

DE-GAN: A Conditional Generative Adversarial Network for Document Enhancement

Mohamed Ali Souibgui and Yousri Kessentini

Abstract—Documents often exhibit various forms of degradation, which make it hard to be read and substantially deteriorate the performance of an OCR system. In this paper, we propose an effective end-to-end framework named Document Enhancement Generative Adversarial Networks (DE-GAN) that uses the conditional GANs (cGANs) to restore severely degraded document images. To the best of our knowledge, this practice has not been studied within the context of generative adversarial deep networks. We demonstrate that, in different tasks (document clean up, binarization, deblurring and watermark removal), DE-GAN can produce an enhanced version of the degraded document with a high quality. In addition, our approach provides consistent improvements compared to state-of-the-art methods over the widely used DIBCO 2013, DIBCO 2017 and H-DIBCO 2018 datasets, proving its ability to restore a degraded document image to its ideal condition. The obtained results on a wide variety of degradation reveal the flexibility of the proposed model to be exploited in other document enhancement problems.

Index Terms—Document analysis, Document enhancement, Degraded document binarization, Watermark removal, Deep learning, Generative adversarial networks.



1 INTRODUCTION

AUTOMATIC document processing consists in the transformation into a form that is comprehensible by a computer vision system or by a human. Thanks to the development of several public databases, document processing has made a great progress in recent years [1], [2]. However, this processing is not always effective when documents are degraded. Lot of damages could be done to a document paper. For example: Wrinkles, dust, coffee or food stains, faded sun spots and lot of real-life scenarios [3]. Degradation could be presented also in the scanned documents because of the bad conditions of digitization like using the smart-phones cameras (shadow [4], blur [5], variation of light conditions, distortion, etc.). Moreover, some documents could contain watermarks, stamps or annotations. The recovery is even harder when certain types of these later take the text place for instance in cases where the stains color is the same or darker than the document font color (Fig. 1 shows some examples). Hence, an approach to recover a clean version of the degraded document is needed.

In this study, we are focusing on two document enhancement problems. Degraded documents recovery, i.e., to produce a clean (grayscale or binary) version of the document given any type of degradation, and watermark removal. The faced obstacles are as follows: Overlaps of noise or watermarks with the text, dense watermarks, intense dirt or degradation can cover the entire text and reading it becomes very hard, there is no prior knowledge about the degradation or the watermark that should be removed, etc. An ideal system should be good in performing two tasks

simultaneously, removing the noise and the watermarks as well as retaining the text quality in the document images.

Recently, a great success is made by deep neural networks in natural images generation and restoration, especially deep convolutional neural networks (auto-encoders and variational auto-encoders (VAE)) [6], [7], [8] and generative adversarial networks (GANs) [9], [10]. GANs, which were introduced in [11], are now considered as the ideal solution for image generation problems [10] with a high quality, stability and variation compared to the auto-encoders. Generative models gained more attention because of the ability of capturing high dimensional probability distributions, imputation of missing data and dealing with multimodal outputs. Despite that, document analysis research community is not benefiting enough from those approaches, yet. Using them is very limited, for instance, in font translation [12], handwritten profiling [13] and staff-line removal from a music score images [14], where a promising results were found.

In [9], Isola et al. show that conditional generative adversarial networks (cGANs), a variation of GANs, performs good in image-to-image translation (labels to facade, day to night, edges to photo, BW to color, etc.). While GANs learn a generative model of data, conditional GANs (cGANs) learn a conditional generative model, where it conditions on an input image and generate a corresponding output image. Since document enhancement follows the same process, means, we want to preserve the text and remove the damage in a conditioned image, cGANs shall be the suitable solution, and this is what motivated us for this study.

The main contributions of this paper are: As primary, to the best of our knowledge, this is the first occurrence of GANs, conditional GANs specifically, in a framework that addresses different document enhancement problems (clean up, binarization and watermark removal). Second, we used a simple but flexible architecture that could be exploited

- M. A. Souibgui is with Computer Vision Center, Edifici O, Bellaterra, 08193, Spain and Computer Science Department, Universitat Autònoma de Barcelona, Spain.
E-mail: msouibgui@cvc.uab.es
- Y. Kessentini, Digital Research Center of Sfax, B.P. 275, Sakiet Ezzit, 3021 Sfax, Tunisia, MIRACL Laboratory, University of Sfax, Sfax, Tunisia.
E-mail: yousri.kessentini@crms.rnrt.tn

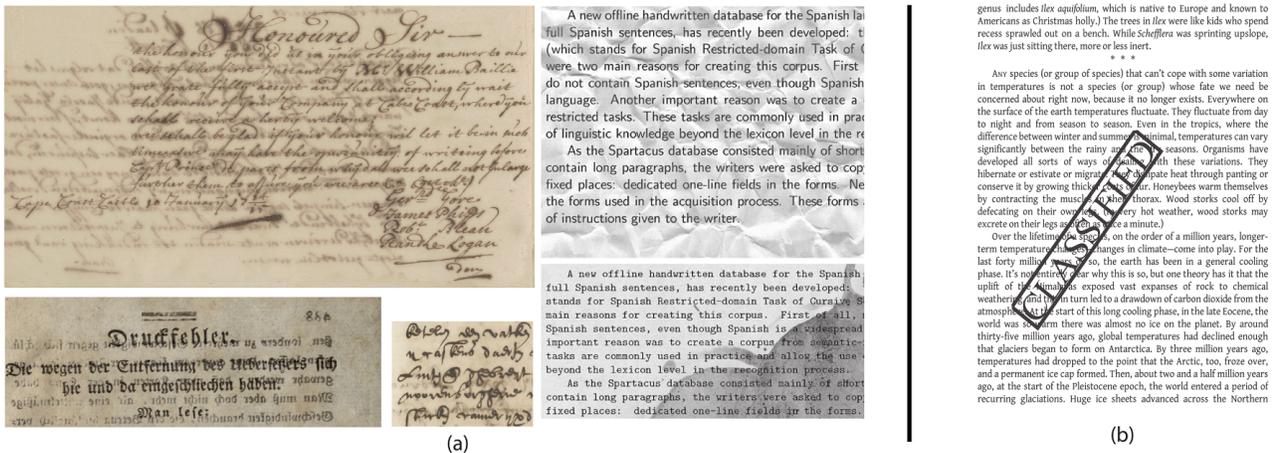


Fig. 1. Examples of the documents used in this study: (a): Degraded documents, (b): A document with dense watermark.

to tackle any document degradation problem. Third, we introduce a new document enhancement problem consists in dense watermarks and stamps removal. Finally, we experimentally prove that our approach achieves a higher performance compared to the state-of-the-art methods in degraded document binarization.

The rest of the paper is organized as follows. In Section 2, a summary of previous works on document enhancement, especially for document clean up and binarization and watermark removal in documents as well as in natural images. We review also some related works using the GANs in image-to-image translation. Then, we provide our proposed approach in Section 3. Some experimental results and comparison with traditional and recent methods are described in section 4. Finally, a conclusion with some future research directions are presented in Section 5.

2 RELATED WORKS

In this work, we focus on the enhancement of degraded document images by addressing different kinds of degradation which are document clean up, binarization, and watermark removal. From a document analyst viewpoint, this recovery of a clean version from the degraded document falls in the research field called document enhancement. Where we can find, in addition to those three, many other ways to enhance a document. For instance: unshadowing [4], [15], super-resolution [16], deblurring [5], dewarping [17], etc. In what follows, we cover some related works to our addressed problems.

2.1 Degraded document recovering and binarization

Dirty document cleaning is related to document image binarization, especially the degraded ones. Where the goal is to produce a binary but clean document. That is why, dealing with these two problems was almost the same. The idea is to classify the pixels of the document as one of two categories: degradation or text. Afterward, assigning zeros to the text pixels and ones for the degradation will generate a binary

clean image. While generating a gray-scale or colored image is done by preserving the same value for the text pixels.

Classic document binarization methods [18], [19], [20], [21], [22], [23] were based on thresholding, many algorithms were developed for the goal of finding the suitable global or local threshold(s) to apply as a filter. According to the threshold(s), pixels are classified to be belonging on the text (zero) or the degradation (one). Lore et al. [24] presented an algorithm called FAIR, based on edge detection to localize the text in a degraded document image. A global threshold selection method was proposed in [25], basing on fuzzy expert systems (FESs), the image contrast is enhanced. Then, the range of the threshold value is adjusted by another FES and a pixel-counting algorithm. Finally, the threshold value is obtained as the middle value of that range. A machine learning based approach was proposed in [26], the goal was the determination of the binarization threshold in each image region given a three-dimensional feature vector formed by the distribution of the gray level pixel values. The support vector machine (SVM) was used to classify each region into one of four different threshold values. An other and similar SVM based approach was introduced in [27]. The main drawbacks of these classic methods is that the results are highly sensitive to document condition. With a complex image background or a non uniform intensity, problems occurred.

Later, evolved techniques were proposed. Moghaddam et al. [28] proposed a variational model to remove the bleed-through from the degraded double-sided document images. For the cases where the verso side of the document is not available, a modified variational model is also introduced. By transferring the model to the wavelet domain and using the hard wavelet shrinkage, the interference patterns was removed. Other energy based methods were also introduced. In [29], authors considered the ink as a target and tried to detect it by maximizing an energy function. This technique was applied also for scene text binarization [30], which is a similar task. Similarly, Xiong et al. [31] estimated the background and subtracted it from the image by a mathematical morphology. Then the Laplacian energy based

segmentation is performed on the enhanced document image to classify the pixels. Although these sophisticated image processing techniques, document binarization results are still unsatisfactory. For this reason, some deep learning frameworks were recently used to tackle this problem. The goal here is not to train a model for predicting a threshold, it is to directly separate the foreground text from the background noise given, of course, a considerable amount of paired data (degraded images and their binarized versions). These deep learning based models lead to better results compared to the other hand-crafted methods. Several End-to-end frameworks, based on fully convolutional neural-network (encoder-decoder way), was used to binarize and enhance the document image [32], [33], [34]. Afzal et al. [35] formulated the binarization of document images as a sequence learning problem. Hence, the 2D Long Short-Term Memory (LSTM) was employed to process a 2D sequence of pixels for the classification of each pixel as text or background. In [36], an other Fully convolutional network was trained with a combined Pseudo F-measure and F-measure loss function for the task of document image binarization. A method that inspires from the two previous approaches, i.e., a recurrent neural network based algorithm using grid LSTM cells for image binarization, as well as a pseudo F-Measure based weighted loss function could be found in [37]. Vo et al. [38] proposed a hierarchical deep supervised network (DSN) architecture to predict the text pixels. They claimed that their architecture incorporates side layers to decrease the learning time, while taking a lot of training data.

It is to note that in this paper our object is not to binarize the document images but to clean the degraded ones and preserve them in their basic grey or colored level. But, we will test our approach in this problem for the purpose of comparison with the state-of-the art approaches.

2.2 Watermark removal

Watermark removal is also related to classical document binarization or image matting, where the goal is to decompose a single image into background and foreground knowing that this time the text is in the background while the watermark is in the foreground. But, this problem was not proposed in document processing. In fact, the appeared works that deal with watermark removal was in natural images processing. In [39], authors used an image inpainting algorithms to remove the watermark. Before that, a statistical method was used to detect the watermark region. Dekel et al. [40] proposed to estimate the outline sketch and alpha matte of the same watermark from a batch of different images. Two watermarks were used in this study, the goal was testing the effectiveness of a single visible watermark to protect a large set of images. Wu et al. [41] used the generative adversarial networks [11] to remove watermark from faces images used in a biometric system. Cheng et al. [42] proposed a method based on convolutional neural networks (CNN). First, object detection algorithms were used to detect the watermark region in natural images and then pass it to an other model to remove the watermark. In our study, we investigate for the first time the problem of watermark removal in document images, this leads us

to compare our approach with some results obtained on natural images for the same purpose.

2.3 Generative adversarial networks for image-to-image transform

As mentioned above, GANs are now achieving impressing results in image generation and translation. In this paragraph, we investigate the use of this mechanism in related problems to document processing and enhancement. This shall gives intuitions to document analysis community about exploiting GANs for these tasks. In [43], it was demonstrated that GANs lead to improvements in semantic segmentation. Ledig et al. presented SRGAN [44], a Generative Adversarial Network for image Super-Resolution. Through it, they achieved a photo-realistic reconstructions for large upscaling factors ($4\times$). In [44], conditional GANs were used for several image-to-image translation tasks (these tasks are related to document enhancement), given a paired data. This work was extended to [45], where CycleGAN, a GAN that uses impaired data, was proposed as a solution. An other model called "pix2pix-HD" and deals with high-resolution (e.g. 2048×1024) photorealistic image-to-image translation tasks was appeared in [46]. Furthermore, an unsupervised method for image-to-image translation was proposed in [47], where authors train two GANs, or "DualGAN" as they denoted. In their architecture, the primal GAN learns to translate images from a domain U to a domain V , while the dual GAN learns to invert the task. The closed loop architecture allows images from each domain to be translated and then reconstructed. Hence, a loss function that accounts for the reconstruction error of images can be used to train the translators.

3 PROPOSED APPROACH

We consider the problems of document enhancement as an image to image translation task where the goal is to *generate* clean document images given the degraded ones. Since GANs have outperformed auto-encoders in generating high fidelity samples and while we are using paired data, we propose to use a cGAN. We called our model *DE-GAN* (for Document Enhancement conditional Generative Adversarial Network). GANs were initially proposed in [47] and consist in two neural networks, a generator G and a discriminator D characterized by the parameters φ_G and φ_D , respectively. The generator have the goal of learning a mapping from a random noise vector z to an image y , $G_{\varphi_G}: z \rightarrow y$. While the discriminator has the function of distinguishing between the image generated by G and the ground truth one. Hence, given y , D should be able to tell if it is *fake* or *real* by outputting a probability value, $D_{\varphi_D}: y \rightarrow P(\text{real})$. Those two networks compete against each other in a min-max game, in other words if one wins the other loses. The generator aims to cheat the discriminator by producing a close image to the ground truth, however, the discriminator will improve his prediction of the image being fake, and this is what is called the adversarial learning. cGANs follow the same process, except that, they introduced an additional parameter x . Which is the conditioned image. Here, the generator is learning the mapping from

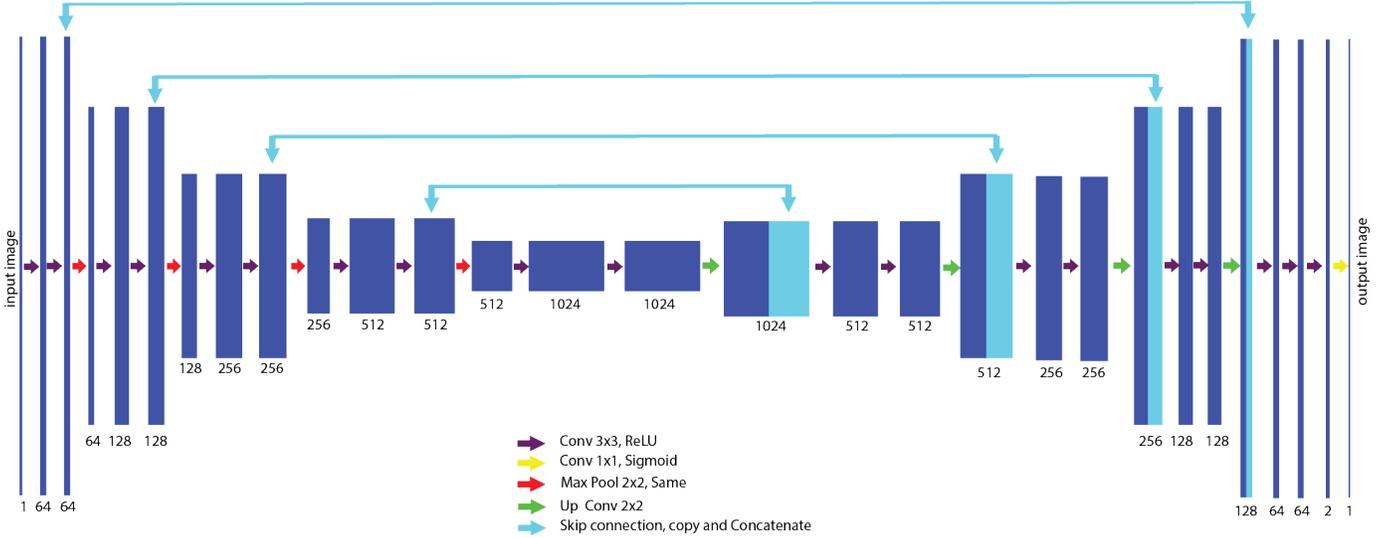


Fig. 2. The generator follows the U-net architecture [48]. Each box corresponds to a feature map. The number of channels is denoted on bottom of the box. The arrows denote the different operations.

an observed image x and a random noise vector z , to y , $G_{\varphi_G}: \{x, z\} \rightarrow y$ and the discriminator is looking, also, to the conditioned image which makes his process as: $D_{\varphi_D}: \{x, y\} \rightarrow P(\text{real})$.

In our situation, the generator will generate a clean image denoted by I^C given the degraded (or watermarked) one which we will denote I^W . The generator aims, of course, to produce an image that is very close to the ground truth image denoted by I^{GT} . The training of cGANs for this task is done by the following adversarial loss function:

$$L_{GAN}(\varphi_G, \varphi_D) = \mathbb{E}_{I^W, I^{GT}} \log[D_{\varphi_D}(I^W, I^{GT})] + \mathbb{E}_{I^W} \log[1 - D_{\varphi_D}(I^W, G_{\varphi_G}(I^W))] \quad (1)$$

Using this function, the generator should produce, after several epochs, a similar image to the ground truth, i.e., the watermark and the degradation will be removed and this may fool the discriminator. But, it is not guaranteed that the text will be preserved in a good condition. To overcome this, we employ an additional log loss function between the generated image and the ground truth, for the purpose of forcing the model to generate images that have the same text as the ground truth. It is to note also that this additional loss boosts the training speed, the added function is:

$$L_{log}(\varphi_G) = \mathbb{E}_{I^{GT}, I^W} [-(I^{GT} \log(G_{\varphi_G}(I^W)) + ((1 - I^{GT}) \log(1 - G_{\varphi_G}(I^W)))] \quad (2)$$

Thus, the proposed loss of our network, denoted by L_{net} becomes:

$$L_{net}(\varphi_G, \varphi_D) = \min_{\varphi_G} \max_{\varphi_D} L_{GAN}(\varphi_G, \varphi_D) + \lambda L_{log}(\varphi_G) \quad (3)$$

Where, λ is a hyper-parameter that was set to 100 for text cleaning and 500 in watermark removal and document binarization. The architecture of generator and discriminator networks are described in the next sections.

3.1 Generator:

The generator is performing an image-to-image translation task. Usually, auto-encoder models are used for this problem [49], [50], [51]. These models consist, mostly, in a sequence of convolutional layers called encoder which perform down-sampling until a particular layer. Then, the process is reversed to a sequence of up-sampling and convolutional layers called decoder. There are two disadvantages of using an encoder-decoder model for the proposed problem: First, due to down-sampling (pooling), lot of information is lost and the model will have difficulties to recover them later when predicting an image with the same size as the input. Second, image information flow pass through all the layers, including the bottleneck. Thus, sometimes, a huge amount of unwanted redundant features (inputs and outputs are sharing a lot of same pixels) are exchanged. Which leads to energy and time loss. For this reason, we employ skip connections following the structure of a the model called U-net [48]. Skip connections are added every two layers to recover images with less deterioration, it is to note also that skip connections are used when training a very deep model to prevent the gradient vanishing and exploding problems. Some batch normalization layers are also added to accelerate the training. The architecture of the generator used in this study is illustrated in Fig. 2, it is similar to [48] where it was introduced for the purpose of biomedical image segmentation.

3.2 Discriminator

The defined discriminator is a simple Fully Convolutional Network (FCN), composed of 6 convolutional layers, that output a 2D matrix containing probabilities of the generated image being real. This model is presented in Fig. 3. As shown, the discriminator receives two input images which are the degraded image and its clean version (ground truth or cleaned by the generator). Those images were concatenated together in a $256 \times 256 \times 2$ shape tensor. Then, the

We take the DIBCO 2013 Dataset [52] for testing. While training our model was done with different versions of DIBCO Databases [53], [54], [55], [56], [57], [58]. Same as the previous test, a set of 6824 training pairs (patches of size 256×256) was taken from its 80 total images. The obtained results are compared with several approaches in Table 2.

TABLE 2
Results of image binarization on DIBCO 2013 Database.

Model	PSNR	F-measure	F_{ps}	DRD
Otsu [18]	16.6	83.9	86.5	11.0
Niblack [20]	13.6	72.8	72.2	13.6
Sauvola et al. [19]	16.9	85.0	89.8	7.6
Gatos et al. [59]	17.1	83.4	87.0	9.5
Su et al. [60]	19.6	87.7	88.3	4.2
Tensmeyer et al [36]	20.7	93.1	96.8	2.2
Xiong et al. [31]	21.3	93.5	94.4	2.7
Vo et al. [38]	21.4	94.4	96.0	1.8
Howe [61]	21.3	91.3	91.7	3.2
DE-GAN	24.9	99.5	99.7	1.1

Out of the results, we can say that DE-GAN is superior than the current state-of-the-art methods according to the following metrics [52]: Peak signal-to-noise ratio (PSNR), F-measure, pseudo-F-measure (F_{ps}) and Distance reciprocal distortion metric (DRD). Some examples of DIBCO 2013 images binarization by DE-GAN are presented in Fig. 6.

Degraded images	
Ground truth	
Predicted images	

Fig. 6. Binarization of degraded documents by DE-GAN, the result is satisfactory, except in some parts that were highly dense (the red boxes in the predicted images row)

To reflect the results of the previous Table, an illustrative comparisons between those different methods could be found in Fig. 7 and Fig. 8. It is easy to visualize the superiority of our method over the classic methods, like those of [18], [19], [20], which fail to remove the background degradation from the document when it get very dense, because they are basing on thresholds that make the degraded pixels classified as a text, or classifying the text pixels as a damage to be removed. For the recent approaches [38], [61], they yield a better result than the classic ones and separate the text from the background successfully. However, our

method gives a higher performance in terms of closeness to the ground truth image.

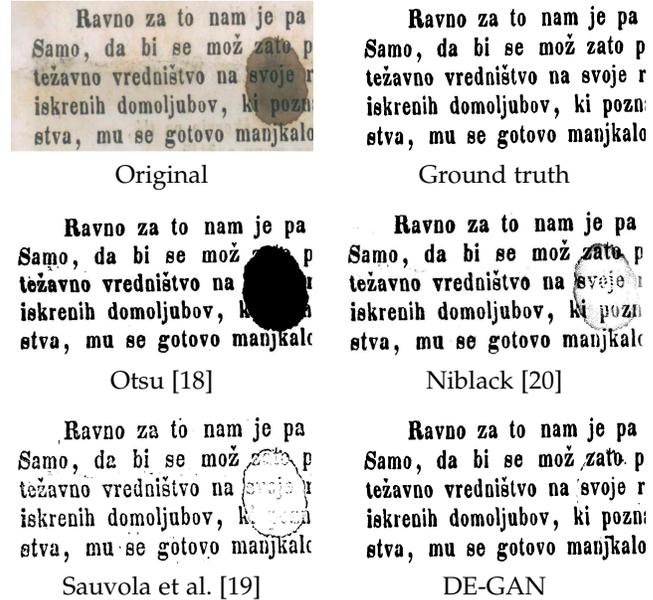


Fig. 7. Qualitative binarization results produced by different methods of a part from the sample (PR5), which is included in DIBCO 2013 dataset

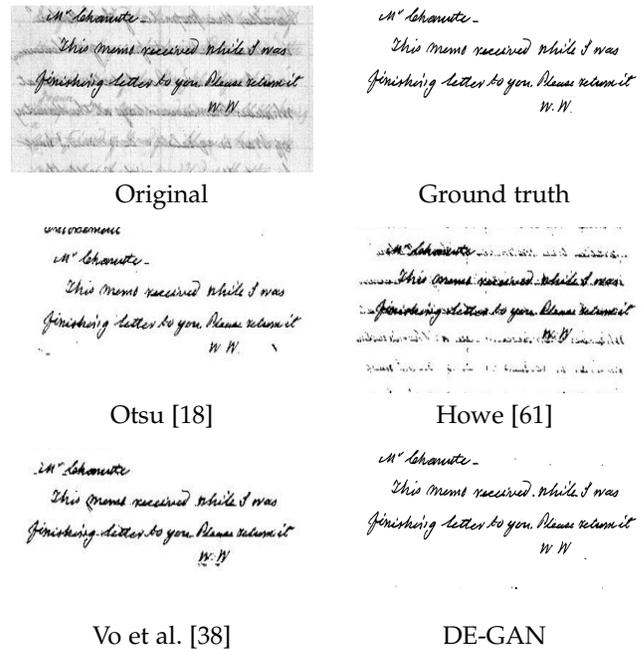


Fig. 8. Qualitative binarization results produced by different methods of a part from the sample (HW5), which is included in DIBCO 2013 dataset

Moreover, we tested DE-GAN on a recent DIBCO dataset, which is DIBCO 2017 [58]. We train our model on 6098 patches from similar datasets [52], [53], [54], [55], [56], [57]. The comparison is done with the top 5 ranked approaches in ICDAR 2017 competition on document image binarization [58]. 18 research groups have participated in the competition with 26 distinct algorithms. The results are

presented in table 3, where you can notice the superiority of our DE-GAN over the different methods. It is to note that most of these approaches are based on encoder-decoder models and the winner team was using a U-net with several data augmentation techniques. However, GANs were not exploited in this competition. An example to compare our output with the winner algorithm is given in figure 9.

TABLE 3
Results of image binarization on DIBCO 2017 Database, a comparison with DIBCO 2017 competitors approaches.

Model	PSNR	F-measure	F _{ps}	DRD	Rank in the competition
10 [58]	18.28	91.04	92.86	3.40	1
17a [58]	17.58	89.67	91.03	4.35	2
12 [58]	17.61	89.42	91.52	3.56	3
1b [58]	17.53	86.05	90.25	4.52	4
1a [58]	17.07	83.76	90.35	4.33	5
DE-GAN	18.74	97.91	98.23	3.01	-

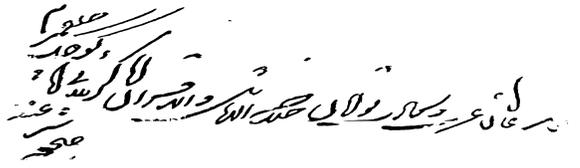
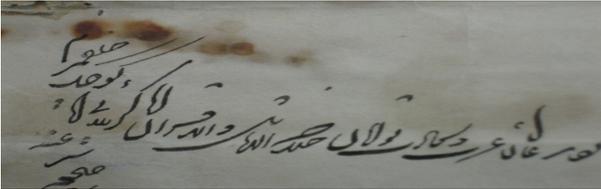
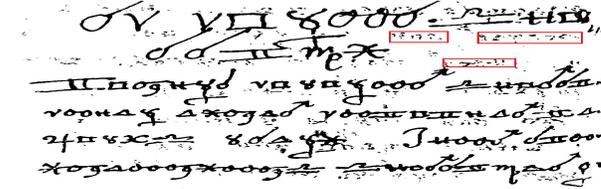
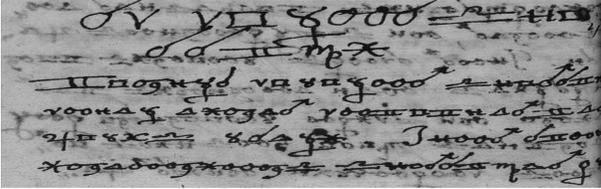
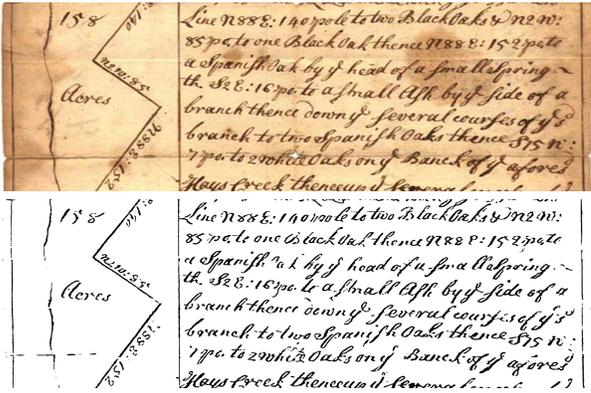


Fig. 9. Qualitative binarization results produced by different of the sample 16 in DIBCO 2017 dataset, here we compare DE-GAN with the winner's approach.

In addition, we compared our model with the most recent approaches, presented in the H-DIBCO 2018 competition [62] that was held in ICFHR 2018 conference. The results are presented in Table 4. As shown, our approach has the best performance on DIBCO 2017 test set and gives the second best DRD, PSNR, F-measure and pseudo F-Measure on H-DIBCO 2018 test set. We note that the winner system in the competition integrates a lot of pre-processing and a post-processing steps in their algorithm, that make it more efficient for this particular H-DIBCO 2018 dataset. On the contrary, we are presenting a simple end-to-end model that shows a good ability in a several datasets and enhancements tasks without any additional processing step. Finally, for a more practical usage of the model, we tried to binarize some real (naturally degraded) documents as well, the degradation consists in stains and show-through. The obtained results are given in Fig. 10, the model is producing a better versions of the real images, which will certainly improves their recognition rate.

4.2 Watermark removal

After testing our model in document cleaning and binarization, we will evaluate it on the problem of watermark

Fig. 10. Binarization of three historical degraded documents by DE-GAN, the binarized version is presented under each original image. Some parts are not well recovered as shown in the red boxes.

removal. Dense watermarks (or stamps) can cause a huge deterioration in the foreground of the document, which make it hard to be read. However, this problem was not investigated by document analysis community. We decided to be the first that address it using DE-GAN. Hence, it was not possible to find a public dataset for testing. We created our own database which contains 1000 pairs (image of a document with a dense watermark and stamps and its clean version).

The used watermarks have random texts, sizes, colors, fonts, opacities and locations (see Fig. 11). As shown, these watermarks are sometimes covering the entire text making it unseeable by the unaided eye. The code used to produce this

Watermarked images	Ground truth	Predicted images
<p>concept of evolution, or transformation as it was known in Paris at the time, and he tried—generally, it seems, successfully—to humiliate any colleagues who advanced the theory. Curiously, it was the very same skills that led him to discover extinction that made evolution seem to him so preposterous, an affair as unlikely as levitation.</p> <p>As Cuvier liked to point out, he put his faith in anatomy; this was what had allowed him to distinguish the bones of a mammoth from those of an elephant and to recognize as a giant salamander what others took to be a man. At the heart of his understanding of anatomy was a notion he termed “correlation of parts.” By this he meant that the components of an animal all fit together and are optimally designed for its particular way of life. Thus, for example, a carnivore will have an intestinal system suited to digesting flesh. At the same time, its jaws will be constructed for devouring prey; its teeth, for tearing and dividing its flesh; the entire system of its locomotive organs, for pursuing and being in its some organs for detecting its prey.</p> <p>Conversely, an animal with hooves must necessarily be an herbivore, since it has “no means of seizing prey.” It will have “teeth with a flat crown, to grind seeds and grasses,” and a jaw capable of lateral motion. Were any one of these parts to be altered, the functional integrity of the whole would be destroyed. An animal that was born with, say, teeth or jaw organs that were somehow different from its parents’ would not be able to survive, let alone give rise to a whole new kind of creature.</p> <p>In Cuvier’s day, the most prominent proponent of transformation was his senior colleague at the Museum of Natural History, Jean-Baptiste Lamarck. According to Lamarck, there was a force, the “power of life”—that pushed organisms to become increasingly complex. At the same time, animals and also plants often had to cope with changes in their environment. They did so by adjusting their habits; these new habits, in turn, produced physical modifications that were then passed down to their offspring. Birds that sought prey in lakes spread out their toes when they hit the water, and in this way eventually developed webbed feet and</p>	<p>concept of evolution, or transformation as it was known in Paris at the time, and he tried—generally, it seems, successfully—to humiliate any colleagues who advanced the theory. Curiously, it was the very same skills that led him to discover extinction that made evolution seem to him so preposterous, an affair as unlikely as levitation.</p> <p>As Cuvier liked to point out, he put his faith in anatomy; this was what had allowed him to distinguish the bones of a mammoth from those of an elephant and to recognize as a giant salamander what others took to be a man. At the heart of his understanding of anatomy was a notion he termed “correlation of parts.” By this he meant that the components of an animal all fit together and are optimally designed for its particular way of life. Thus, for example, a carnivore will have an intestinal system suited to digesting flesh. At the same time, its jaws will be constructed for devouring prey; its teeth, for tearing and dividing its flesh; the entire system of its locomotive organs, for pursuing and being in its some organs for detecting its prey.</p> <p>Conversely, an animal with hooves must necessarily be an herbivore, since it has “no means of seizing prey.” It will have “teeth with a flat crown, to grind seeds and grasses,” and a jaw capable of lateral motion. Were any one of these parts to be altered, the functional integrity of the whole would be destroyed. An animal that was born with, say, teeth or jaw organs that were somehow different from its parents’ would not be able to survive, let alone give rise to a whole new kind of creature.</p> <p>In Cuvier’s day, the most prominent proponent of transformation was his senior colleague at the Museum of Natural History, Jean-Baptiste Lamarck. According to Lamarck, there was a force, the “power of life”—that pushed organisms to become increasingly complex. At the same time, animals and also plants often had to cope with changes in their environment. They did so by adjusting their habits; these new habits, in turn, produced physical modifications that were then passed down to their offspring. Birds that sought prey in lakes spread out their toes when they hit the water, and in this way eventually developed webbed feet and</p>	<p>concept of evolution, or transformation as it was known in Paris at the time, and he tried—generally, it seems, successfully—to humiliate any colleagues who advanced the theory. Curiously, it was the very same skills that led him to discover extinction that made evolution seem to him so preposterous, an affair as unlikely as levitation.</p> <p>As Cuvier liked to point out, he put his faith in anatomy; this was what had allowed him to distinguish the bones of a mammoth from those of an elephant and to recognize as a giant salamander what others took to be a man. At the heart of his understanding of anatomy was a notion he termed “correlation of parts.” By this he meant that the components of an animal all fit together and are optimally designed for its particular way of life. Thus, for example, a carnivore will have an intestinal system suited to digesting flesh. At the same time, its jaws will be constructed for devouring prey; its teeth, for tearing and dividing its flesh; the entire system of its locomotive organs, for pursuing and being in its some organs for detecting its prey.</p> <p>Conversely, an animal with hooves must necessarily be an herbivore, since it has “no means of seizing prey.” It will have “teeth with a flat crown, to grind seeds and grasses,” and a jaw capable of lateral motion. Were any one of these parts to be altered, the functional integrity of the whole would be destroyed. An animal that was born with, say, teeth or jaw organs that were somehow different from its parents’ would not be able to survive, let alone give rise to a whole new kind of creature.</p> <p>In Cuvier’s day, the most prominent proponent of transformation was his senior colleague at the Museum of Natural History, Jean-Baptiste Lamarck. According to Lamarck, there was a force, the “power of life”—that pushed organisms to become increasingly complex. At the same time, animals and also plants often had to cope with changes in their environment. They did so by adjusting their habits; these new habits, in turn, produced physical modifications that were then passed down to their offspring. Birds that sought prey in lakes spread out their toes when they hit the water, and in this way eventually developed webbed feet and</p>
<p>e; thus, for example, a carnivore will have an intestinal system suited to digesting flesh. At the same time, its jaws will be constructed for devouring prey; its teeth, for tearing and dividing its flesh; the entire system of its locomotive organs, for pursuing and being in its some organs for detecting its prey.</p>	<p>e; thus, for example, a carnivore will have an intestinal system suited to digesting flesh. At the same time, its jaws will be constructed for devouring prey; its teeth, for tearing and dividing its flesh; the entire system of its locomotive organs, for pursuing and being in its some organs for detecting its prey.</p>	<p>e; thus, for example, a carnivore will have an intestinal system suited to digesting flesh. At the same time, its jaws will be constructed for devouring prey; its teeth, for tearing and dividing its flesh; the entire system of its locomotive organs, for pursuing and being in its some organs for detecting its prey.</p>
<p>Engage in Focused Thinking</p> <p>The old saying rings as if it had nothing else to say.</p> <p>—BIBLES OF MODERNITY CONSULTS DIRECTOR</p> <p>Philosopher Bertrand Russell once asserted, “To be able to concentrate for a considerable time is essential to intellectual achievement. Successful thinking requires a considerable amount of time and effort. It is not a matter of luck and talent. Focused thinking can be learned through practice.”</p> <p>1. Focused Thinking Harnesses Energy Toward a Desired Goal</p> <p>Focus harnesses energy and power to create something, whether it is an object or an idea. It is the ability to concentrate on a single task and to ignore all other distractions. It is the ability to focus on a single goal and to work toward it with determination and persistence. It is the ability to harness your energy and power toward a single goal and to work toward it with determination and persistence.</p> <p>2. Focused Thinking Gives Ideas Time to Develop</p> <p>Ideas are developed and refined through focused thinking. It is the ability to concentrate on a single idea and to work toward it with determination and persistence. It is the ability to focus on a single idea and to work toward it with determination and persistence.</p> <p>3. Focused Thinking Brings Clarity to the Target</p> <p>Clarity is the result of focused thinking. It is the ability to concentrate on a single target and to work toward it with determination and persistence. It is the ability to focus on a single target and to work toward it with determination and persistence.</p>	<p>Engage in Focused Thinking</p> <p>The old saying rings as if it had nothing else to say.</p> <p>—BIBLES OF MODERNITY CONSULTS DIRECTOR</p> <p>Philosopher Bertrand Russell once asserted, “To be able to concentrate for a considerable time is essential to intellectual achievement. Successful thinking requires a considerable amount of time and effort. It is not a matter of luck and talent. Focused thinking can be learned through practice.”</p> <p>1. Focused Thinking Harnesses Energy Toward a Desired Goal</p> <p>Focus harnesses energy and power to create something, whether it is an object or an idea. It is the ability to concentrate on a single task and to ignore all other distractions. It is the ability to focus on a single goal and to work toward it with determination and persistence. It is the ability to harness your energy and power toward a single goal and to work toward it with determination and persistence.</p> <p>2. Focused Thinking Gives Ideas Time to Develop</p> <p>Ideas are developed and refined through focused thinking. It is the ability to concentrate on a single idea and to work toward it with determination and persistence. It is the ability to focus on a single idea and to work toward it with determination and persistence.</p> <p>3. Focused Thinking Brings Clarity to the Target</p> <p>Clarity is the result of focused thinking. It is the ability to concentrate on a single target and to work toward it with determination and persistence. It is the ability to focus on a single target and to work toward it with determination and persistence.</p>	<p>Engage in Focused Thinking</p> <p>The old saying rings as if it had nothing else to say.</p> <p>—BIBLES OF MODERNITY CONSULTS DIRECTOR</p> <p>Philosopher Bertrand Russell once asserted, “To be able to concentrate for a considerable time is essential to intellectual achievement. Successful thinking requires a considerable amount of time and effort. It is not a matter of luck and talent. Focused thinking can be learned through practice.”</p> <p>1. Focused Thinking Harnesses Energy Toward a Desired Goal</p> <p>Focus harnesses energy and power to create something, whether it is an object or an idea. It is the ability to concentrate on a single task and to ignore all other distractions. It is the ability to focus on a single goal and to work toward it with determination and persistence. It is the ability to harness your energy and power toward a single goal and to work toward it with determination and persistence.</p> <p>2. Focused Thinking Gives Ideas Time to Develop</p> <p>Ideas are developed and refined through focused thinking. It is the ability to concentrate on a single idea and to work toward it with determination and persistence. It is the ability to focus on a single idea and to work toward it with determination and persistence.</p> <p>3. Focused Thinking Brings Clarity to the Target</p> <p>Clarity is the result of focused thinking. It is the ability to concentrate on a single target and to work toward it with determination and persistence. It is the ability to focus on a single target and to work toward it with determination and persistence.</p>
<p>inking Gives Ideas Time to and develop ideas. I often bring my creative ideas together, we try to be exhaustive in our thinking of a potential breakthrough often results to the next level, you must shift from being a</p>	<p>inking Gives Ideas Time to and develop ideas. I often bring my creative ideas together, we try to be exhaustive in our thinking of a potential breakthrough often results to the next level, you must shift from being a</p>	<p>inking Gives Ideas Time to and develop ideas. I often bring my creative ideas together, we try to be exhaustive in our thinking of a potential breakthrough often results to the next level, you must shift from being a</p>
<p>The Power on Your Side</p> <p>Quimby said it was it were, dead to come from the dead. Ou</p>	<p>The Power on Your Side</p> <p>Quimby said it was it were, dead to come from the dead. Ou</p>	<p>The Power on Your Side</p> <p>Quimby said it was it were, dead to come from the dead. Ou</p>
<p>and a change came Quimby said it was it were, dead to come from the dead. Ou</p>	<p>and a change came Quimby said it was it were, dead to come from the dead. Ou</p>	<p>and a change came Quimby said it was it were, dead to come from the dead. Ou</p>

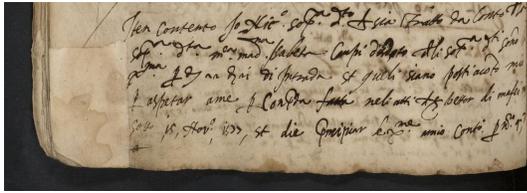
Fig. 13. Watermark removal by DE-GAN

additional loss), it would be useful if we tried some other similar models that are based on GANs and dedicated to the same image-to-image translation problem. For this aim, cycleGAN [45] and pix2pix-HD [46] models are considered for the comparison. We evaluate these models on H-DIBCO 2018 dataset [62] with the same conditions and data used to train the DE-GAN. The quantitative and qualitative obtained results are presented in Table 6 and Fig. 14, respectively. Experimental results shows the superiority of DE-GAN compared to cycleGAN and pix2pix-HD in achieving higher PSNR, F-measure and Fps and a lower DRD. We note

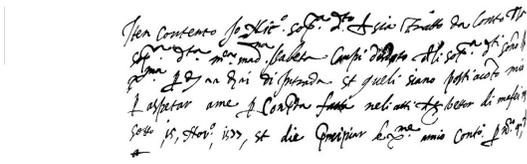
that the unsupervised training capabilities of CycleGAN are quite useful since paired data is harder to find in document enhancement applications. For pix2pix-HD, the results are promising, since the training samples that we used for training were few (the number of DIBCO samples is small if we split them to patches with size 512×1024 , that's why we used some flips of images to augment the data). With more data, we believe that pix2pix-HD could perform much better.

TABLE 6
Results of image binarization for DIBCO 2018 Database

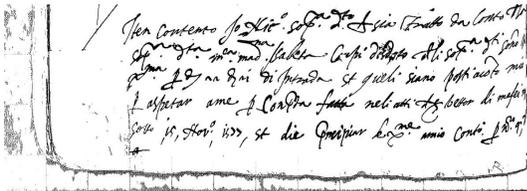
Model	PSNR	F-measure	F _{ps}	DRD
cycleGAN	11.00	56.33	58.07	30.07
pix2pix-HD	14.42	72.79	76.28	15.13
DE-GAN	16.16	77.59	85.74	7.93



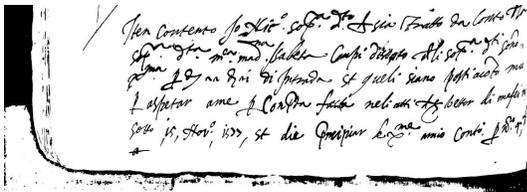
Original



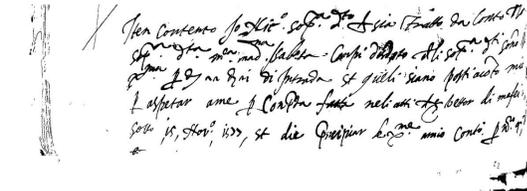
Ground truth



CycleGan



Pix2pix-HD



DE-GAN

Fig. 14. Qualitative binarization results produced by different models of the sample (9) from H-DIBCO 2018 dataset

4.4 Document deblurring

The DE-GAN model presented in this paper is able to outperform many state-of-the-art approaches in different problems like binarization, denoising and watermark removal. To experimentally prove the efficiency and the flexibility of the proposed method, we evaluate it on a more challenging scenario, which is document deblurring. We use 4000 patches from the dataset developed in [63] to train our model, and 932 patches for testing. Noting that, in [63]

a convolutional neural network architecture is proposed to address the problem. Thus, we will compare the results with this CNN and pix2pix-HD models trained on this selected data. The obtained results are presented in Table 7. We can see that GAN’s models surpasses the CNN. This is much clear in the qualitative results of some patches presented in Fig 15. We can also see that DE-GAN gives similar results to pix2pix-HD, however, it is more accurate for predicting some characters. For example, in the second patch row, third line, the word “kind” is correctly predicted by DE-GAN but it is predicted as “bind” by pix2pix-HD. We note that the used dataset is composed of 300x300px image patches, which can explain why pix2pix-HD does not give a better performance (it works generally with larger input patch with a size of 512x1024, or 1024x2048).

TABLE 7
The obtained results of document deblurring

Method	PSNR
CNN [63]	19.36
pix2pix-HD [46]	19.89
DE-GAN	20.37

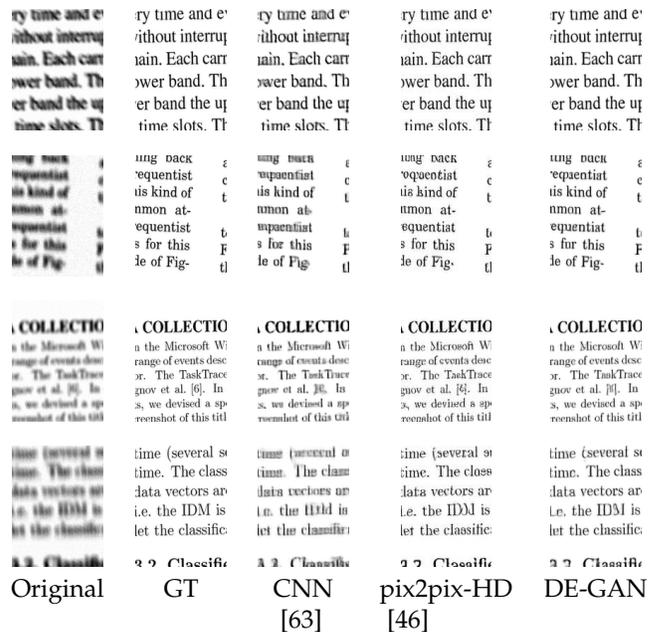


Fig. 15. Qualitative deblurring results of some patches produced by different methods

4.5 OCR evaluation

After the quantitatively and qualitatively evaluation of the resulted enhanced images presented previously, we compare in what follows the performance of OCR on degraded and enhanced documents. For this aim, we took a set of 4 images (2 degraded ones from DIBCO datasets, and 2 images with a dense watermark from our dataset). Then, we used Tesseract OCR [64] to recognize those images and their enhanced versions with DE-GAN. We found that the proposed enhancement method boosts the baseline OCR performance by a large margin, the character error rate is

decreased from 0.37 for the degraded documents to 0.01 for the enhanced ones. Fig. 16 shows a tiny example of this process. In each row, you can find a line of a degraded document image and the text produced by the OCR system, then its enhanced version followed the OCR text.

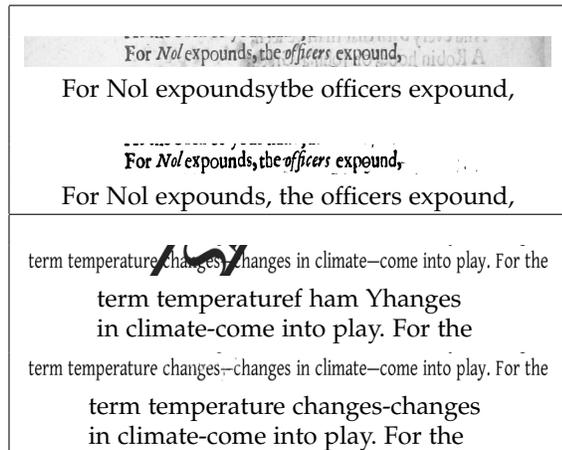


Fig. 16. Qualitative results for Tesseract recognition of some text lines

5 CONCLUSION

In this paper we proposed a Document Enhancement Generative Adversarial Network named DE-GAN to restore severely degraded document images. DE-GAN is a modified version of the pix2pix with a deeper generator and a different additional loss (adversarial + log) to generate an enhanced document given the degraded version. To the best of our knowledge, this is the first application of GANs for studying document enhancement problem. Moreover, we present a new problem in document enhancement that is dense watermark (or stamps) removal, hoping that it takes the attention of document analysis community. Extensive experiments show that DE-GAN achieved interesting results in different document enhancement tasks that outperform the fully convolutional networks, cycleGAN and pix2pix-HD models. Furthermore, we achieve improved results compared to many recent state-of-the-art methods on benchmarking datasets like DIBCO 2013, DIBCO 2017 and H-DIBCO 2018.

We showed that the proposed enhancement method boosts the baseline OCR performance by a large margin. Hence, as an immediate future work, we plan to add the OCR evaluation in the discriminator part. Thus, we can give the discriminator the ability of reading the text to decide if it is real or fake, which will force it to generate more readable images. We intend, also, to test the performance of the DE-GAN on mobile captured documents which present many problems like shadow, real blur, low resolution, distortion, etc.

ACKNOWLEDGEMENT

This work has been partially supported by the Swedish Research Council (grant 2018-06074, DECRYPT), the Spanish project RTI2018-095645-B-C21 and the CERCA Program / Generalitat de Catalunya..

REFERENCES

- [1] K. Chellapilla, S. Puri, and P. Simard, "High performance convolutional neural networks for document processing," in *International Workshop on Frontiers in Handwriting Recognition*, 2006.
- [2] S. Schreiber, S. Agne, I. Wolf, A. Dengel, and S. Ahmed, "Deepdesrt: Deep learning for detection and structure recognition of tables in document images," in *ICDAR*, 2017.
- [3] F. Zamora-Martinez, S. España-Boquera, and M. J. Castro-Bleda, "Behaviour-based clustering of neural networks applied to document enhancement," in *Computational and Ambient Intelligence*, pp. 144–151, 2007.
- [4] S. Bako, S. Darabi, E. Shechtman, J. Wang, K. Sunkavalli, and P. Sen, "Removing shadows from images," in *ACCV*, 2016.
- [5] X. Chen, X. He, J. Yang, and Q. Wu, "An effective document image deblurring algorithm," in *CVPR*, 2011.
- [6] X.-J. Mao, C. Shen, and Y.-B. Yang, "Image restoration using very deep convolutional encoder-decoder networks with symmetric skip connections," in *NIPS*, 2016.
- [7] C. Dong, C. C. Loy, K. He, and X. Tang, "Image super-resolution using deep convolutional networks," *IEEE transactions on pattern analysis and machine intelligence*, vol. 38, pp. 295–307, 2016.
- [8] D. P. Kingma and M. Welling, "Auto-encoding variational bayes," *arXiv preprint arXiv*, 2013.
- [9] P. Isola, J.-Y. Zhu, T. Zhou, and A. A. Efros, "Image-to-image translation with conditional adversarial networks," in *CVPR*, 2017.
- [10] T. Karras, T. Aila, S. Laine, and J. Lehtinen, "Progressive growing of gans for improved quality, stability, and variation," *arXiv preprint arXiv*, 2017.
- [11] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial nets," in *Advances in neural information processing systems*, pp. 2672–2680, 2014.
- [12] A. K. Bhunia, A. K. Bhunia, P. Banerjee, A. Konwer, A. Bhowmick, P. P. Roy, and U. Pal, "Word level font-to-font image translation using convolutional recurrent generative adversarial networks," *arXiv preprint arXiv*, 2018.
- [13] A. Ghosh, B. Bhattacharya, and S. B. R. Chowdhury, "Handwriting profiling using generative adversarial networks," in *AAAI Conference on Artificial Intelligence*, 2017.
- [14] A. Konwer, A. K. Bhunia, A. Bhowmick, A. K. Bhunia, P. Banerjee, P. P. Roy, and U. Pal, "Staff line removal using generative adversarial networks," in *ICPR*, pp. 1103–1108, 2018.
- [15] N. Kligler, S. Katz, and A. Tal, "Document enhancement using visibility detection," in *CVPR*, pp. 2374–2382, 2018.
- [16] R. K. Pandey and A. G. Ramakrishnan, "Language independent single document image super-resolution using cnn for improved recognition," *arXiv preprint arXiv*, 2017.
- [17] C. L. Tan, L. Zhang, Z. Zhang, and T. Xia, "Restoring warped document images through 3d shape modeling," *IEEE transactions on pattern analysis and machine intelligence*, vol. 28, pp. 195–208, 2006.
- [18] N. Otsu, "A threshold selection method from gray-level histograms," *IEEE transactions on systems*, vol. 9, no. 1, pp. 62–66, 1979.
- [19] J. Sauvola and M. Pietik, "Adaptive document image binarization," *Pattern recognition*, vol. 33, pp. 225–236, 2000.
- [20] W. Niblack, *An introduction to digital image processing*. Strandberg Publishing Company Birkerød, 1985.
- [21] N. Phansalkart, S. More, A. Sabale, and M. Joshi, "Adaptive local thresholding for detection of nuclei in diversity stained cytology images," in *ICCCSP*, 2011.
- [22] G. chutani, T. Patnaik, and V. Dwivedi, "An improved approach for automatic denoising and binarization of degraded document images based on region localization," in *ICACCI*, 2015.
- [23] M. Cheriet, J. N. Said, and C. Y. Suen, "A recursive thresholding technique for image segmentation," *IEEE transactions on pattern analysis and machine intelligence*, vol. 7, pp. 918–921, 1998.
- [24] T. Lelore and F. Bouchara, "Fair: A fast algorithm for document image restoration," *IEEE transactions on pattern analysis and machine intelligence*, vol. 35, pp. 2039–2048, 2013.
- [25] M. Annabestani and M. Saadatmand-Tarzjan, "A new threshold selection method based on fuzzy expert systems for separating text from the background of document images," *Iranian journal of science and technology, transactions of electrical engineering*, pp. 1–13, 2018.

- [26] Chien-HsingChou, Wen-HsiungLin, and FuChang, "A binarization method with learning-built rules for document images produced by cameras," *Pattern Recognition*, vol. 43, pp. 1518–1530, 2010.
- [27] W. Xiong, J. Xu, Z. Xiong, J. Wang, and M. Liu, "Degraded historical document image binarization using local features and support vector machine (svm)," *Optik*, vol. 164, pp. 218–223, 2018.
- [28] R. F. Moghaddam and M. Cheriet, "A variational approach to degraded document enhancement," *IEEE transactions on pattern analysis and machine intelligence*, vol. 32, pp. 1347–1361, 2010.
- [29] R. Hedjam, M. Cheriet, and M. Kalacska, "Constrained energy maximization and self-referencing method for invisible ink detection from multispectral historical document images," in *ICPR*, 2014.
- [30] S. Milyaev, O. Barinova, T. Novikova, P. Kohli, and V. Lempitsky, "Fast and accurate scene text understanding with image binarization and off-the-shelf ocr," *International Journal on Document Analysis and Recognition*, 2015.
- [31] W. Xiong, X. Jia, J. Xu, Z. Xiong, M. Liu, and J. Wang, "Historical document image binarization using background estimation and energy minimization," in *ICPR*, 2018.
- [32] G. Meng, K. Yuan, Y. Wu, S. Xiang, and C. Pan, "Deep networks for degraded document image binarization through pyramid reconstruction," in *ICDAR*, pp. 2379–2140, 2017.
- [33] J. Calvo-Zaragoza and A.-J. Gallego, "A selectional auto-encoder approach for document image binarization," *Pattern Recognition*, vol. 86, pp. 37–47, 2019.
- [34] K. G. Lore, A. Akintayo, and S. Sarkar, "Llnet: A deep autoencoder approach to natural low-light image enhancement," *Pattern Recognition*, vol. 61, pp. 650–662, 2017.
- [35] M. Z. Afzal, J. Pastor-Pellicer, F. Shafait, T. M. Breuel, A. Dengel, and M. Liwicki, "Document image binarization using lstm: A sequence learning approach," in *HIP@ICDAR*, pp. 79–84, 2015.
- [36] C. Tensmeyer and T. Martinez, "Document image binarization with fully convolutional neural networks," in *ICDAR*, pp. 99–104, 2017.
- [37] F. Westphal, N. Lavesson, and H. Grahn, "Document image binarization using recurrent neural networks," in *IAPR*, pp. 263–268, 2018.
- [38] Q. N. Vo, S. H. Kim, H. J. Yang, and G. Lee, "Binarization of degraded document images based on hierarchical deep supervised network," *Pattern Recognition*, vol. 74, pp. 568–586, 2018.
- [39] C. Xu, Y. Lu, and Y. Zhou, "An automatic visible watermark removal technique using image inpainting algorithms," in *ICSAI*, pp. 1152–1157, 2017.
- [40] T. Dekel, M. Rubinstein, and W. T. F. Ce Liu, "On the effectiveness of visible watermarks," in *CVPR*, pp. 2146–2154, 2017.
- [41] J. Wu, H. Shi, S. Zhang, Z. Lei, Y. Yang, and S. Z. Li, "De-mark gan: Removing dense watermark with generative adversarial network," in *CVPR*, pp. 2146–2154, 2018.
- [42] D. Cheng, X. Li, W.-H. Li, C. Lu, F. Li, H. Zhao, and W.-S. Zheng, "Large-scale visible watermark detection and removal with deep convolutional networks," in *PRCV*, pp. 27–40, 2018.
- [43] P. Luc, C. Couprie, S. Chintala, and J. Verbeek, "Semantic segmentation using adversarial networks," *arXiv preprint arXiv*, 2016.
- [44] C. Ledig, L. Theis, F. Huszár, J. Caballero, A. Cunningham, A. Acosta, A. Aitken, A. Tejani, J. Totz, Z. Wang, and W. Shi, "Photo-realistic single image super-resolution using a generative adversarial network," in *CVPR*, 2016.
- [45] J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, "Unpaired image-to-image translation using cycle-consistent adversarial networks," *arXiv preprint arXiv*, 2017.
- [46] T.-C. Wang, M.-Y. Liu, J.-Y. Zhu, A. Tao, J. Kautz, and B. Catanzaro, "High-resolution image synthesis and semantic manipulation with conditional gans," in *CVPR*, 2018.
- [47] Z. Yi, H. Zhang, P. Tan, , and M. Gong, "Dualgan: unsupervised dual learning for image-to-image translation," *arXiv preprint arXiv*, 2018.
- [48] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in *MICCAI*, pp. 234–241, 2015.
- [49] E. Shelhamer, J. Long, and T. Darrell, "Fully convolutional networks for semantic segmentation," *IEEE transactions on pattern analysis and machine intelligence*, vol. 39, pp. 640–651, 2016.
- [50] J. Xie, L. Xu, and E. Chen, "Image denoising and inpainting with deep neural networks," in *NIPS*, pp. 350–358, 2012.
- [51] V. Badrinarayanan, A. Kendall, and R. Cipolla, "Segnet: A deep convolutional encoder-decoder architecture for scene segmentation," *IEEE transactions on pattern analysis and machine intelligence*, vol. 39, pp. 2481–2495, 2017.
- [52] I. Pratikakis, B. Gatos, , and K. Ntirogiannis, "Icdar 2013 document image binarization contest (dibco 2013)," in *ICDAR*, pp. 1471–1476, 2013.
- [53] B. Gatos, K. Ntirogiannis, and I. Pratikakis, "Icdar 2009 document image binarization contest (dibco 2009)," in *ICDAR*, pp. 1375–1382, 2009.
- [54] I. Pratikakis, B. Gatos, and K. Ntirogiannis, "Icdar 2011 document image binarization contest (dibco 2011)," in *ICDAR*, pp. 1506–1510, 2011.
- [55] I. Pratikakis, B. Gatos, and K. Ntirogiannis, "Icfhr 2012 competition on handwritten document image binarization (h-dibco 2012)," in *ICFHR*, pp. 817–822, 2012.
- [56] K. Ntirogiannis, B. Gatos, and I. Pratikakis, "Icfhr2014 competition on handwritten document image binarization (h-dibco 2014)," in *ICFHR*, pp. 809–813, 2014.
- [57] I. Pratikakis, K. Zagoris, G. Barlas, and B. Gatos, "Icfhr 2016 competition on handwritten document image binarization (h-dibco 2016)," in *ICFHR*, pp. 2167–6445, 2016.
- [58] I. Pratikakis, K. Zagoris, G. Barlas, and B. Gato, "Icdar2017 competition on document image binarization (dibco 2017)," in *ICDAR*, pp. 2379–2140, 2017.
- [59] B. Gatos, I. Pratikakis, , and S. Perantonis, "An adaptive binarization technique for low quality historical documents," in *InternationalWorkshop on Document Analysis Systems*, pp. 102–113, 2014.
- [60] B. Su, S. Lu, and C. Tan, "Robust document image binarization technique for degraded document images," *IEEE transactions on image processing*, vol. 22, pp. 1408–1417, 2013.
- [61] N. Howe, "Document binarization with automatic parameter tuning," *International Journal on Document Analysis and Recognition (IJDR)*, vol. 16, pp. 247–258, 2013.
- [62] I. Pratikakis1, K. Zagoris1, P. Kaddas, and B. Gatos, "Icfhr2018 competition on handwritten document image binarization (h-dibco 2018)," in *ICFHR*, pp. 489–493, 2018.
- [63] M. Hradiš, J. Kotera, P. Zemčík, and F. Šroubek, "Convolutional neural networks for direct text deblurring," in *BMVC*, 2015.
- [64] R. Smith, "An overview of the tesseract ocr engine," in *ICDAR*, pp. 629–633, 2007.



Mohamed Ali Souibgui Received his bachelor and master degrees in computer science from the University of Monastir, Tunisia, in 2015 and 2018, respectively. He is currently working toward the PhD degree in the Computer Vision Center, Autonomous University of Barcelona, Spain. His research interests include machine learning, computer vision and document analysis.



Yousri Kessentini is graduated in Computer Science engineering from the National Engineering School of Sfax (ENIS) in 2003 and received his Ph.D. degree in the field of pattern recognition from the University of Rouen, France in 2009. He was postdoctoral researcher at ITE-SOFT company and LITIS laboratory from 2011 to 2013. Currently he is Assistant Professor at CRNS and the head of the DeepVision research team. His main research areas concern deep learning, document processing and recognition, data fusion, and computer vision. He is certified as an official instructor and ambassador from the NVIDIA Deep Learning Institute. He has coordinate several research projects in partnership with industry and the author and co-author of several papers.