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Artificial colorization of digitized microfilms: a preliminary study

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Abstract

A lot of available digitized manuscripts online are actually digitized microfilms, a technology dating back from the 1930s. With the progress of artificial colorization, we make the hypothesis that microfilms could be colored with these recent technologies, testing *InstColorization*. We train a model over a new dataset of 18 788 color images that are artificially gray-scaled for this purpose. With promising results in terms of colorization but clear limitations due to the difference between artificially grayscaled images and "naturaly" grayscaled microfilms, we evaluate the impact of this artificial colorization on two downstream tasks using *Kraken*: layout analysis and text recognition. The results show little to no improvements which limits the interest of artificial colorization on manuscripts in the computer vision domain.

> Many low resolution digital scans of microfilms exist. These are surrogates of surrogates. They can still be (and are) profitably used, for example to corroborate a particular reading. I am however skeptical of using them as a single source for making an edition. Perhaps, indeed, 99% of a manuscript can still be deciphered by using them, but it is about that 1% of cases in which the scribe fumbled a bit with his pen and it is unclear what the word reads. In those 1% cases, you do not wish to have a low-resolution, black and white reproduction of a reproduction as your sole witness
>
> L. W. C. van Lit [2019]

I INTRODUCTION

In the digital age, and specifically in the last couple of years with the pandemic, transcribing using digital surrogates has become a common way to work through the edition of medieval works. However, if the technology of high definition and color digital photography is much preferred for these goals, we still often encounter microfilms of ancient manuscripts. In the late 1920s and early 1930s (Nicoll [1953]), the microfilm technology allowed for the constitution of early collections of manuscripts' surrogates. These collections, first aimed at facilitating the access of remote manuscripts (Stevens [1950]), was also pursued for other reasons such as preserving manuscripts in the context of the Second World War (Project [1944]). In France, the "Institut de Recherche en Histoire des Textes" (IRHT) had started photographing manuscripts first, moved to microfilming until digital photography's quality became good enough to switch technology (Holtz [2000]). With an abundance of microfilms, while transitioning to color capture, cultural heritage institutions have made digitized microfilms available to the wide audience through platforms such as Gallica at the bibliothèque nationale de France.

Scanning microfilm implies lower risks[1] and as such lower costs that it is a quicker way to build a first online collection. As a matter of fact, in 2001, the cost of microfilm digitization was ten times lower than the one of color digitization (Council on Library & Information Resources [2001]). As of 2021, while microfilming scans are generally clearly priced, such as the pricing at the New York Public Library (150$ per reels), digitization of old, fragile and rarer books are mostly quoted on demand, or rated per day or hour of work (350$ at NYPL)[2]. Until cultural heritage institutions have the ability and time to digitize all their manuscripts in color, for many works, the only available version remains digitized microfilms. But there are situations where this will not be possible: unfortunately, there are manuscripts whose only surviving exemplars are microfilm surrogates, such as many manuscripts from the *bibliothèque municipale de Chartres* whose microfilms were produced by the IRHT before they were destroyed during WW2[3]. For these manuscripts, their original colors are lost.

Nowadays, with the recent development of deep learning colorization, there is hope for the ability to bring back some color to these old microfilms. Colorizing deep learning networks using generative adversarial networks (GAN) or other architectures showed the ability for colorizing so-called black and white photographs. Colorizing more than 100-year-old pictures of ancestors and villages has been widely popular in news media and social ones - enough for companies to create business around it[4] -, and it provides an interesting testing ground for computer vision. The computer science side of this work has heavily outweighed the humanities and social sciences side in this domain: most if not all papers on this topic follow the same dataset-new model-output based architecture with little to no space for questioning the results[5]. And if this technology of colorization seems to be of more interest for outreaching strategies of cultural heritage institutions than for researchers, the bias behind these colorization has been clearly shown, with ethical questions raised by many: people tend to be whitened in specific contexts (Goree [2021]), colorful local dresses made grayish or dulled (Katz [2021]). Using these colorization to study the past would raise epistemological questions more than they would provide insight. However, in the context of manuscripts, if the output cannot be taken as the real colors that the manuscript had, this colorization might also provide a better and clearer image of manuscripts, by automatically balancing colors and providing more than one color space and enhance the efficiency of downstream tasks for text acquisition. This can be of interest for libraries and the likes in terms of outreaching, while disclaiming the same limitations as the one for photographs.

In order to evaluate the effectiveness of deep learning colorization tools on digitized manuscripts, we tested *InstColorization* from Su et al. [2020], a tool specifically designed for this purpose[6]. The paper will begin by outlining the experimental setup, which includes the creation of new

[1]Destroying or damaging a manuscript would lead to great loss in terms of knowledge, while harming microfilms most often simply represents a delay for the presence of the original manuscript online.

[2]https://www.nypl.org/help/get-what-you-need/bookscanning

[3]On 26 May 1944, the town hall of Chartres containing the library was bombed by the American air force. “45% of the manuscripts were totally destroyed”, while the remaining survived in varying states (https://www.manuscrits-de-chartres.fr/fr/incendie-et-ses-consequences)

[4]See the services of MyHeritage for example, https://www.myheritage.fr/incolor, which states in French “Import dull black and white picture and be *fascinated* by the results”. Italic for emphasize is ours.

[5]See Joshi et al. [2020], Boutarfass and Besserer [2020], Chen et al. [2018]. We must note that for the later, the question of dataset bias was taken into account at least for the purpose of colorizing a specific and “new” domain, Chinese black and white films

[6]We emphasize the term "tool" as we believe that reusability is of utmost importance. Although there may be other model architectures that offer better results, we chose InstColorization due to its reusability, which includes its openness, well-documented nature, and ability to apply to full-scale images.

datasets for colorization, manuscript segmentation, and handwritten text recognition (HTR). We will then present our findings based on the analysis of a sample of microfilms, examining both the resulting colors and the impact of this post-processing step on layout segmentation and HTR. In the concluding section, we will provide a roadmap for future research, which includes a more comprehensive evaluation of the effect of colorizing microfilms on readers, as well as the creation of new datasets. Furthermore, we will discuss the strengths and limitations of our output.

II METHOD

We design an experiment that aims at both producing colorized microfilms and evaluating the impact of colorization on other computer vision tasks. We train a model for colorization using a new dataset for the paper which we evaluate qualitatively. Then, we train handwritten text recognition models alongside layout segmentation ones with *Kraken* which we evaluate quantitatively or qualitatively when the first is not possible.

2.1 Colorization

2.1.1 Dataset

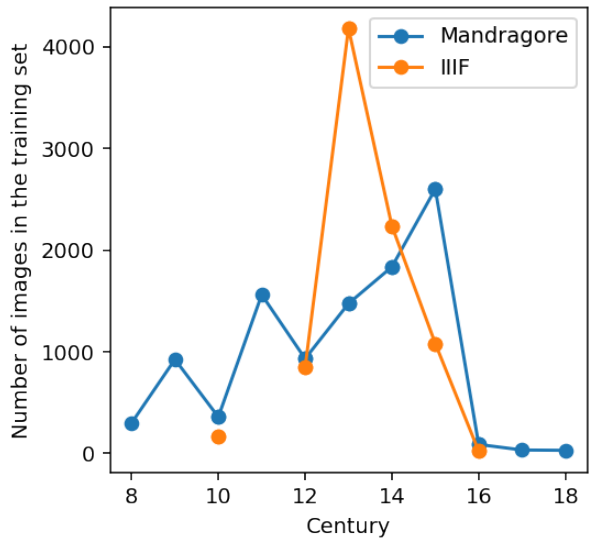


Figure 1: Distribution of pictures per century. IIIF pictures are drawn from manuscripts and mostly come with other folios. On the other hand, Mandragore data are more likely to be taken from different original materials.

In order to train the colorizer, we offer a dataset that is built around 5 cornerstones:

- It is chronologically centered around the Middle Ages, from the 8th century to the 16th (see Figure 1).
- It is focused on west European manuscripts.
- It is balanced in accordance with overall numbers of surviving manuscripts while not allowing a standard deviation of the population per century too high, allowing the resulting models to be generic and fine-tuned if necessary.
- It must contain both highly decorated pages and very simple ones.

This results in an 18 788 files-large dataset made from two data sources. 8 660 digitized pages or cover in color from 50 different manuscripts mostly coming from the *Gallica* and *e-Codices* platforms, which might or might not display decorated elements, illustrations and texts

(hereafter conveniently named as *IIIF* in figures). In this part of the dataset, 3 "manuscripts" were specifically chosen for the diversity of their content over time as they were composite books made of manuscript fragments and display overlap of papers (see the second row of Figure 2). Some of these also marginally contain printed content. For the second part of the corpus, we used the *Mandragore* database (Aniel [1992]), a dataset whose aim is to collect and annotate illuminations and decorations in general in manuscripts. This part is composed by 10 128 pictures randomly drawn from the occidental manuscripts[7], distributed over 2 612 different original codices. Those pictures can be complete or cropped page centered around a specific illustration. 1 903 manuscripts of the 2 612 are represented by a single picture, 23 manuscripts have more than 50, 3 have more than 100. The overall dataset presents paper colors (including shades), black ink for the text; as far as colors go, red and blue are dominant in drop capitals, decorations, illustration and rubricated texts, green and gold are present in the dataset in a smaller fashion.

Figure 2: First row: random examples of pictures from the Mandragore part of the training dataset. Second row: 2 pages from composite books in the IIIF part of the dataset and 3 random one from "original" manuscripts. Images display ratio are changed for the purpose of displaying multiple example on the same page.

2.1.2 Training Set-up

Our primary goal is not to develop a colorizing network, but rather to assess its performance on full-scale images, specifically microfilms. To achieve this, we require colorizing tools with three key capabilities: clear documentation in a paper, easy installation with well-defined dependencies, and the ability to make predictions, rather than just compute scores, on full-scale images. Given these predicaments, we reuse the tool from "Instance-aware Image Colorization" (Su et al. [2020]), thereafter *InstColorization*, which provides a simple, detailed and reusable way to train and fine-tune models. *InstColorization*[8] is built around 3 colorization networks, each trained independently, as well as an object detection one (see Figure 3) which is not directly trainable with the available code in the repository but reuses an external pre-trained parameter file.

The training is run with the same parameters from the original scripts of the paper with half precision to reduce training time: the final training time takes a little under 78 hours with a RTX2080TI GPU spanned over 150 epochs for both the full and detected object instances and 30 epochs for the fusion model with 256x256 pixels resized input. The network itself is

[7]Randomness only affects the selection inside group of centuries.

[8]https://github.com/ericsujw/InstColorization

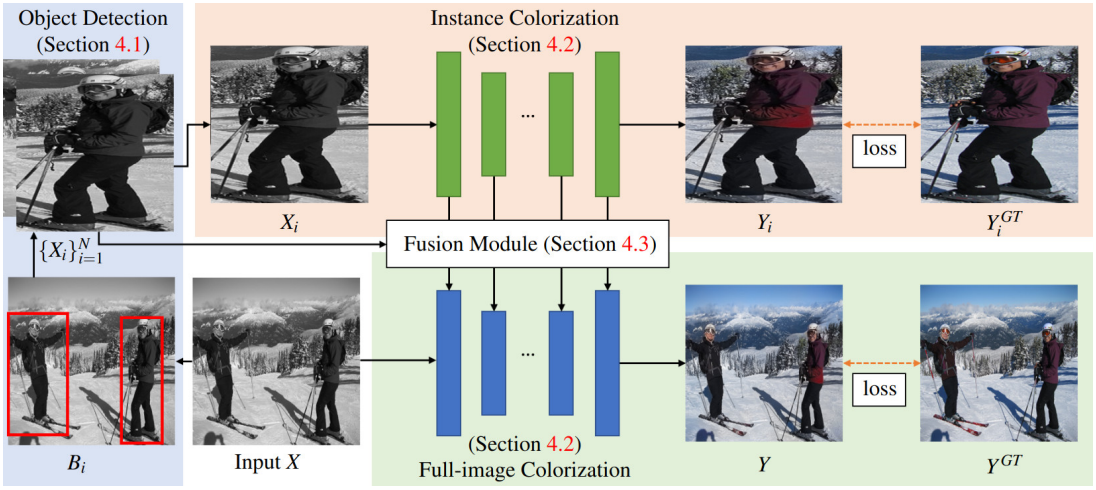


Figure 3: Method overview drawn from "Instance-aware Image Colorization" (Su et al. [2020]). An image is colorized entirely (4.2, bottom) while each detected object in it (4.1) is also colorized independently (4.2 up). The final result is the output of a fusion networks (4.3), which takes the output of previously colorized objects and the full-image in order to produce a general colorized output.

responsible for grayscaling images and we do not tweak the software outside of its way of loading images and their detected objects[9]. The final dataset presented earlier is actually the result of a filtering by the model when the object detection model did not yield any result for detected objects: the first version of our dataset was as large as 27 415 files, but 8 620 of its members were rejected by the object detection method[10].

2.2 Text acquisition tasks

2.2.1 Dataset

For all computer vision tasks, our dataset is based on the CREMMA Medieval dataset (Pinche [2021a]), built with eScriptorium (Kiessling et al. [2019]), an interface for HTR ground truth production, and *Kraken* (Kiessling [2019]), an HTR and layout segmentation engine. It is composed of seven Old French manuscripts written between the 13th and 14th centuries (see Table 1), mainly scanned in high definition and color except for one manuscript (Vatican) which is a black and white document, most probably binarized by the holding institution. As the dataset is made from pre-existing transcriptions, the sample size is very different from one source manuscript to the other. The basis of the dataset is composed of a graphemic transcription (see after for the transcription principles) of *La Vie de saint Martin* and of the *Dialogues sur les vertus de saint Martin* from the hagiographic collection *Li Seint Confessor* of Wauchier de Denain (Pinche [2021b]). It is supplemented with carefully aligned data from other projects: transcriptions[11] of *Chanson d'Otinel* (Camps [2017]) from the Geste project[12], transcription of *Manuscrit du Roi* for the Maritem project[13], crowdsourced transcriptions of the collaborative projects of the Standford Library: Image du Monde (BnF. Bibliothèque de

[9]We simply made sure that files containing dots such as `x.y.jpg` would not be collapsed into single files with the original implementation looking for dot as separators between file extension and filenames (`x.jpg`)

[10]This advocates for training object detection models on such materials in the future if *InstColorization* were to be used for this task.

[11]Cologny, Bodmer, 168 and Vatican, Reg. Lat., 1616

[12]https://github.com/Jean-Baptiste-Camps/Geste

[13]Produced by V. Mariotti within https://anr.fr/Projet-ANR-18-CE27-0016

l'Arsenal. Ms-3516[14]) and the Bestiaire de Guillaume le Clerc de Normandie (Bibliothèque nationale de France fr. 2442[15]), and a few folios transcribed in relation with the new project of editing *Les Sept Sages de Thèbes*[16].

As the data come from different projects, it is standardized to strengthen any layout segmentation and HTR model[17]. The layout segmentation follows the Segmento ontology[18], separating the main column, margin, numbering, drop capital. We chose a graphemic[19] transcription method to have a sign in the image corresponding to a sign in our text: all the abbreviations are kept, and *u/v* or *i/j* are not dissimilated. But we exclude graphetic transcription method which distinguish different forms of letters (*e.g.*, *s* and *long s*), considering that it would reduce the number of examples per character, as well as highly impact digital transcription time and introduce even more disagreement between transcribers[20]. Finally, the spaces in the dataset are not homogeneously represented in the ground truth text annotation, with transcriber reproducing the manuscript spacing while others use lexical spaces. It must be stressed that spaces are the most important source of error in medieval HTR models[21]: for the model Bicerin (Pinche [2021a]), spaces represent 33.9% of errors[22]). In the current state of the art of HTR, some workflows (Camps et al. [2021, 2020]) chose to solve this problem with a secondary tool such as Boudams (Clérice [2019]), a deep learning tool built for word segmentation in Latin or Medieval French.

Manuscript Identifier	Date	Pages	Columns	Lines	Color
BnF, Arsenal 3516	13th	10	40	1991	Yes
BnF, ms fr. 22549	14th	3	9	411	Yes
BnF, ms fr. 24428	13th	20	40	1295	Yes
BnF, ms fr. 412	13th	49	98	4551	Yes
BnF, ms fr. 844	13th	18	36	1026	Yes
Cologny, bodmer, 168	13th	22	44	1927	Yes
Vaticane, Reg. Lat., 1616	14th	41	41	1726	No
Total		163	308	12927	

Table 1: CREMMA Medieval dataset statistics. Sample pictures are available in the appendix, Figure 14.

Of these, the microfilmed manuscripts (see Table 2) all dating from the end of the 13th century or the 14th century and written in Old French are kept for evaluating performances as our test dataset[23]. They all come from hagiographic collections and present dialectal differences. In all these sources, the layout is similar and the writing is easy to read with rare but present abbreviations. The text is organized in 2 columns per page and in 40 or 42 written lines if there is no decoration. The scanned microfilms each present two pages. Each of them has some

[14]https://fromthepage.com/stanfordlibraries/image-du-monde-en-vers

[15]https://fromthepage.com/stanfordlibraries/guillaume-le-clerc-de-normandie-s-bestiary

[16]Manuscript, BnF, fr.22550, this project just started in Geneva under the direction of Y. Foehr (Geneva) and S. Ventura (Brussels).

[17]To ensure the quality of the data, continuous integration workflow were put in place checking the segmentation vocabulary (HTRVX, Clérice and Pinche [2021b], a XML schema validator), but also the homogeneity of the signs of the characters used in the dataset through a list of authorized signs and translation table with ChocoMufin, Clérice and Pinche [2021a]

[18]https://github.com/SegmOnto/examples

[19]We use the terminology graphemic (*graphématique*) and graphetic (*allographétique*) following D. Stutzmann definitions, see Stuzmann [2011]

[20]Distinction of specific forms can be difficult and would require only expert transcribers for such corpora

[21]And it definitely happens that editors disagree between agglutinated and split forms of words.

[22]The same issue was found on Transkribus and a previous version of Kraken two years before (Camps et al. [2020]

[23]All the microfilm scans come from Gallica and all the original manuscripts come from French manuscripts department of the bibliothèque nationale de France (BnF).

peculiarities: marginalia, interlinear lines, running titles, rubrics, drop capitals or decorations that can make segmentation difficult. In our case, the manuscript fr. 411, an unfinished manuscript, presents the case of a missing capital and decoration and shows instead white spaces waiting to be illuminated.

Manuscript ID	Ms, fr. 13496	Ms, fr. 17229	Ms, fr. 411
Date	Late 13th c.	Late 13th c.– early 14th c.	14th c.
Annotated text	Saint Jerome's Life	Saint Lambert's Life	Saint Lambert's Life
HTR Ground Truth Locus	fol. 245v - fol.246r	fol. 163v - fol.164r	fol. 125v - fol.126r
No. of Document	1	1	1
No. of transcribed columns	4	4	4
No. of transcribed lines	159	160	150
Segmentation Ground Truth Locus	fol. 245v - fol.248r	fol. 163v - fol.169r	fol. 125v - fol.131r
No. of Document	3	6	6
No. of Segmented Columns	12	24	24
Decoration	yes	yes	no
Drop Capital	yes	yes	no
Rubric	no	yes	no
Running Title	no	no	yes
Numbering	yes	yes	yes
Marginalia / interlinear	yes	no	no

Table 2: Presentation of the digitized microfilmed manuscripts. Documents are double paged, composed by the verso of a folio and the recto of the following one.

2.2.2 Training Setup

As *Kraken* is able to make use of color channel - since a couple year - at training and prediction time for both layout and HTR, avoiding any binarization or gray-levelling at the preprocessing step (Kiessling [2020]), we use *Kraken* for all our training and evaluation steps[24]. We train two different models for the segmenter: one for lines where they are grouped into a single category (numbering, rubricated and normal - *Default* in Segmonto - lines are merged into a single class), one for regions but only for main regions, as preliminary expriments show that illustrations and drop capital are not well recognized yet given the size of this dataset. We train models for 50 epochs and keep the best model of all across all metrics.

For HTR, we train models over two versions of the same training and evaluating sets from the CREMMA project (microfilms excluded): in one version, we use all the available data (thereafter called BW models), in the second (NOBW models) we withdraw the black and white manuscript (Vatican, Reg. Lat., 1616). We run training procedures for HTR models with *Kraken* with and without augmentation for each version of the corpus (BW and NOBW). After training, we take the 10 best models of each training run, summing up to 40 models in total: each combination of augment and dataset version always reaches over 90% accuracy for its 10 best models on the evaluation set.

For each computer vision task using Kraken, we use the *CREMMA Medieval* dataset with a 90/10 split for train and evaluation steps. The microfilms part of CREMMA Medieval are used as the test set, in both their colorized and original states. The segmentation test dataset only differs from the HTR one on its size: each manuscript contains more folio with up to 12 "modern pages" or 6 folios.

[24]The oldest public record we could find was the issue 117 from 2019 on Kraken's repository where Ben Kiessling provided us with the color configuration (https://github.com/mittagessen/kraken/issues/117)

2.2.3 *Test Setup*

We were not able to produce a quantitative test for the region segmentation. We could find only two existing tools for this purpose. The first one was built by PRIMA (Clausner et al. [2011]) and is working only with Windows, required a different version of PageXML from the one produced by *Kraken* as well as binarized images. The second one[25], built originally for ICDAR 2017, required images creation with various levels of colors that are incompatible with some of our data, when we have overlap of zones (Alberti et al. [2017]). We fallback on qualitative evaluation of predictions, mostly looking at difference in between both models. We understand the limitation of such an approach but must also stress the size of the test sample (less than a thirty zones) which would probably diminish the robustness of a quantitative evaluation.

Secondly, for baseline and mask evaluation, we predict segmentation with the produced model and evaluate it using the same tool[26] as ICDAR 2017 and 2019 for evaluating line segmentation (Alberti et al. [2017]), comparing segmentation results for both the original black and white microfilms and the colorized ones.

Finally, we evaluate HTR performances' gains or drops by comparing the accuracy of models on the microfilm and colorized microfilms. Each of the 40 models is used to evaluate the prediction against the original ground truth, we then compare each test result from the colorized output with the microfilm original picture so that we retrieve a delta accuracy: $\Delta = \text{Accuracy}_{Colorized} - \text{Accuracy}_{Microfilm}$.

III RESULTS

3.1 Colorization

The training output is promising in the three different training phases (see Figure 5). On the training set, the paper of the manuscript is clearly distinguished from the background, illustrations are well colorized, including gold and green that are rarer overall, illustrated capitals (such as the E and 2 Qs in the second row of Figure 5) and rubricated texts are correctly colorized.

We then applied the models on to different microfilms (lost microfilms for Chartres, test microfilms for HTR and segmentation, random microfilms from *Gallica*) as well as artificial grayscaled color digitizations. First of all, the colorization algorithm works really well on grayscale images (see Figure 6) and images without any decoration (see Figure 8): the page is correctly identified and colorized differently from any part of the background. In the context of photography artifacts present in the picture, such as what seems to be a clamp in Figure 8, the colorization might be hazardous while not affecting the overall colorization of the microfilm. For artificially grayscaled image, colors are retrieved correctly, including green and gold, and the colors do not seem to be less colorful than the original. Finally, colored inks on microfilms are variably predicted, ranging from hints of colors (see Figures 9 and 2) to probably correct but dulled colors (see Figure 8), rubricated text being the less recognized by the colorizer on our test set.

Regarding the limitations of artificial colorization of colored inks on microfilm, we make the hypothesis that the issue comes mostly from the difference in the contrast present in microfilms and artificially grayscaled images which form our training set. We confirm it by having a closer look at manuscripts such as BnF fr. 24369 whose content is both available in color and

[25] https://github.com/DIVA-DIA/DIVA_Layout_Analysis_Evaluator
[26] https://github.com/DIVA-DIA/DIVA_Line_Segmentation_Evaluator

microfilms: it is clear that the contrast ratio and color levels are extremely different between the two. Given the age of microfilms, it is not impossible that, as it was the only possible surrogate at the time, contrasts were intensified at the time of photography in order to make the content easier to read rather than trying to capture the diversity of contrasts over a full folio[27]. We reproduce similar levels of contrast on artificially grayscaled images by adjusting color levels[28] with a page from one of the manuscripts of our training set (BnF, fr. 24369) and the output is clearly as bad if not worse than the output based on the digitized microfilm (see Figure 9). Regarding this dullness of colors and the difficulty for the resulting model to address this, we make the hypothesis that introducing Contrast and Color level transformations during training might improve the robustness of the prediction: we propose a first experiment of artificially corrected microfilms using CLAHE, Posterization and JitterColors from the *Albumentations* library that shows different levels of vibrant colors, sometimes at the expanse of more important bleed-through of the verso of each page (see Figure 10). These first results show the limit of post-processing as much as they advocate for in-training grayscale transformations to allow for better prediction on microfilms as the model learn to colorize images.

[27] Also, the photographs were in black and white...

[28] We applied the following number in Gimp Color Level adjuster: Black 170, Clamp 4.25, White 255. The result is a bit darker at the border of the page, and the illustration is a little less readable

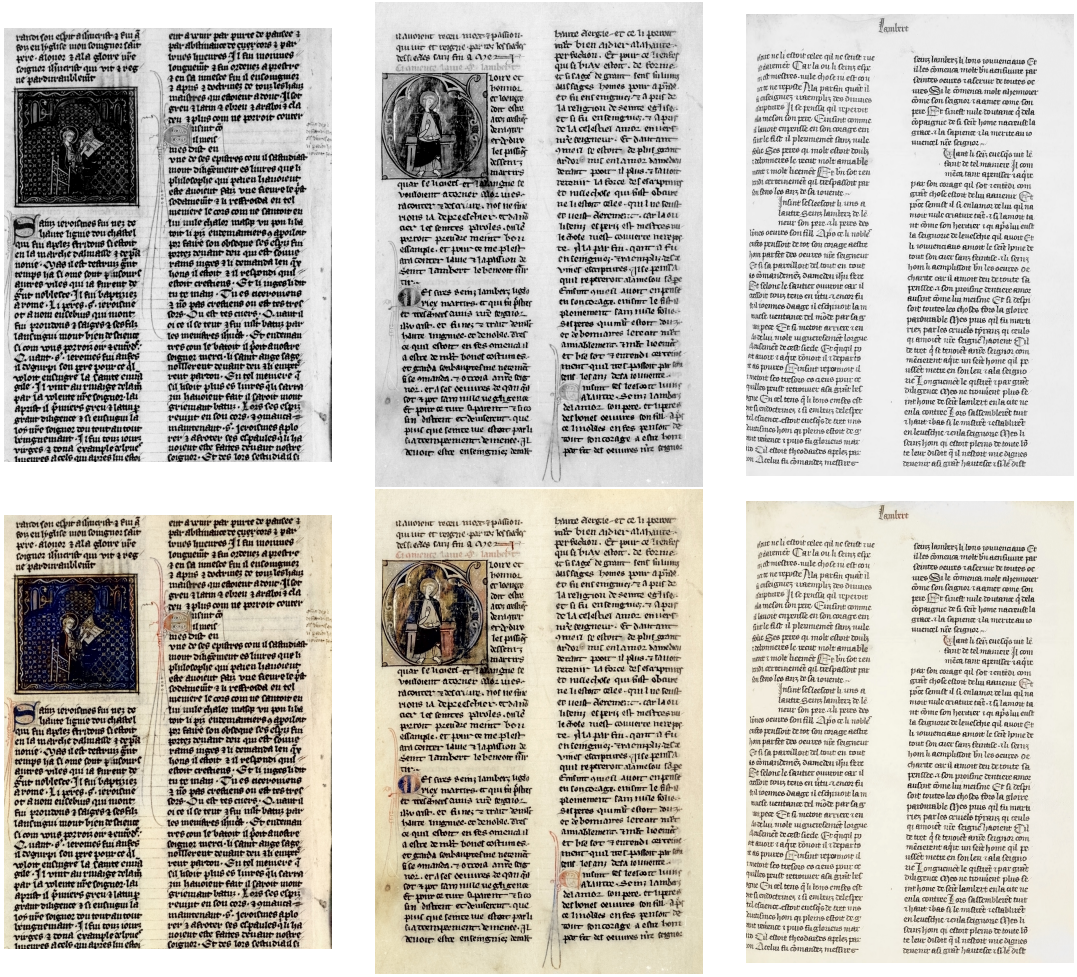


Figure 4: Partial reproduction of manuscripts BnF, ms. fr. 13496, 17229 and 411 from the segmentation and HTR test set (a single page is shown for convenience). Second row contains the colorized version. While the colorization is not perfect, we see that some patterns are recognized, namely the blue background on fr. 13496 and the dull but colorized drop capitals on the first two manuscripts.

Figure 5: Output of training in epoch 145 (instance network), 149 (full network) and 29 (fusion network on images part of the training set). The first column contains original colored images, the second automatically grayscaled ones, the last one the production from the network.

Figure 6: 13th century Latin Manuscript, artificially grayscaled digitization on the left, prediction on the right (BnF. Département des Manuscrits. français 375, 3v). This page is not part of the training dataset.

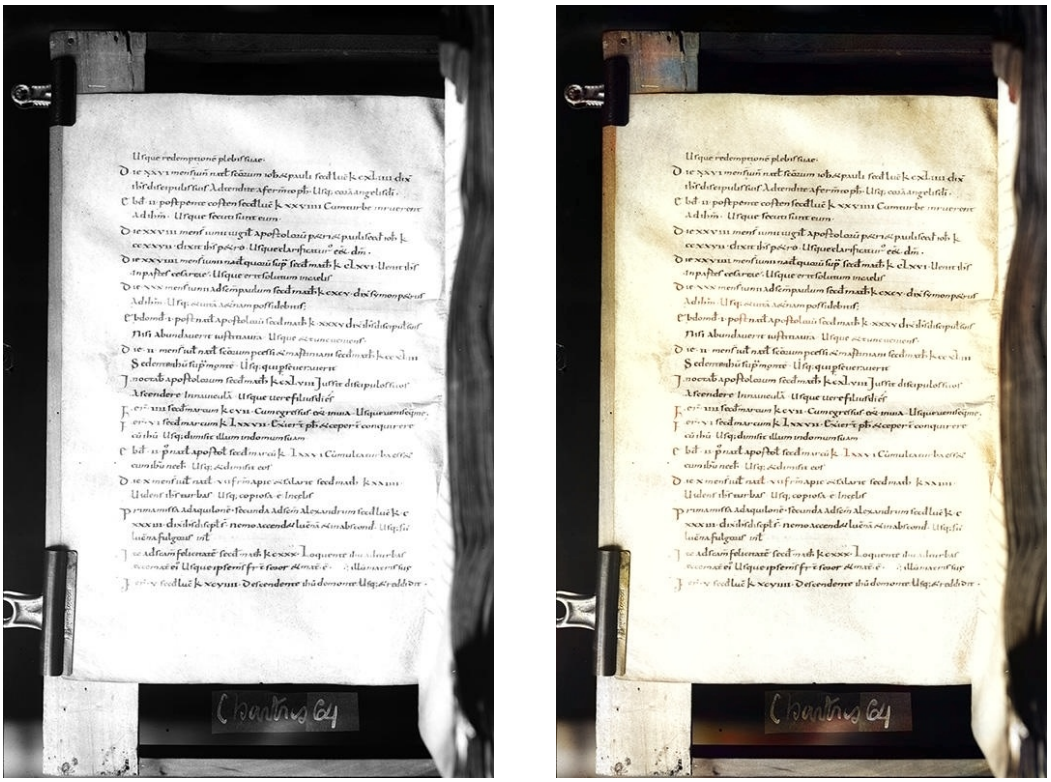


Figure 7: 9th century Latin Manuscript, lost in WWII, microfilm on the left, prediction on the right (Chartres, BM, ms. 64, unknown folio)

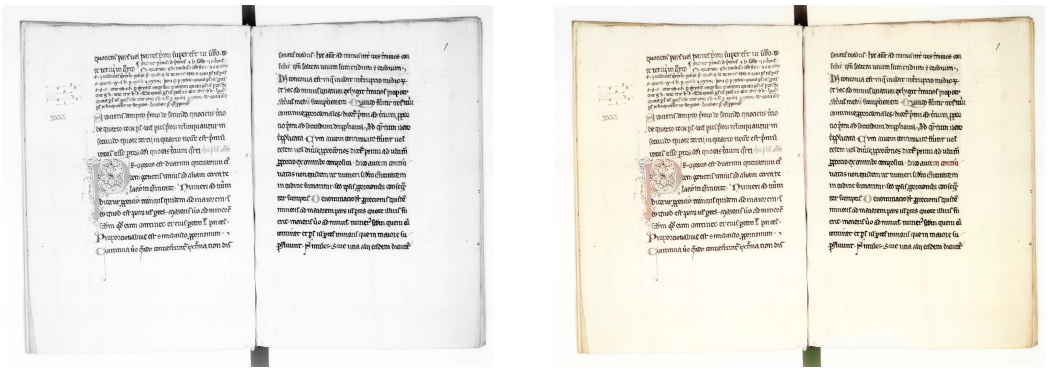
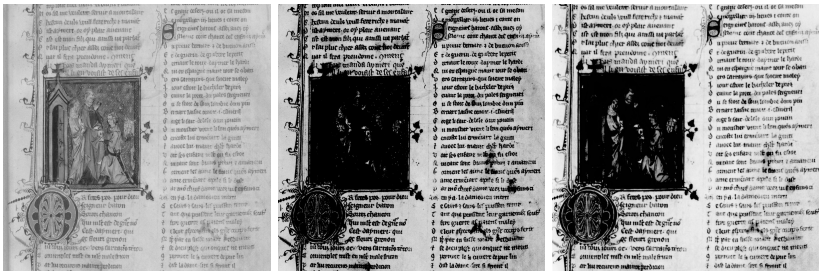


Figure 8: 13th century Latin Manuscript, microfilm on the left, prediction on the right (BnF. Département des Manuscrits. Latin 16644, 7v-8r)



(a) Greyscale version (b) Art. contrast of a. (c) Orig. Microfilm

(d) Orig. Color (e) Art. Colorized a (f) Art. colorized b (g) Art. colorized c

Figure 9: Manuscrit français 24369 (30r). This manuscript exists in two versions: a modern digitization in color (d) and a microfilm digitization (c). (a) and (b) are derived from the original color manuscript, with artificial contrast added for the latter. Contrast is shown here to have an important impact on the the artificial colorization at prediction time: while the greyscale version is relatively well colorized, both the microfilm and the manually contrasted feels less natural. See Figure 15 for more examples.

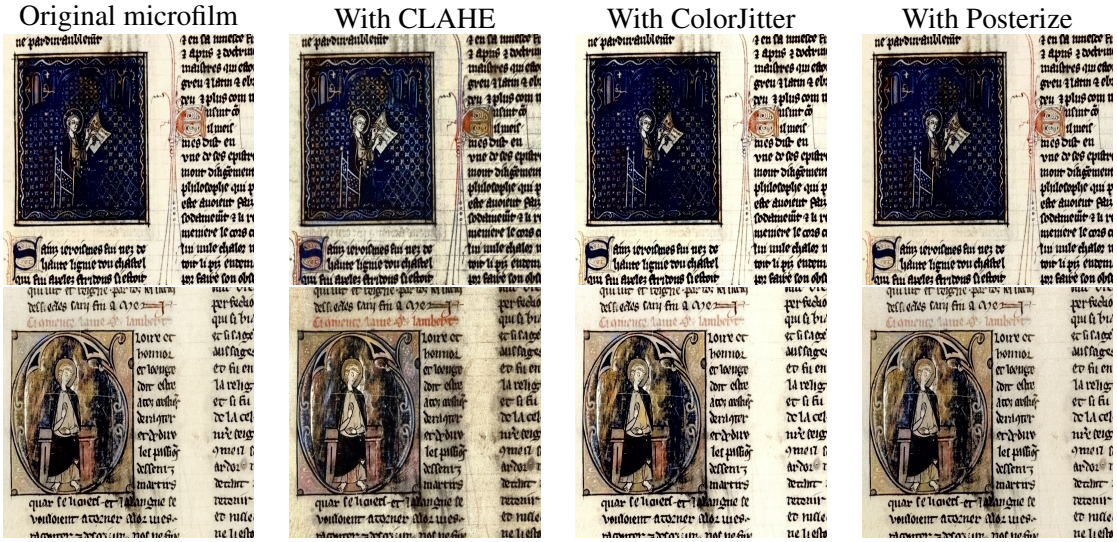


Figure 10: Impact on colorization of using pre-processing tools on original microfilms using the Albumentation library from Buslaev et al. [2020] (details from fr. 13496 and ms. 17229)

3.2 Impact on computer vision tasks

3.2.1 Layout segmentation

Figure 11: Segmentation overlay of main regions on 125v-126r of fr. 411 and 163v-164r of fr. 17229. On the right is the original grayscale microfilm, on the left the artificially colorized one.

Qualitatively evaluated, region segmentation is nearly not impacted by colorization. There are some very small differences (see Figure 11 for examples), specifically around illustrations. The region segmentation model has light difficulties around illustration on fr. 17229 - 163v with differences depending on the colorized status of the input: the colored version is able to capture all the text from below the illustration while missing most of the rubricated text over it, while the original microfilm captured the later but missed a part of the text below. Both versions include some noise regarding the illustration [29].

Quantitatively evaluated, line segmentation is nearly unchanged (less than 1% of improvement or metric drop) with a rather "large" variation (see Table 3). The manuscripts react differently, specifically on the line metric, where fr. 13496 always profit from colorization while other manuscripts have much more nuanced results. The results vary but are limited to less than 1% difference in score: given the high scores, around 99%, improvement cannot be expected.

3.2.2 Handwritten Text Recognition

The results are generally good in terms of character accuracy for medieval manuscripts while providing room for improvement (*cf.* figure 13). The mean accuracy delta over 120 tests (40 models $\times$ 3 manuscripts) is +0.025% while the median is 0.02% with the lowest outlier rating at -0.13% and highest one at +0.25% (see Figure 12). This means that the HTR models are as robust to color changes as the line segmentation models on *Kraken*. The delta varies depending on the manuscript (it seems that fr. 411 is affected more positively and more often than others: it might be due to the fact the manuscript is lacking illustrations and drop capitals) but so minimally that it should not advocate for colorizing manuscripts before running them through

[29] We provide the PageXML prediction output on our repository for each of the ground truth microfilm page for segmentation

	Delta			Colorized Microfilm			Original Microfilm		
Mss, Range	Lines	M. Pixel	Pixel	Lines	M. Pixel	Pixel	Lines	M. Pixel	Pixel
fr. 411									
125v-126r	0.3	0.1	0.1	98.4	99.1	98.6	98.7	99.2	98.7
126v-127r	-0.3	0.1	0.1	100.0	99.5	99.5	99.7	99.6	99.6
127v-128r	-0.6	0.0	0.0	98.8	99.4	99.3	98.2	99.4	99.3
128v-129r	0.0	0.1	0.1	99.7	99.5	99.4	99.7	99.5	99.5
129v-130r	0.3	0.0	0.3	98.5	99.5	99.1	98.8	99.6	99.3
130v-131r	0.3	0.0	0.0	99.0	99.6	99.5	99.4	99.6	99.5
fr. 17229									
163v-164r	0.3	0.0	0.3	99.4	99.6	99.1	99.7	99.6	99.4
164v-165r	0.3	0.0	0.0	99.4	99.8	99.7	99.7	99.8	99.8
166v-167r	0.3	-0.1	-0.1	99.4	99.7	99.4	99.7	99.6	99.3
167v-168r	-1.0	0.0	-0.4	99.4	99.7	99.3	98.4	99.7	98.9
168v-169r	0.3	-0.0	0.1	97.6	99.8	98.9	98.0	99.8	99.0
fr. 13496									
245v-246r	0.0	-0.0	-0.0	99.4	99.6	99.6	99.4	99.5	99.5
246v-247r	0.0	0.0	0.0	98.0	99.6	99.1	98.0	99.6	99.1
247v-248r	0.3	0.0	0.0	98.4	99.5	96.0	98.7	99.5	96.0

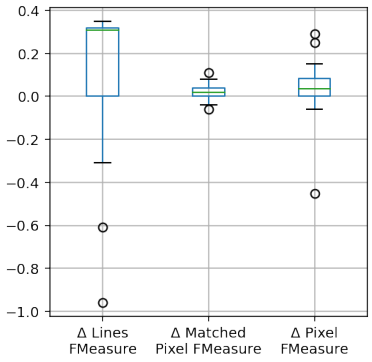


Table 3: Evaluating line segmentation impact: delta of different FMeasure between colorized and non-colorized of line detection. Positive outputs means colorized are better segmented than original microfilms. Delta Metrics are in % while raw scores . “M. Pixel” stands for Matched Pixel.

a HTR pipeline. The use of *BW and NOBW* corpora and *Augmentation vs. No Augmentation* does not yield any significant difference with a 0.04 median difference for the datasets and a null one for augmentation. From the perspective of HTR and *Kraken*, the results are however promising, as it shows a real capability of learning despite color differences, including when no grayscale or binarized images have been seen in the original training dataset.

IV CONCLUSION

Colorization of cultural heritage artifact through means of deep learning is a research area that has been left to the computer science side of research, while researchers in humanities and professional colorists are raising questions about the possible biased induced in this method. On the other hand, the general public has fancied the output of such tools to rediscover (fantasized ?) colors in their personal or local history. While photos and movies have been treated again and again, we made the hypothesis that colorizing manuscripts can be a new area of research, providing another version of manuscripts that are not yet digitized in color. This new research question provides three possible outcomes: providing a new outreach option for cultural heritage institutions, enhancing interpretability of images for computer vision software, improving the readability of microfilmed documents for humans. We tested this new research question with a single tool, *InstColorization*, on a newly built dataset of nearly 20 000 manuscripts pictures from the western Medieval Ages. We are able to automatically color for the first time digitized microfilms: backgrounds of pages are done efficiently while different inks are a little duller than expected. Of the two other downstream tasks, we provided a first answer to the question

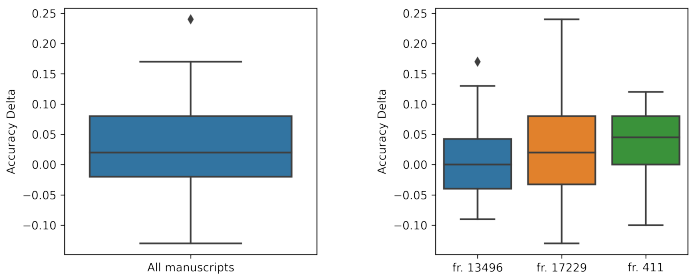


Figure 12: On the left, box plot of the accuracy delta with all 40 models regardless of the manuscript. On the right, box plot of the accuracy delta with all models distinguishing manuscripts.

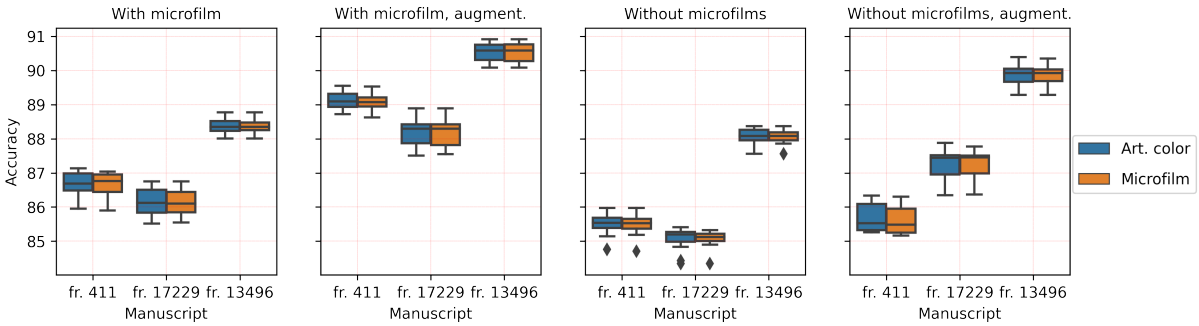


Figure 13: HTR accuracy distribution over 10 models given the HTR training set (with or without microfilms), data augmentation for HTR, and the artificial colorization of three different manuscripts.

of computer vision, through the evaluation of colorization's impact on layout segmentation and HTR, showing limited to non-existent impact. The test dataset being limited in size, and some scores nearing 100% in the line segmentation task, we are cautious about the meaning of these results.

V FURTHER RESEARCH

In addition to addressing contrast issues in our own experiment, future research could explore alternative model architectures to test their effectiveness in this context. The current tool, *InstColorization* is limited by its use of natural images object recognition in the current state of this research, and new approaches such as transformer colorizer could provide new insights. Furthermore *InstColorization* only "adds" 3 new channels for colorization, and does not affect contrast which might be the most limiting factor. Finally, we would like to emphasize the significance of introducing noise and artificial contrast issues to artificially grayscaled images to more closely simulate the appearance of microfilms.

In addition, we suggest conducting user studies to assess the potential impact of colorization on readability and engagement for human readers. Furthermore, we propose crowd-sourcing the evaluation of artificial colorization to obtain statistically robust results. A suitable approach for this purpose may be to adopt the methodology used by Manjavacas et al. [2019]. This would enable a more accurate quantification of the impact of artificial colorization on the readability and overall quality of digitized manuscripts. The evaluation of such output should include

- Crowdsourced transcriptions of microfilms and colored microfilms followed by a quantitative evaluation of inter-annotator agreement. Artificially grayscaled and color scans must be part of the experiment as well to provide a baseline.
- Accompanying the first, on the same dataset, a readability scoring polls.
- Finally, an appreciation scoring polls, to quantify how much of interest colorization is.

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VII CODE

Code, logs and output can be found at https://github.com/PonteIneptique/ganuscript.

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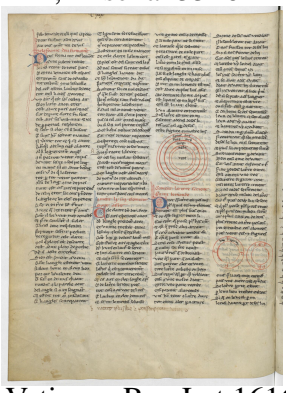
A DATASET SAMPLES

BnF, fr. 3516

BnF, Arsenal 3516



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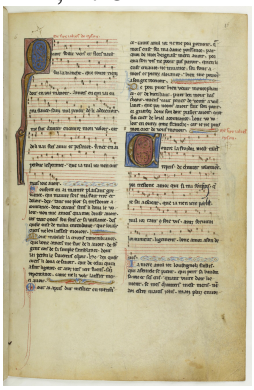

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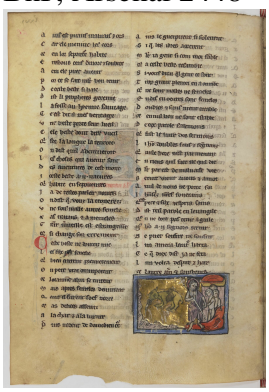

Vaticane Reg Lat 1616

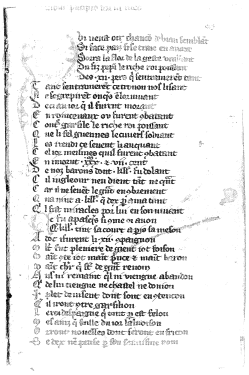

Figure 14: Samples from the HTR and segmentation training dataset

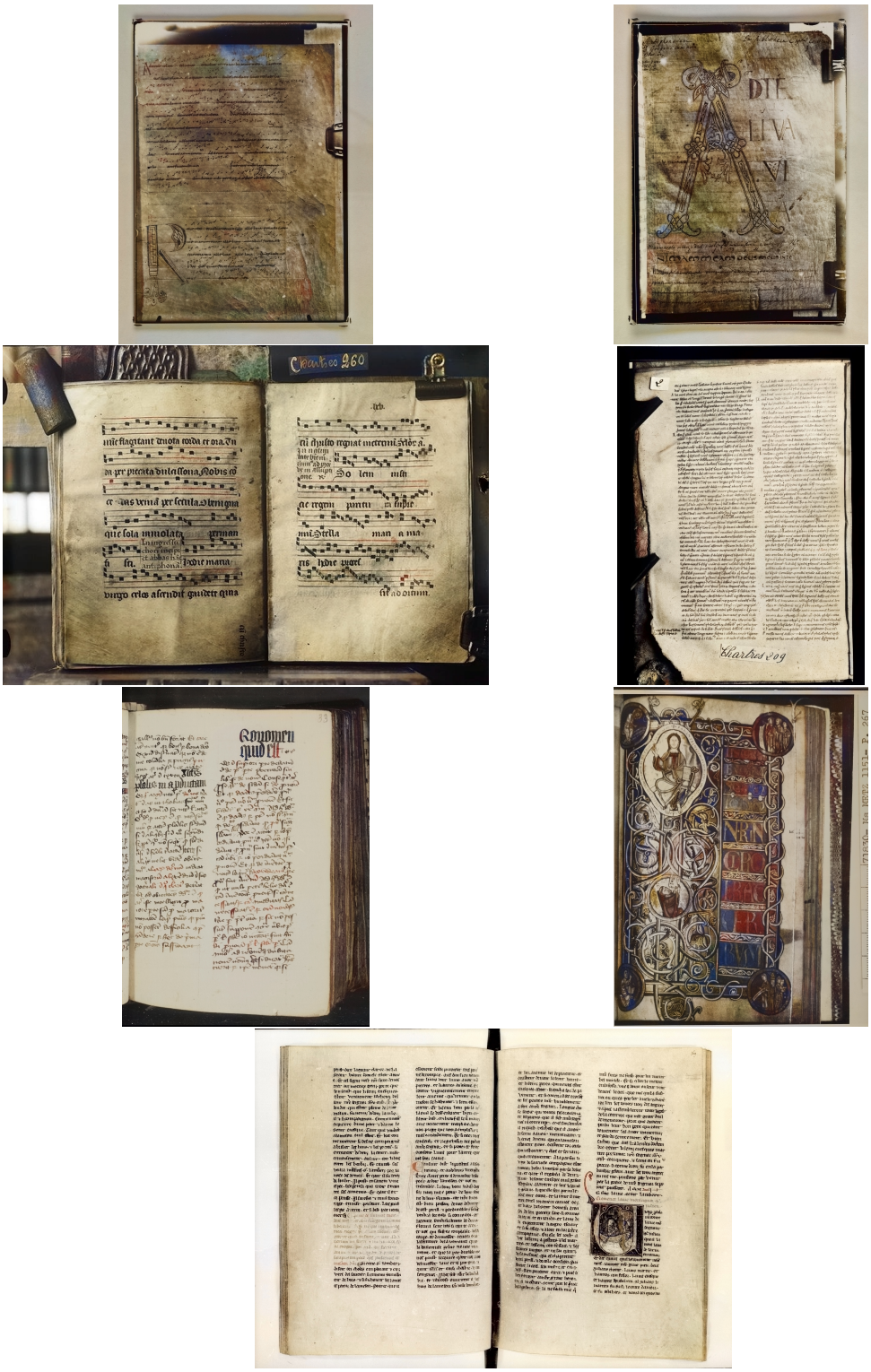

Figure 15: Samples from colorization output on microfilms (test only). First 4 are manuscripts from Chartes (0047, 0260, 0209), the following two are from Metz (0643 and 1151), the last if from our HTR testing set (BnF fr. 17229)