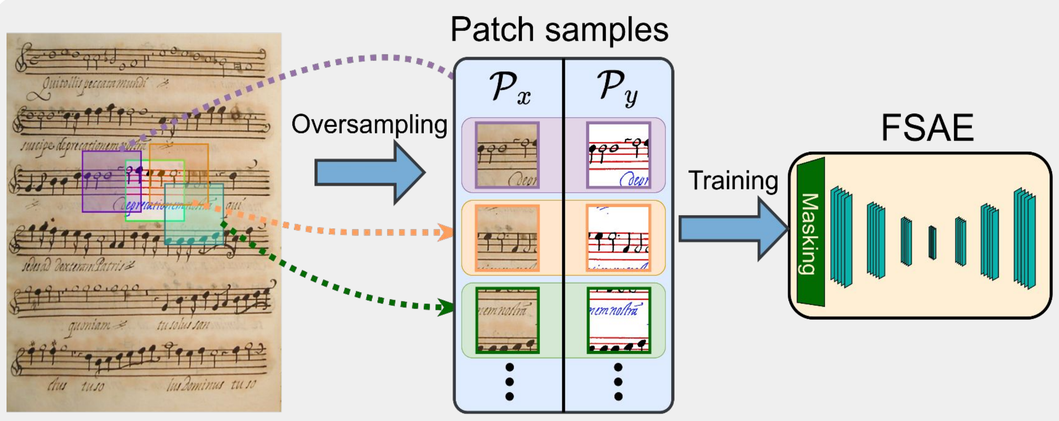


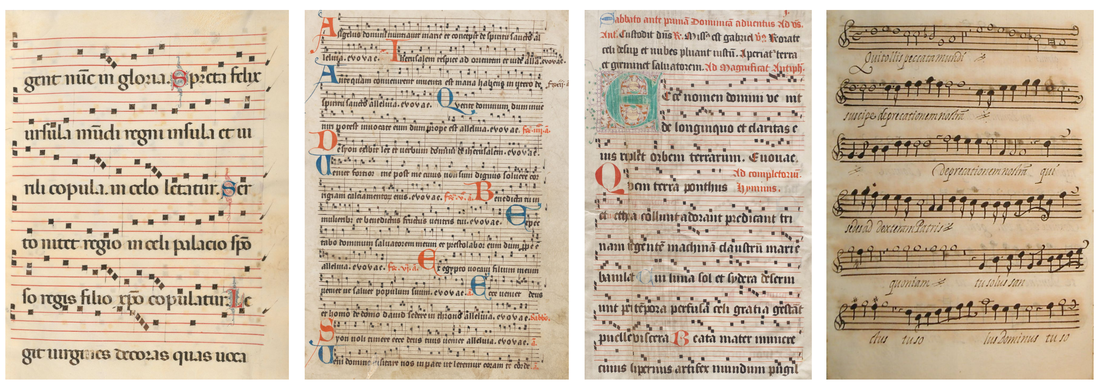
Fig. 2: Scheme of the few-shot method in which we based.

We study how the selection of an image portion (**step 1**) affects the FSAE's training with different selection policies:

1. Random selection.
2. Sequential selection.
3. Ink-rate selection.
4. Entropy-based selection.

Experiments

Corpora



a) ***MS73*** b) ***Einsiedeln*** c) ***Salzinnes*** d) ***Capitan***

Fig. 3: Examples of the corpora considered for experiments.

[1] *Castellanos, Gallego, Fujinaga: A few-shot neural approach for layout analysis of music score images. In ISMIR Conference (2023)*

Results and analysis

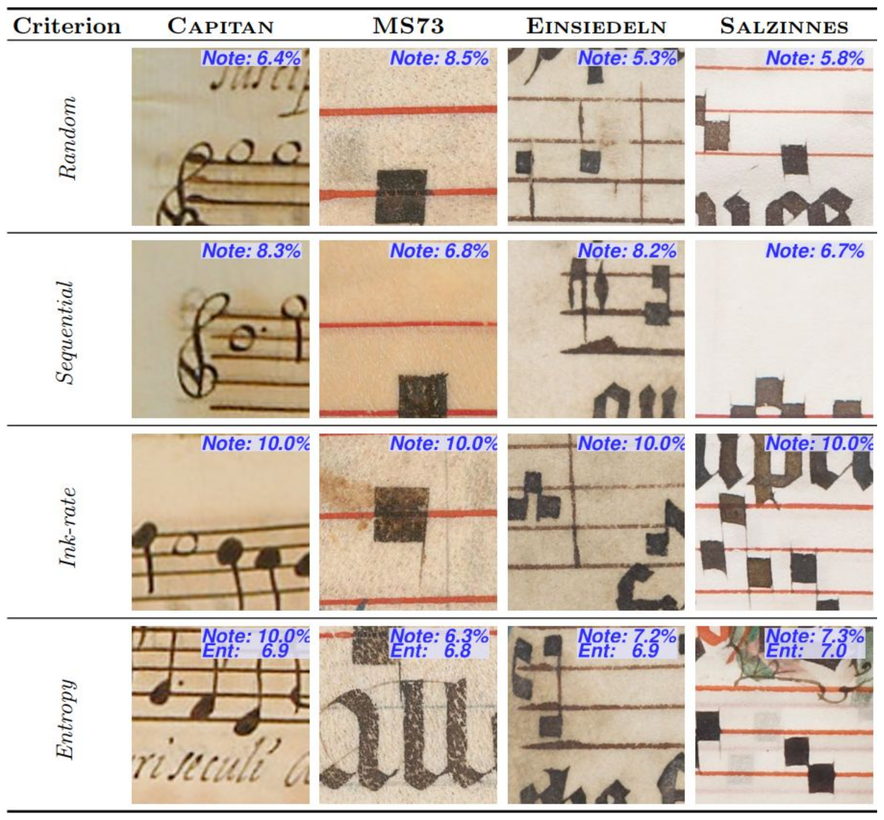


*Fig. 4: Examples of selected patch samples according to a specific criterion for the **Notes** layer.*

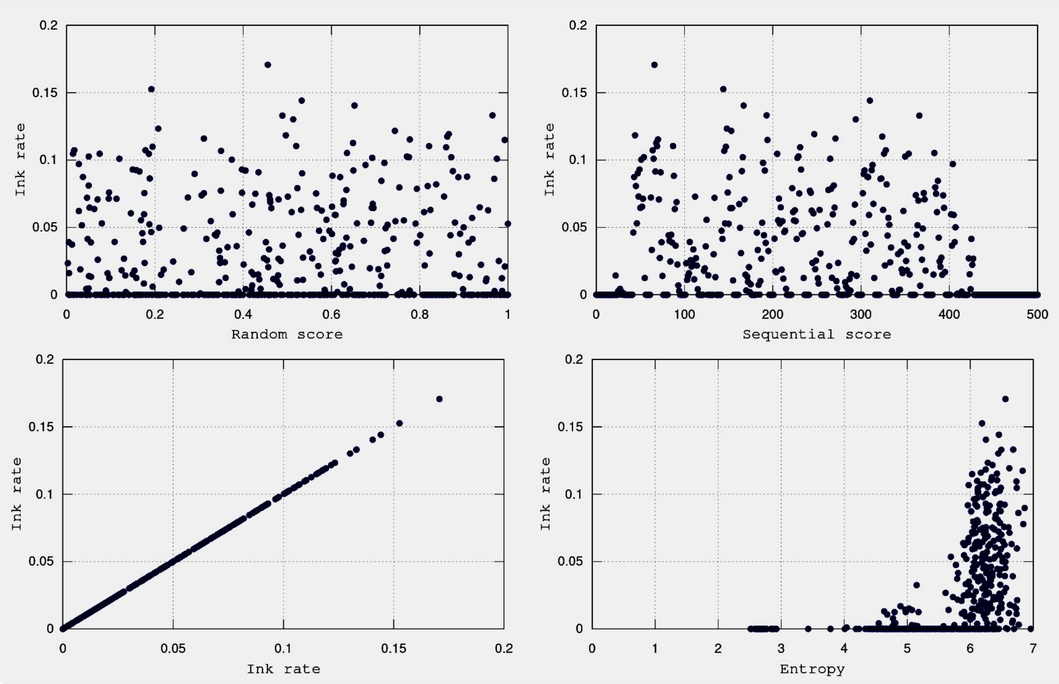


*Fig. 5: Analysis of the ink rate levels for the **Notes** layer according to the selected policy.*

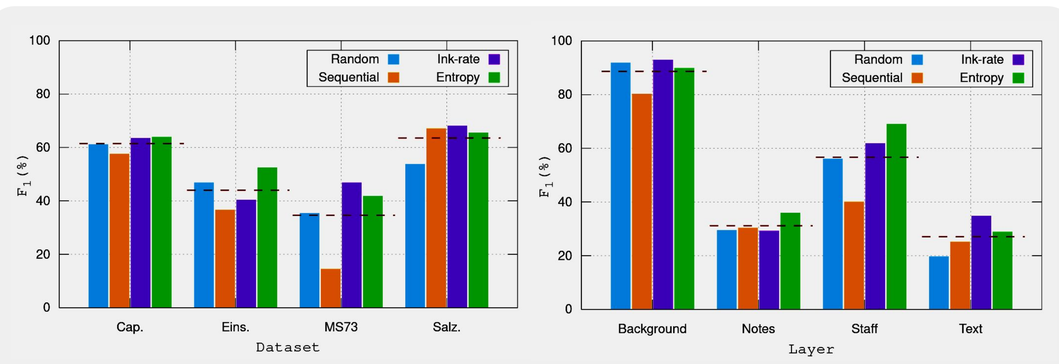


Fig. 6: F_1 results for the four selection policies. Dashed lines denote the average result.

Metric	Random	Sequential	Ink-rate	Entropy
F_1 (%)	49.2	43.9 $^{-5.3}$	54.6 $^{+5.4}$	**55.9** $^{+6.7}$

Tab. 1: Average F_1 (%) results for each patch selection method. Superscript values denote the percentage improvement with respect to the random method.

Conclusions

- Strategies based on entropy and ink rate are the most effective.
- Sequential and random do not consider the amount of information, resulting in lower performance.
- On average, entropy seems to be the best option with a 6.7% improvement in F_1 score, but not always.
- Other strategies should be studied.

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