ShabbyPages: A Recipe for Repeatable, Synthetic, Modern Document Images

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Abstract. The *ShabbyPages* document image dataset is produced using the *Augraphy* document image augmentation tool. The development of the computation pipeline used to generate the corpus is discussed, and the results presented. The final corpus contains over 6000 "born-digital" ground truth document images, sourced on the Web, with synthetically-noised counterparts ("shabby pages") that appear to have been printed and faxed, photocopied, or otherwise altered through physical processes. The release of this dataset and the recipe for its production attempts to address a growing need for labeled training document images for supervised learning tasks. The results of initial experiments are discussed, in which the corpus is used to train performant convolutional denoisers which remove real noise features with a high degree of human-perceptible fidelity, establishing baseline performance for a new *ShabbyPages* benchmark.

1 Introduction

Denoising is a fundamental concern for many document processing workflows, wherein unwanted artifacts introduced to a document image via noisy processes like scanning are removed. The effectiveness of the denoising stage of document processing pipelines has implications for downstream tasks like optical character recognition (OCR) and layout parsing [need to cite]. Recent work in supervised machine learning has yielded promising results at the denoising task [need to cite], increasing the importance of access to large volumes of high-quality training and evaluation data.

Prior work has introduced denoising and binarization datasets, but these are often small in scale, limited in the types of noise features present, not diverse enough to train robust models, and impossible to recreate.

- *DIBCO* datasets, which are widely recognized as critical data for document denoising and binarization, are far too small for large-scale training since each *DIBCO* dataset ranges between 10-20 images total.
- *NoisyOffice* [20] is a denoising dataset that is also quite small, having *72* training samples, and contains only a few types of noise — primarily artificial wrinkles and stains, with little variation.
- *DDI-100* [21] is larger corpus in scale than *NoisyOffice* and the *DIBCO* datasets, but is again limited in the degree of feature diversity [1].

In this paper, we introduce a new dataset designed primarily for the document denoising task, which addresses each of the concerns listed above. This new dataset, *ShabbyPages*, is large-scale, having *6202* synthetic training images and *200* real testing images. *ShabbyPages* is more diverse than alternatives like *NoisyOffice*, as it contains documents from various language groups and contains documents with graphical elements like tables and figures. In the next sections, we provide motivation and context for *ShabbyPages*' creation, compare it at length to other important datasets in the same space, describe the corpus construction process, and finally demonstrate its utility by benchmarking document denoising models trained on the dataset.

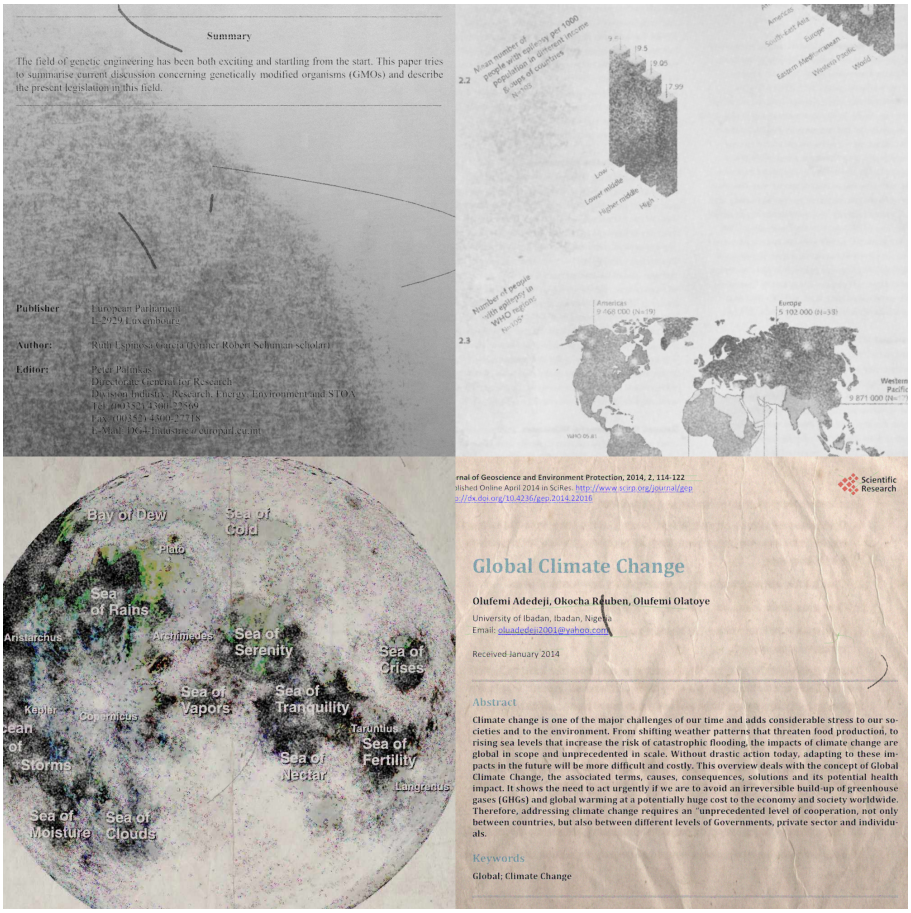


Fig. 1. Sample patches from *ShabbyPages*.

2 The Dataset

ShabbyPages joins a rapidly growing number of open-source datasets freely available online. Human activity today generates a tremendous amount of data, with many people choosing to publish theirs on websites like Kaggle [**?**], Hugging Face Hub [**?**], and many more. All of this data is arranged into categories: sets exist which contain text, images, audio, and data from other modalities, with each set often collected and designed for a purpose. Of the many image datasets available, the authors understand few to have been designed for groundtruthed supervised learning of document-specific tasks like binarization or denoising. In fact, we could find only one other set compiled specifically for doing so with images of *modern* documents: *NoisyOffice* [2].

2.1 Features

Modern artificial neural networks produce a latent representation of their training data, a space from which outputs are sampled. In deep networks, these representations live within multiple layers, each of which corresponds to a feature of the input data. Document images are a particularly interesting category, as the data within the documents each picture represents is itself frequently multi-modal; the document may contain an image and its description, a table with statistics, multiple regions of structured and formatted text, and even other documents, making their internal representations by neural networks often quite complicated.

Networks with a wider variety of latent representations frequently perform better when generalizing their learned functions to other tasks. For this reason, procuring a large-enough volume of robust-enough training data is paramount. Several sets of such images exist, many intended for processing by deep neural nets; Table [**?**] contains a comparison of some of the key hyperproperties of the *ShabbyPages* set compared with other popular document image datasets.

Diversity. We use the diversity metric as defined in [8,9] to help us measure intra-dataset variety. This metric is defined as

$$Diversity(X) = \frac{1}{|X|^2} \sum_{a \in X} \sum_{b \in X} \|f(a) - f(b)\|_2$$

where $f(\cdot)$ is an embedding function mapping the input image into an n-dimensional vector space. Here, we use CLIP's ViT model [18], which embeds each image into a 512-dimensional space. The intuition behind the diversity metric is that datasets where images are highly similar will have lower diversity scores, and datasets where images share less visual similarity will have higher diversity scores. A dataset with low diversity might not be representative enough of the real world, and low diversity may further correlate with task easiness.

2.2 Statistics

ShabbyPages contains documents from multiple classes, which contain many types of information.

Table [**?**] contains some statistics for the dataset, in grayscale, at a standard resolution of 150 ppi.

Table 1. ShabbyPages dataset statistics.

Statistic	**Value**
Num. Images	6202
DPI	150
Max image size	3336x12157
Min image size	532x532

2.3 Other Datasets

By now, hundreds of datasets exist for the document denoising task (several listed in [**?**]), the most similar to *ShabbyPages* being *NoisyOffice* [20]. *NoisyOffice* is very limited, however, consisting of two font weights, three font sizes, three font types, and four noise types, for a total of just 72 unique images. The *NoisyOffice* collection was created by permuting these font/size/base combinations, and the resulting set is feature-poor. *NoisyOffice* also lacks non-English and non-Latin characters, as well as graphical elements like images, logos, and tables. To add noise, the creators produced four different types of background noise (folds, wrinkles, coffee stains, and footprints), and then overlayed digitally-generated text onto these.

Another dataset, *DDI-100* [21], was constructed in a manner similar to *NoisyOffice*. *DDI-100* is far larger than *NoisyOffice*, but has been criticized for not containing enough diversity or noise to be an effective benchmark [1]. Additionally, the pipeline code for creating the noisy versions of both *NoisyOffice* and *DDI-100* is not available, and thus these datasets cannot be reproduced. Moreover, while *DDI-100* has noise-free document images with noisy counterparts, the noisy images also exhibit geometric transformations — as seen in Figure 2 — making it unsuitable for benchmarking document binarizers or denoisers using standard metrics like SSIM, PSNR, or MSE, which require clean-noisy correspondences to be free of geometric transformations.

Other prior work includes several datasets for the related task of document image binarization, which seeks to convert a document image into a binary image, where foreground text is black and background pixels are white. Among the most important in this class are the *DIBCO* collections [5,11,12,13,14,10,16,17,15]. As summarized in Table 2, the *DIBCO* family of datasets is very small, ranging between 10 and 20 samples each (for a total of 106 images across *DIBCO-9* through *DIBCO-18*). Similar to *NoisyOffice*, the *DIBCO* datasets do not contain graphical elements like images, tables, charts, etc. The Persian Heritage Image Binarization Dataset (PHIBD) [**?**,**?**] is similar to the *DIBCO* benchmarks, consisting of a small number of images of handwritten Persian writing. Others, like

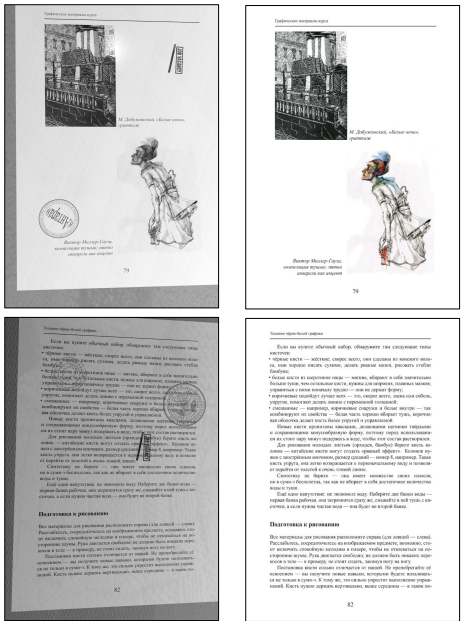


Fig. 2. Example noisy-clean pairs from DDI-100. Geometric transformations are required to map the noisy samples to their corresponding clean ground-truth images, making DDI-100 unsuitable for binarization and denoising.

the Bickley Diary set [19] and the 2019 Time-Quality Binarization Competition set [**?**] have also been used for benchmarking document binarization approaches, but these do not appear to be publicly available [**?**]. Ultimately, the sizes of these document binarization corpora severly limit the types of algorithms and models that can be used. Examples of noisy-clean image pairs from some of these collections are displayed in Figure 3.

Other popular document image datasets — like RVL-CDIP [6], Tobacco-3482 [CITE], Tobacco-800 [4], and FUNSD [cite] — include large amounts of real noise, but none of these have corresponding clean ground-truth document images to train or evaluate document denoisiers and binarizers.

3 Construction

This section describes the dataset generation methodology; code for all of this is available on GitHub.

ShabbyPages was born out of a desire to address shortcomings in the popular datasets discussed in the previous section. Reproducibility was a primary concern, so *ShabbyPages* includes not only the groundtruth images, but also the original digital documents used to produce them, and the software for fully recreating the set, allowing anyone to quickly produce a new member of the

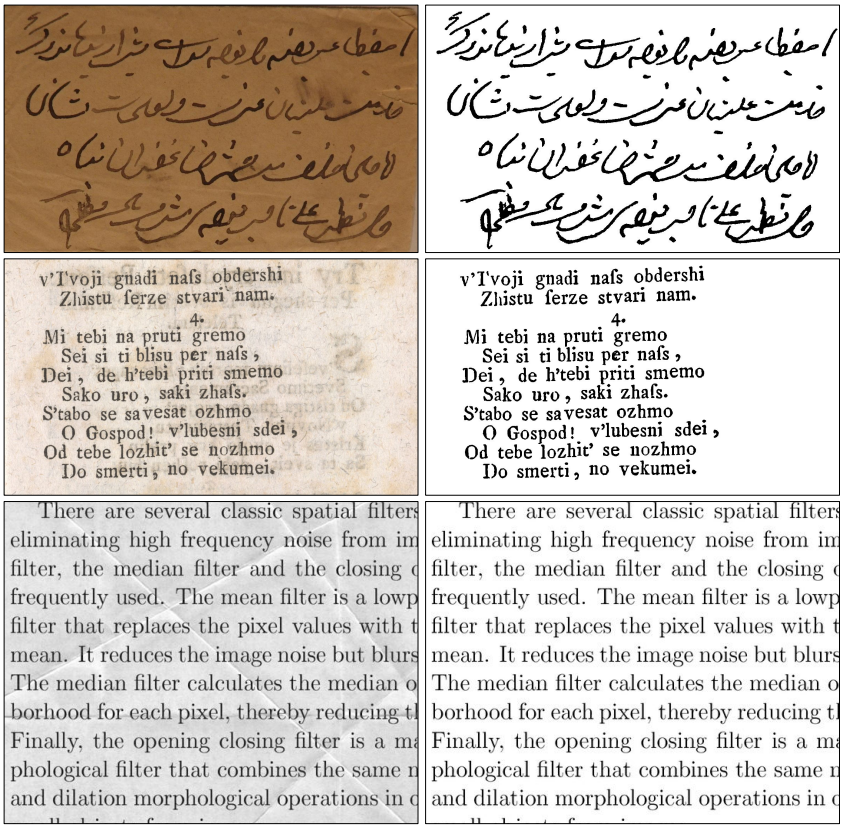


Fig. 3. Example noisy-clean pairs from PHIBD (top row), *DIBCO-13* (middle row), and *NoisyOffice* (bottom row).

Shabby family, optionally re-exporting groundtruths at a different resolution beforehand. The 6202 images in the *ShabbyPages* release set are really just the first sample from the space of these documents; we encourage readers to build their own. *NoisyOffice* is the only other set we examined that contains its digital provenance, but the released database materials lack a means of reproducing the simulated printing method used to create the *NoisyOffice* training data; *Augraphy*'s `PaperFactory` augmentation is such a tool. The other sets are not even theoretically extensible in this way.

3.1 Data Gathering

A team of workers searched the public internet for PDFs of many different kinds, from culturally-important sources like government agencies, NGOs, and large multinational corporations. 600 unique documents were retrieved, totaling 6202 pages. Care was taken to retrieve freely-available and attributable documents;

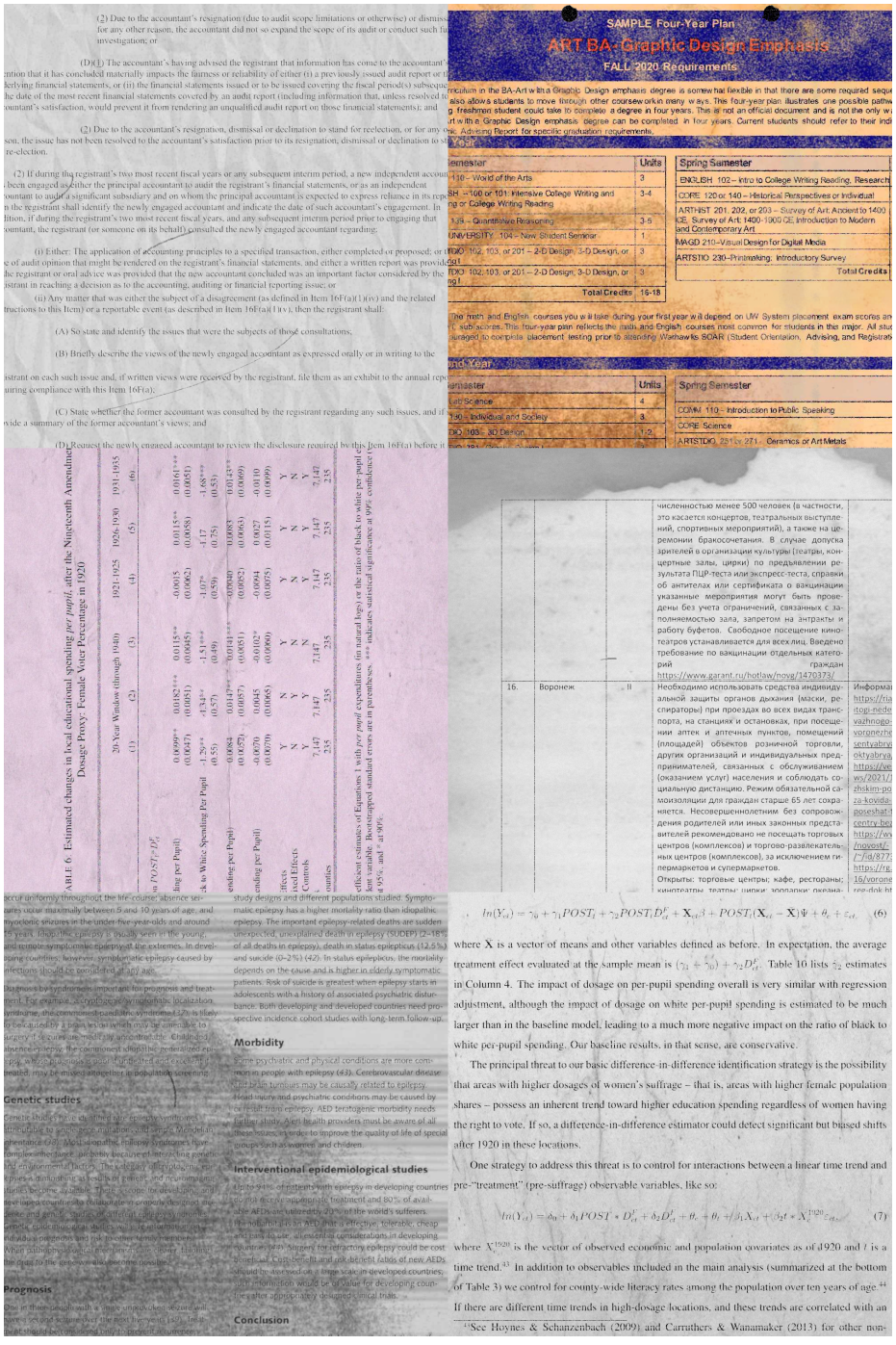


Fig. 4. Sample noisy patches from ShabbyPages.

Table 2. Summary of datasets for document binarization (above line) and document denoising (below line) tasks.

Dataset	Dataset Size	Synthetic Noise	Ground-Truths	Diversity	Varied fonts/sizes	Varied paper styles	Multilingual	Contains graphics	Reproducible
DIBCO-9 [5]	10	✗	✓		✓	✓	✓	✗	n/a
DIBCO-10 [11]	10	✗	✓		✓	✓	✗	✗	n/a
DIBCO-11 [12]	16	✗	✓		✓	✓	✓	✗	n/a
DIBCO-12 [13]	14	✗	✓		✓	✓	✗	✗	n/a
DIBCO-13 [14]	16	✗	✓		✓	✓	✓	✗	n/a
H-DIBCO-14 [10]	10	✗	✓		✓	✓	✓	✗	n/a
H-DIBCO-16 [16]	10	✗	✓		✓	✓	✓	✗	n/a
DIBCO-17 [17]	20	✗	✓		✓	✓	✓	✗	n/a
H-DIBCO-18 [15]	10	✗	✓		✓	✓	✓	✗	n/a
Bickley Diary [19]	7	✗	✓		✗	✗	✗	✗	n/a
PHIBD [**?**]	15	✗	✓		✓	✓	✗	✗	n/a
NoisyOffice [2]	72	✓	✓	0.317	✓	✗	✗	✗	✗
DocCreator [7]	6,059	✓	✓		✓	✓	✓	✗	✓
DDI-100 [21]	100k+	✓	✓						✗
ShabbyPages (ours)	6,202	✓	✓	0.488	✓	✓	✓	✓	✓

a manifest is included in the dataset which contains an ordered table of the filenames, the languages present in the document, the download URL for the file, and an English name or acronym for the source organization or person. A similar process was completed to collect paper textures on which to "print" the documents: 300 unique textures were gathered, all of which are either in the public domain or carry CC-0, CC-BY, or CC-BY-SA licenses; metadata about these textures appears in another manifest. We also manually reviewed the gathered documents to verify that no personal identity information was present within the corpus.

3.2 PDF to PNG

The pdftoppm tool from the poppler-utils package was used to split the PDF documents into individual pages. Each page was converted to a PNG image at 150dpi, a common printing resolution. Because the majority of these documents were created with the standard US Letter dimensions, this resulted in the most common image dimension being 1275 pixels wide by 1650 pixels tall.

```
pdftoppm document_name.pdf document_name -png -r 150
```

3.3 Developing the Pipeline

The *Augraphy* library presents an easy-to-use API for constructing feature pipelines, which has been designed for interoperability with other augmentation tools, and within the broader data ecosystem. While *Augraphy*'s default pipeline has what we believe to be quite realistic defaults, we wanted a broader range of features from this dataset than those the default pipeline could produce. To address this, we broke all of the parameters for every augmentation constructor out into separate variables, tweaking these and committing the new pipeline to GitHub. We created an automated daily build in GitHub Actions to render a random selection of ground-truth images with the updated pipeline, then our team met frequently to discuss the output and make adjustments to the augmentation parameters, until we were consistently satisfied with the results.

The pipeline uses 23/26 augmentations from *Augraphy*; we excluded augmentations that would make it hard to do pixel to pixel comparisons against groundtruths.

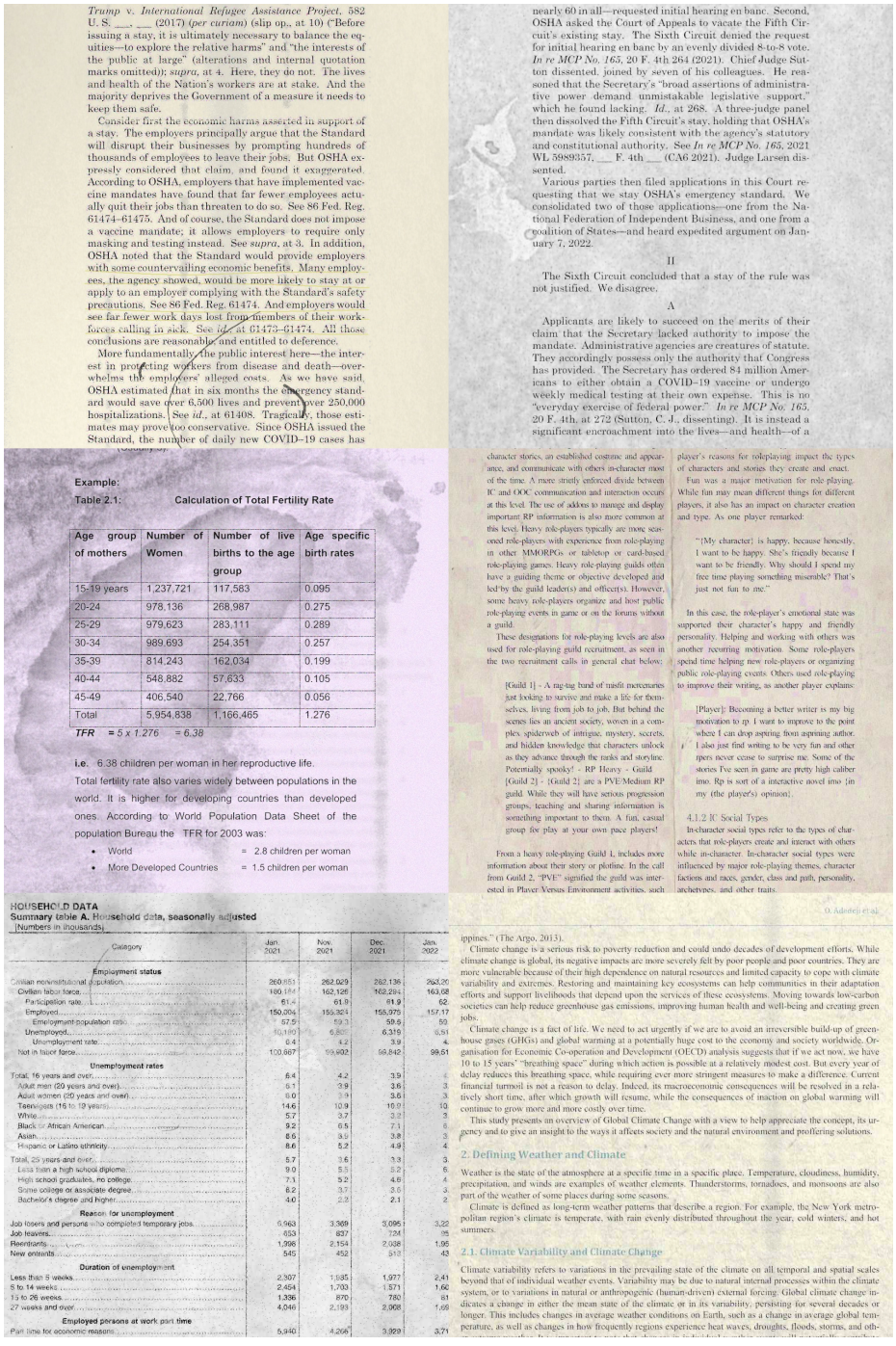
PaperFactory was used with 300 textures, dramatically increasing the possible variations in the final dataset. We did not use Brightness or Brightness-Texturize, because these can interact poorly with some of the paper textures we chose. We also omitted the BookBinding augmentation, which can alter the document image geometry by adding additional pixels, making the result unsuitable for analysis by many common metrics.

Augraphy by design includes a high degree of randomness: most augmentations make several calls to a pseudorandom number generator, on which several transforms depend. All or none of these augmentations may have applied to each input image, and only one pipeline run was completed per image.

The conjunction of all these factors implies *ShabbyPages* is a sample from a massive space. Indeed, the cosine similarity computed over OpenAI's CLIP representations of each output image averages to 0.49, much higher than *Noisy-Office*'s 0.31.

3.4 Processing *Augraphy* Pipelines

Execution time is dependent on which augmentations are executed at runtime; a long *Augraphy* pipeline can take several seconds to process large images. The library is under active development with performance enhancements underway, but the time cost to generate large datasets sequentially is prohibitive when dealing with thousands of files, so we use a multi-process pooling technique to distribute the workload across many processor execution threads. For each process, a new pipeline with new probability coefficients was generated, representing a nontrivially-different sequence of document operations. Each of the 6202 base images was passed through a unique pipeline, with the output saved to a separate directory. *Augraphy*'s API design made it very easy to write the code to accomplish this; the entire *ShabbyPages* generation script is fewer than 30 lines long including imports, with the most critical piece represented below:



Trump v. *International Refugee Assistance Project*, 582 U. S. ___, ___ (2017) *(per curiam)* (slip op., at 10) ("Before issuing a stay, it is ultimately necessary to balance the equities—to explore the relative harms" and "the interests of the public at large" (alterations and internal quotation marks omitted)); *supra*, at 4. Here, they do not. The lives and health of the Nation's workers are at stake. And the majority deprives the Government of a measure it needs to keep them safe.

Consider first the economic harms asserted in support of a stay. The employers principally argue that the Standard will disrupt their businesses by prompting hundreds of thousands of employees to leave their jobs. But OSHA expressly considered that claim, and found it exaggerated. According to OSHA, employers that have implemented vaccine mandates have found that far fewer employees actually quit their jobs than threaten to do so. See 86 Fed. Reg. 61474–61475. And of course, the Standard does not impose a vaccine mandate; it allows employers to require only masking and testing instead. See *supra*, at 3. In addition, OSHA noted that the Standard would provide employers with some countervailing economic benefits. Many employees, the agency showed, would be more likely to stay at or apply to an employer complying with the Standard's safety precautions. See 86 Fed. Reg. 61474. And employers would see far fewer work days lost from members of their workforces calling in sick. See *id.*, at 61473–61474. All those conclusions are reasonable and entitled to deference.

More fundamentally, the public interest here—the interest in protecting workers from disease and death—overwhelms the employers' alleged costs. As we have said, OSHA estimated that in six months the emergency standard would save over 6,500 lives and prevent over 250,000 hospitalizations. See *id.*, at 61408. Tragically, those estimates may prove too conservative. Since OSHA issued the Standard, the number of daily new COVID–19 cases has

nearly 60 in all—requested initial hearing en banc. Second, OSHA asked the Court of Appeals to vacate the Fifth Circuit's existing stay. The Sixth Circuit denied the request for initial hearing en banc by an evenly divided 8-to-8 vote. *In re MCP No. 165*, 20 F. 4th 264 (2021). Chief Judge Sutton dissented, joined by seven of his colleagues. He reasoned that the Secretary's "broad assertions of administrative power demand unmistakable legislative support," which he found lacking. *Id.*, at 268. A three-judge panel then dissolved the Fifth Circuit's stay, holding that OSHA's mandate was likely consistent with the agency's statutory and constitutional authority. See *In re MCP No. 165*, 2021 WL 5989357, ___ F. 4th ___ (CA6 2021). Judge Larsen dissented.

Various parties then filed applications in this Court requesting that we stay OSHA's emergency standard. We consolidated two of those applications—one from the National Federation of Independent Business, and one from a coalition of States—and heard expedited argument on January 7, 2022.

II

The Sixth Circuit concluded that a stay of the rule was not justified. We disagree.

A

Applicants are likely to succeed on the merits of their claim that the Secretary lacked authority to impose the mandate. Administrative agencies are creatures of statute. They accordingly possess only the authority that Congress has provided. The Secretary has ordered 84 million Americans to either obtain a COVID–19 vaccine or undergo weekly medical testing at their own expense. This is no "everyday exercise of federal power." *In re MCP No. 165*, 20 F. 4th, at 272 (Sutton, C. J., dissenting). It is instead a significant encroachment into the lives—and health—of a

Example:

Table 2.1: Calculation of Total Fertility Rate

Age group of mothers	Number of Women	Number of live births to the age group	Age specific birth rates
15-19 years	1,237,721	117,583	0.095
20-24	978,136	268,987	0.275
25-29	979,623	283,111	0.289
30-34	989,693	254,351	0.257
35-39	814,243	162,034	0.199
40-44	548,882	57,633	0.105
45-49	406,540	22,766	0.056
Total	5,954,838	1,166,465	1.276

TFR = 5 x 1.276 = 6.38

i.e. 6.38 children per woman in her reproductive life.

Total fertility rate also varies widely between populations in the world. It is higher for developing countries than developed ones. According to World Population Data Sheet of the population Bureau the TFR for 2003 was:

- World = 2.8 children per woman
- More Developed Countries = 1.5 children per woman

character stories, an established costume and appearance, and communicate with others in-character most of the time. A more finely enforced divide between IC and OOC communication and interaction occurs at this level. The use of addons to manage and display important RP information is also more common at this level. Heavy role-players typically are more seasoned role-players with experience from role-playing in other MMORPGs or tabletop or card-based role-playing games. Heavy role-playing guilds often have a guiding theme or objective developed and led by the guild leader(s) and officer(s). However, some heavy role-players organize and host public role-playing events in game or on the forums without a guild.

These designations for role-playing levels are also used for role-playing guild recruitment, as seen in the two recruitment calls in general chat below:

> [Guild 1] - A rag-tag band of misfit mercenaries just looking to survive and make a life for themselves. living from job to job. But behind the scenes lies an ancient society, woven in a complex spiderweb of intrigue, mystery, secrets, and hidden knowledge that characters unlock as they advance through the ranks and storyline. Potentially spooky! - RP Heavy - Guild
>
> [Guild 2] - [Guild 2] are a PVE/Medium RP guild. While they will have serious progression groups, teaching and sharing information is something important to them. A fun, casual group for play at your own pace players!

From a heavy role-playing Guild 1, includes more information about their story or plotline. In the call from Guild 2, "PVE" signified the guild was interested in Player Versus Environment activities, such

player's reasons for roleplaying impact the types of characters and stories they create and enact.

Fun was a major motivation for role-playing. While fun may mean different things for different players, it also has an impact on character creation and type. As one player remarked:

> "[My character] is happy, because honestly, I want to be happy. She's friendly because I want to be friendly. Why should I spend my free time playing something miserable? That's just not fun to me."

In this case, the role-player's emotional state was supported their character's happy and friendly personality. Helping and working with others was another recurring motivation. Some role-players spend time helping new role-players or organizing public role-playing events. Others used role-playing to improve their writing, as another player explains:

> [Player]: Becoming a better writer is my big motivation to rp. I want to improve to the point where I can drop aspiring from aspiring author. I also just find writing to be very fun and other rpers never cease to surprise me. Some of the stories I've seen in game are pretty high caliber imo. Rp is sort of a interactive novel imo [in my (the player's) opinion].

4.1.2 IC Social Types

In-character social types refer to the types of characters that role-players create and interact with others while in-character. In-character social types were influenced by major role-playing themes, character factions and races, gender, class and path, personality, archetypes, and other traits.

HOUSEHOLD DATA

Summary table A. Household data, seasonally adjusted

(Numbers in thousands)

Category	Jan. 2021	Nov. 2021	Dec. 2021	Jan. 2022
Employment status				
Civilian noninstitutional population	260,851	262,029	262,135	263,26
Civilian labor force	160,184	162,128	162,284	163,08
Participation rate	61.4	61.9	61.9	62.
Employed	150,004	155,324	155,975	157,17
Employment-population ratio	57.5	59.3	59.5	59
Unemployed	10,180	6,804	6,310	5,91
Unemployment rate	6.4	4.2	3.9	4.
Not in labor force	100,667	99,902	99,842	99,51
Unemployment rates				
Total, 16 years and over	6.4	4.2	3.9	4.
Adult men (20 years and over)	5.1	3.9	3.6	3.
Adult women (20 years and over)	6.0	3.9	3.6	3.
Teenagers (16 to 19 years)	14.6	10.9	10.9	10
White	5.7	3.7	3.5	3.
Black or African American	9.2	6.5	7.1	6.
Asian	6.6	3.9	3.8	3.
Hispanic or Latino ethnicity	8.6	5.2	4.9	4.
Total, 25 years and over	5.7	3.6	3.3	3.
Less than a high school diploma	9.0	5.5	5.2	6.
High school graduates, no college	7.1	5.2	4.6	4.
Some college or associate degree	6.2	3.7	3.5	3.
Bachelor's degree and higher	4.0	2.2	2.1	2.
Reason for unemployment				
Job losers and persons who completed temporary jobs	6,963	3,969	3,696	3,22
Job leavers	653	837	724	95
Reentrants	1,998	2,154	2,038	1,95
New entrants	545	452	518	43
Duration of unemployment				
Less than 5 weeks	2,307	1,685	1,977	2,41
5 to 14 weeks	2,454	1,703	1,571	1,62
15 to 26 weeks	1,336	870	780	81
27 weeks and over	4,046	2,193	2,908	1,69
Employed persons at work part time				
Part time for economic reasons	5,940	4,266	3,929	3,71

ippines." (The Argo, 2013).

Climate change is a serious risk to poverty reduction and could undo decades of development efforts. While climate change is global, its negative impacts are more severely felt by poor people and poor countries. They are more vulnerable because of their high dependence on natural resources and limited capacity to cope with climate variability and extremes. Restoring and maintaining key ecosystems can help communities in their adaptation efforts and support livelihoods that depend upon the services of these ecosystems. Moving towards low-carbon societies can help reduce greenhouse gas emissions, improving human health and well-being and creating green jobs.

Climate change is a fact of life. We need to act urgently if we are to avoid an irreversible build-up of greenhouse gases (GHGs) and global warming at a potentially huge cost to the economy and society worldwide. Organisation for Economic Co-operation and Development (OECD) analysis suggests that if we act now, we have 10 to 15 years' "breathing space" during which action is possible at a relatively modest cost. But every year of delay reduces this breathing space, while requiring ever more stringent measures to make a difference. Current financial turmoil is not a reason to delay. Indeed, its macroeconomic consequences will be resolved in a relatively short time, after which growth will resume, while the consequences of inaction on global warming will continue to grow more and more costly over time.

This study presents an overview of Global Climate Change with a view to help appreciate the concept, its urgency and to give an insight to the ways it affects society and the natural environment and proffering solutions.

2. Defining Weather and Climate

Weather is the state of the atmosphere at a specific time in a specific place. Temperature, cloudiness, humidity, precipitation, and winds are examples of weather elements. Thunderstorms, tornadoes, and monsoons are also part of the weather of some places during some seasons.

Climate is defined as long-term weather patterns that describe a region. For example, the New York metropolitan region's climate is temperate, with rain evenly distributed throughout the year, cold winters, and hot summers.

2.1. Climate Variability and Climate Change

Climate variability refers to variations in the prevailing state of the climate on all temporal and spatial scales beyond that of individual weather events. Variability may be due to natural internal processes within the climate system, or to variations in natural or anthropogenic (human-driven) external forcing. Global climate change indicates a change in either the mean state of the climate or in its variability, persisting for several decades or longer. This includes changes in average weather conditions on Earth, such as a change in average global temperature, as well as changes in how frequently regions experience heat waves, droughts, floods, storms, and oth-

Fig. 5. Sample noisy patches from ShabbyPages.

```
def run_pipeline(filename):
  image = cv2.imread(filename)
  # returns the current ShabbyPages pipeline
  pipeline = get_pipeline()
  data = pipeline.augment(image)
  shabby_image = data['output']
  cv2.imwrite(filename + '-shabby.png',
              shabby_image)
```

Processing all 6202 images took less than half an hour on the 64 cores of a Graviton3 c7g.16xlarge instance on AWS. In testing, we rendered several tens of thousands of such images, with the cumulative computation time still less than one day due to *Augraphy*'s efficiency.

3.5 *ShabbyPages*

In keeping with the spirit of *NoisyOffice*, our original inspiration, and to provide out-of-distribution test data for ours and other projects, we developed a separate but related dataset which we call *ShabbyPages*. To build this, we isolated reproduction steps for several physical operations, designed real-world augmentation pipelines with these, and then engaged a team of workers to use these instructions to produce several copies of printed born-digital documents with real noise.

Five individuals were recruited for this task, which involved printing 40 pages of documents and manually applying various effects such as folds, wrinkles, smudges, highlighters, pencils, crayons, splatters of ink or other liquids, printing, scanning, faxing and other creative and reasonable treatments determined by these workers. The process continued over a period of two weeks, incurring a cost of approximately $1,000 USD. While there are plenty of opportunities to streamline the operation, scaling this process is expensive in terms of both time and money, and may have unpredictable results.

Several challenges arose in the construction of this dataset. Old fax machines, faulty commercial printers, and other hardware suitable for inducing the intended effects were difficult to source, and frequently non-functional when they could be found. Environmental concerns like the volume of paper and ink used, and the energy expenditure both in electricity and human terms, also factored into our decision to pursue synthetic augmentations for *ShabbyPages*. Manually producing a database of noisy documents is a time-consuming and repetitive task; creating just 100 real-world documents with real noise features required the labor of several people. Nevertheless, despite the limited size of the resulting dataset, the scarcity of real-world datasets with ground truth images makes the *ShabbyPages* corpus extremely valuable. This type of dataset is critical for benchmark comparison with synthetically-augmented document images, and for other tasks such as denoising and binarizing: we use *ShabbyPages* later for a human-perception evaluation of denoising performance.

4 Experimentation with the *ShabbyPages* Set

Denoising and binarization are two important techniques for the removal of unwanted data from images. Both approaches can be achieved by supervised learning of relationships between features of the input and output data. In this section, we train two NAFNet [3] instances as denoisers on both the *NoisyOffice* and the *ShabbyPages* datasets. We evaluate these models' predictions in a cross-validation test on both datasets, both by visual inspection and by metric computation. We then perform a similar experiment where the same NAFNets are trained to not only remove noise from the test images, but also to classify the foreground and backgorund pixels, predicting a binarized clean document. The model was "off-the-shelf"; besides rigging up the training inputs and choosing a reasonable training epoch limit, we made no significant alterations to the provided hyperparameters.

4.1 Denoising

Digital computation has enabled humanity to produce ever-growing amounts of both data and reasons to process it. Doing so is easiest when the data is free of unexpected outliers, the signal has less jitter, and perhaps most importantly, when our aesthetic sensibilities are un-challenged.

Denoising grayscale images is a challenging task, as models must determine not only which features should appear in the output, but also the 8-bit pixel intensity over the whole image. We randomly selected ten patches of 400x400 pixels from each page, then trained another NAFNet instance on this data for just 14 epochs (about 22 hours of compute time). For this task, we considered the structural similarity index (SSIM), a common image processing metric which takes into account visually-perceptible data such as luminance and contrast, appropriate for grayscale images. The results of the denoising cross-validation experiment are presented in the table below.

Table 3. Document image denoising cross-test performance of NAFNet models trained on *ShabbyPages* and *NoisyOffice*.

Training Set	Test Set	SSIM↑
ShabbyPages	NoisyOffice-real	**0.96**
NoisyOffice-sim	ShabbyPages	0.83

As can be seen from Table [**?**], the *ShabbyPages*-trained denoiser generalized to *NoisyOffice* far better than the *NoisyOffice*-trained model generalized to *ShabbyPages*. This result is consistent with the much higher diversity present within the *ShabbyPages* set, relative to features found in the *NoisyOffice* database.

Machine learning is ultimately about getting computers to complete tasks which normally require human labor; as further validation for the efficacy of

ShabbyPages in training performant denoisers, we also used our *ShabbyPages*-trained NAFNet model to denoise the *ShabbyPages* set, and present some examples of its performance below.

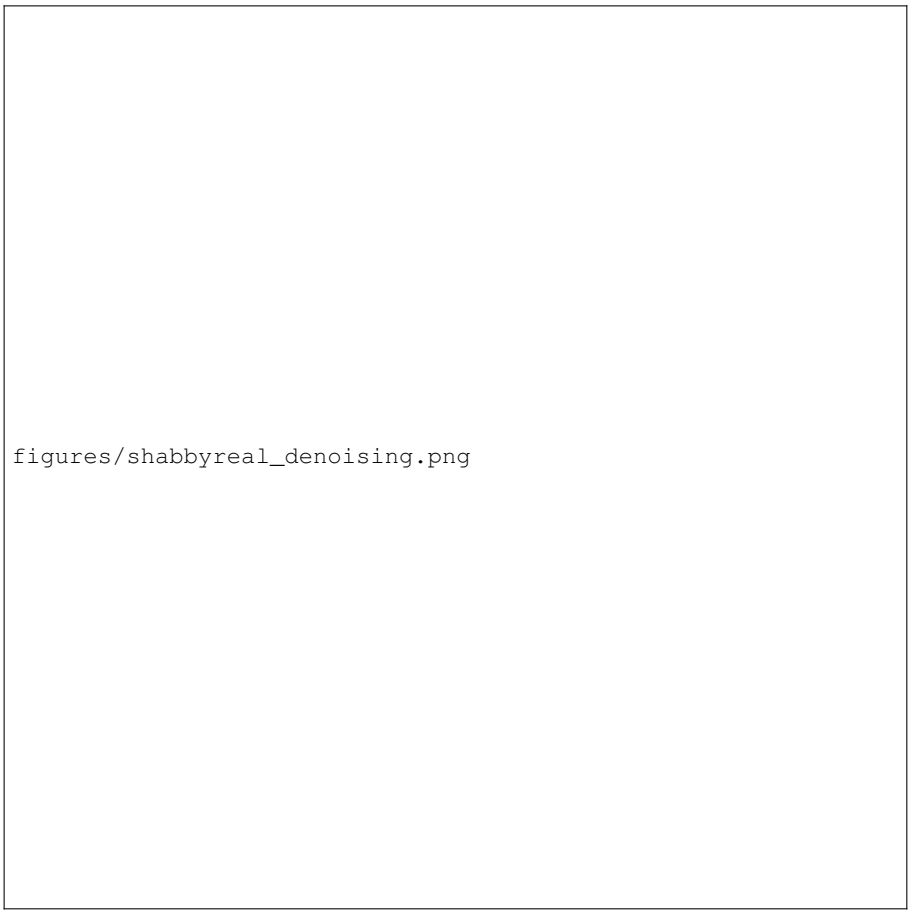


Fig. 6. Sample *ShabbyPages* images and their Shabby_NAFNet-denoised versions.

4.2 Binarization

In this section, we discuss results obtained by training a NAFNet denoiser to both restore augmented images to their ground truths and to classify pixels as foreground.

We first performed an ensemble binarization preprocessing step on the clean groundtruth images. For each image, we computed the Niblack, Sauvola, and Otsu thresholds, using these to binarize three copies of the input. The average

over the resulting matrices was taken elementwise, producing the final binarized groundtruth.

One instance of the model was trained on the full SimulatedNoisyOffice corpus, while the other was trained on a 1050-image subset of *ShabbyPages*, cropped to a single random 500x500 patch. In both cases, the prediction target was the relevant ensemble-binarized groundtruths, and each instance trained for 100 epochs. As a test, these models were used to denoise and binarize both the full NoisyOfficeReal dataset and a 450-image testing subset taken from *ShabbyPages* which does not overlap the training subset.

Multiple common image processing metrics were applied to the predictions made by each model, comparing these to the preprocessed groundtruths. In addition to the structural similarity metric from the denoising task, we add the peak signal to noise ratio (PSNR) and the root mean squared error (RMSE). Both of these metrics are more useful for determining the differences between binary images: together, they give some idea of the degree to which noise artifacts remain in the image after denoizing and binarization affect the visual signal, and how many such artifacts exist. The averages of each metric over all predictions was taken, with the results presented in Table [**?**].

Table 4. Document image binarization performance of a NAFNet model trained and tested on *ShabbyPages* and *NoisyOffice*.

Training Set	Test Set	SSIM↑	PSNR↑	RMSE↓
ShabbyPages	NoisyOffice-real	**0.947**	**38.098**	**3.205**
NoisyOffice-sim	ShabbyPages	0.811	34.562	5.384

We cross-validate these models by predicting cleaned and binarized images using the other testing set as inputs. The *ShabbyPages*-trained model was able to classify foreground and background pixels in the *NoisyOffice* test set with a substantially higher degree of accuracy than the *NoisyOffice*-trained model could classify *ShabbyPages*, even with less-favorable training data. *ShabbyPages* contains a much higher feature diversity than *NoisyOffice*, so these results were unsurprising, although we did expect our model to achieve worse results than it did, since it only saw a single patch from each full page. The *ShabbyPages*-trained model performs well on a much wider range of features, handling tables, graphs, and even simple images quite well. This is a strong indicator that neural networks trained on *ShabbyPages* can outperform those trained on *NoisyOffice* when generalizing to other datasets.

5 Conclusion

Supervised learning requires a collection of training data and accompanying "labels", which in the graphical modality are clean images, free of noise or other degradations. We presented *ShabbyPages*, a large dataset composed of

6202 clean/noisy pairs of synthetically-noisy images taken from 600 digital documents. Information about the set's contents and its relation to other common datasets was explored. The noisy images were created from their clean origins by the application of a pipeline developed with the *Augraphy* library; the production of *ShabbyPages* was detailed in the third section, with all source code and input materials made openly available. *ShabbyPages* was used to train performant denoising and binarization models which generalize well to document images containing real noise.

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