Text-DIAE: Degradation Invariant Autoencoders for Text Recognition and Document Enhancement

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Abstract. In this work, we propose Text-Degradation Invariant Auto Encoder (Text-DIAE) aimed to solve two tasks, text recognition (handwritten or scene-text) and document image enhancement. We define three pretext tasks as learning objectives to be optimized during pre-training without the usage of labelled data. Each of the pre-text objectives is specifically tailored for the final downstream tasks. We conduct several ablation experiments that show the importance of each degradation for a specific domain. Exhaustive experimentation shows that our method does not have limitations of previous state-of-the-art based on contrastive losses while at the same time requiring essentially fewer data samples to converge. Finally, we demonstrate that our method surpasses the state-of-the-art significantly in existing supervised and self-supervised settings in handwritten and scene text recognition and document image enhancement. Our code and trained models will be made publicly available at http://Upon_Acceptance.

Keywords: Self-Supervised Learning, Handwritten Text Recognition, Scene-Text Recognition, Document Image Enhancement.

1 Introduction

Humans are able to read text in noisy scenarios by reconstructing the degraded regions and predicting the missing/blurry content [19,34]. Incorporating such an ability in a model could immensely help in restoration, recognition and understanding of characters and symbols, considering that text carries rich linguistic information that allow humans to reason explicitly according to context. In contrast, automatic reading is done by Optical Character Recognition (OCR) and Handwritten Text Recognition (HTR) systems which often suffer from common degradation scenarios like background noise, blur, shadow, show-through

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Fig. 1. Text-Degradation Invariant Auto-Encoder (Text-DIAE), we employ image reconstruction pretext tasks at pre-training. Masking, blurring and adding noise is employed to learn richer representations that outperform previous approaches.

effects, bleed, smears, watermarks, etc. The degradation significantly decreases the OCR/HTR reading performance, reflecting the possibility of adapting it as a proxy task. In order to endow this human-specific skill to our models, we adapt a self-supervised methodology that serves as a close proxy to a down-stream task.

Common computer vision pipelines using self-supervised frameworks employ a pretext-task (e.g. relative position prediction of patches [21], contrastive views [14], image inpainting [57], etc.) to learn visual representations to later solve a down-stream task. Current self-supervised paradigms [12–14, 17] have adapted transformers [72] to learn visual representations from unlabelled images which are semantically meaningful. More recently, generative self-supervised approaches [5, 22, 30] using auto-encoders have been used to learn representations in the feature space through image patches and visual tokens.

Closely related to our work, some contributions in visual representation learning were addressing text recognition in Handwritten Text Recognition (HTR) [1, 6] and Scene-Text Recognition (STR) [1]. Despite the performance gains, there are some drawbacks of such models; (1) independent sequences of tokens are treated as single data points, which can cause misalignment of similar sequences among a batch, (2) considerable batch size requirements to define negative contrastive pairs, (3) considerably slow convergence rates.

In this work, we present Text-Degradation Invariant Auto-Encoders (Text-DIAE) inspired by the principle of denoising autoencoders [73], refer to Figure 1. Our model focuses on exploring the dynamics of learning representations under different degradation scenarios. Specifically, we propose the usage of a robust self-supervised auto-encoder along with customized pretext tasks (masking, blur and background noise) that are designed to tackle two different problems: text recognition and document image enhancement, can be seen in Figure 1.

The benefits of employing such approach are: we do not define sequences at the feature level. Rather, by employing a transformer-based [72] approach, similar to BERT [20] we utilize the self-attention layers to attend among patches which does not require big batches of negative samples. Also, the combination of these pre-training tasks result in a significantly faster convergence compared to
previous approaches. The resulting representations are evaluated by a scenario that resembles the linear probing evaluation often used in self-supervision [44,78] and follows the scheme of [1]. By this assessment, we find that our method outperforms previous self and semi supervised pipelines. Furthermore, by employing Text-DIAE, we achieve state-of-the-art in handwritten text recognition and document image enhancement, while outperforming scene text recognition under self-supervision settings. To summarize, the main contributions of our work are:

- We propose a self-supervised autoencoder along with different pretext tasks tailored for handwritten, scene text recognition and document image enhancement tasks.
- Extensive experiments demonstrate that our method yields state-of-the-art results in both HTR and document image enhancement, while also outperforming previous self-supervised scene text recognition approaches.
- By employing Text-DIAE, more efficient representations are achieved during pre-training. Our model surpasses previous self-supervised models while seeing an order of magnitude less data points.
- Extensive experimentation is shown as ablation studies that demonstrate the superiority of the learned representations compared to other self-supervised approaches.

2 Related Work

2.1 Self-Supervised Learning

Self-Supervised approaches consists in learning rich representations of an input modality without labels, where pretext tasks are used to learn auxiliary signals that are informative for a given downstream task. Initial approaches relied on auto-encoders [73] trained to remove artificially added noise from an image. Later approaches introduced other pretext tasks that provide rich signals to train a network as a feature extractor. Some pretext tasks employed were image colorization [78], jigsaw puzzle solving [55], patch ordering [21], rotation prediction [25] among others. Recent approaches rely on extensive image augmentation to maximize the agreement among paired samples and contrast with all possible negative samples [3,12–15,31–33,77]. Such approaches have rapidly escalated in performance and currently are on par with supervised methods. More recently, generative approaches like Masked Auto-encoders (MAE) [30] have been introduced to predict a masked latent representation of patches. Similar ideas have been also explored in other recent works like BEiT [5] and PeCo [22] which adopt a discrete variational autoencoder (VAE) to generate discrete visual tokens from the original image. Such kind of pretraining strategies worked well for self-supervised frameworks using vision transformer (ViT), achieving strong fine-tuning results on downstream application tasks like image classification, semantic segmentation etc. Motivated by these works, we expand this generative learning framework to solve text recognition and document enhancement tasks.
2.2 Text Recognition

Ample research in text recognition has been conducted, resulting in handwritten [52, 66] and scene-text [16, 46, 62] recognition pipelines. Most common approaches that tackle text recognition are using supervised methodologies that employ an encoder-decoder mechanism [18, 24, 38, 45, 62, 63, 71, 76] based on a Connectionist Temporal Classification (CTC) [27] network or an Attention-based [18, 63] decoder. Other relevant approaches often extract features and directly use them, which are task-dependent such as retrieval [26, 50, 74], classification [4, 41, 48, 49] and Visual Question Answering (VQA) [7, 64] among others. A recent work [54] tackled the problem of scene text recognition under degraded scenario using a super-resolution unit to enhance the degraded text at the feature-level during training.

Recently, approaches that focus on semi-supervised and self-supervised learning have been explored [68] with domain adaptation techniques on STR [39] and HTR [79]. Under the unsupervised paradigm, [29] formulate text recognition as a task to align the conditional distribution of strings predicted with lexically correct strings sampled from a text database. Closely related to our work, [1] proposes a self-supervised sequence-to-sequence model that separates consecutive text features to be later used in a contrastive loss similar to [14]. Nevertheless, this method requires large batches and relies on a sequential definition of features that can produce misaligned characters or n-grams contained in different words at the moment of applying a contrastive approach.

2.3 Document Image Enhancement

In recent times, many approaches have been proposed to address the enhancement of documents (both handwritten and machine-printed) which suffer several kinds of artefacts/defects such as bleed-through, smears or show-through, watermark, faint characters, contrast variations and so on. This work proposes to tackle two important document enhancement tasks: binarization and deblurring. Adaptive thresholding based on sliding-window operations by Sauvola et. al. [61] formulated a strong handcrafted baseline for binarization task. The rise of deep learning brought newer approaches where [11, 40] map images from the degraded domain to the enhanced one using end-to-end CNN autoencoders. Other state-of-the-art techniques [37, 69, 70, 80] used conditional-Generative Adversarial Network (c-GAN) based approaches to design a generator which produces the enhanced version of the document while the discriminator assesses the quality of binarization. Lately, an end-to-end ViT autoencoder was proposed in [67] to capture high-level global features using self-attention for binarizing degraded documents. Regarding document deblurring, a benchmark was formulated in [35] where a CNN were trained to reconstruct enhanced high-quality images from blurry inputs that consist of a combination of camera-driven motion blurred and de-focused images of text documents. Lately, [69] improved the baseline performance using the similar c-GAN based approach for the binarization task.
Fig. 2. **Pre-training pipeline.** Text-DIAE aims to learn degradation invariant representations. These are later used to reconstruct the input image with a specific learning objective for each degradation type.

## 3 Method

In this section, we present our proposed method for text image recognition and enhancement by describing its building blocks. Our approach uses two steps: a pre-training stage to learn useful representations from unlabeled data, and a supervised fine-tuning phase for the desired downstream task.

### 3.1 Pre-Training Module

The overall pre-training pipeline of Text-DIAE is shown in Fig. 2. For each task, given an unlabeled image $I$ (e.g., a cropped handwritten text, cropped scene text or a scanned document image), we use a function $\phi$ to map $I$ to a degraded form. The function $\phi$ takes as parameters the original image $I$ and the degradation type $T \in \{\text{mask, blur, noise}\}$ where we denote a degraded image by $I_d = \phi(I, T)$.

Our model is composed of an encoder $E$ and a decoder $D$ with learnable parameters $\theta_E, \theta_D$ respectively. The pre-training pipeline trains an encoder function $E$ that maps the degraded image $I_d$ to a latent representation $z_T$ in a multi-task fashion (unmasking, deblurring and denoising) and then learning a decoder $D$ to reconstruct the original image $I$ from the representation $z_T$:

$$z_T = E(\phi(I, T); \theta_E)$$

$$I_r = D(z_T; \theta_D)$$

(1)

The learned visual representations from the latent subspace should be invariant to the applied degradation $T$.

**Encoder.** The encoder architecture consists of a vanilla ViT [23] backbone. Given an input image $I_d$, it is first split into a set of $N$ patches, $I_d^P = \{I_d^P_1, I_d^P_2, \ldots, I_d^P_N\}$. Then, these patches are embedded with a trainable linear projection layer $E$. Text-DIAE uses a distinct linear projection layer for every defined pretext task. These tokens are later concatenated with their 2-D positional information embedded with $E_{pos}$ and fed to $L$ transformer blocks to map these tokens.
Fig. 3. Fine-tuning pipeline. We start from a pretrained encoder as initial weights to solve a specific downstream task. Explicit decoders are used for text recognition (left) and document image enhancement (right).

to the encoded latent representation $z_l$. These blocks are composed of $L$ layers of Multi-head Self-Attention (MSA) and a feedforward Multi-Layered Perceptron (MLP) as depicted in Figure 2. Each of these blocks are preceded by a LayerNorm (LN) [2] and followed by a residual connection:

$$
\begin{align*}
  z_0 &= E(I_d^p) + E_{pos} \\
  z'_l &= \text{MSA}(\text{LN}(z_{l-1})) + z_{l-1}, \quad l = 1, 2, 3 \ldots L \\
  z_l &= \text{MLP}(\text{LN}(z'_l)) + z'_l, \quad l = 1, 2, 3, \ldots L \\
  z_T &= \text{LN}(z_L)
\end{align*}
$$

(2)

**Decoder.** The decoder composed of transformer blocks following the same structure and number of layers as the encoder. The decoder input is the output of encoder $z_T$. The output of the decoder is a set of vectors $I_r = \{I_{r1}^p, I_{r2}^p, \ldots, I_{rn}^p\}$ where each of which corresponds to a flattened patch in the predicted (reconstructed) image. Same as before, a distinct linear layer is used for each pre-text task.

$$
\begin{align*}
  z'_l &= \text{MSA}(\text{LN}(z_{l-1})) + z_{l-1}, \quad l = 1 \ldots L \\
  z_l &= \text{MLP}(\text{LN}(z'_l)) + z'_l, \quad l = 1 \ldots L \\
  I_r &= \text{Linear}(z_L)
\end{align*}
$$

(3)

### 3.2 Fine-Tuning

Our fine tuning process is illustrated in Fig. 3 where we perform two different downstream tasks; text recognition and document image enhancement.
Text Recognition. Text recognition aims to transform an image into the machine encoded form, i.e., sequence of characters. Let $I$ be a cropped text image and $C = \{c_1, c_2, ..., c_N\}$ its ground truth label which corresponds to a sequence of characters, where $N$ is the length of the text. The training is done by passing $I$ to an encoder function $E$ to produce a latent representation $z$. Then, $z$ is later fed to a decoder function $D'$ to produce a sequence of characters $C_p = \{c_{p1}, c_{p2}, ..., c_{pN}\}$ that should match the ground truth label sequence.

We initialize the encoder with the pre-trained weights $\theta_E$ while we employ a sequential transformer decoder [72] as seen in Fig. 3-Left. The decoder is initialized randomly and composed of $L$ transformer blocks of MSA, MLP and Masked-MSA layers preceded by LN layers, and followed by a residual connection. The output of the decoder is a sequence of characters where at each time step $t$, the predicted character is formed by attending to the representation $z$ and previous character embeddings until $t - 1$.

Document Image Enhancement. Document enhancement consists of mapping a degraded document into a clean form. Let $I_d$ be a degraded image and $I_c$ its clean version, then the goal is to learn an encoder function $E$ that maps $I_d$ to a representation $z$ with the same way as in Eqn 2. $E$ weights are initialized from the pre-training stage. The decoder $D''$ generates the clean image $I_c$ from $z$ as in Eqn 3.

3.3 Learning Objectives

Our model makes use of different sets of losses for each phase. During pre-training, we use three different losses. Each one is dedicated to a particular pre-text task: $L_{\text{mask}}$, $L_{\text{blur}}$ and $L_{\text{noise}}$. Each of these losses is a mean squared error (MSE) between the reconstructed image and the masked, blurred or noisy image. Thus, the overall loss for our pre-training stage is:

$$L_{\text{pre-training}} = L_{\text{mask}} + L_{\text{blur}} + L_{\text{noise}}$$ (4)

While fine-tuning on text recognition we use a cross-entropy loss between the predicted sequence of characters $C_p$ and $C$. For document image enhancement fine tuning, we used an MSE loss between the cleaned image $I_c$ and $I$.

4 Experiments

In this section we describe the studied scenarios and experiments performed for text recognition and document enhancement respectively. We ask the reader to refer to the supplementary material for specific implementation details.

Implementation Details. During pre-training we deploy an encoder with 6 layers and 8 attention heads to encode the input, with a dimension of 768. We used this same number of layers and attention heads for the decoder, with a dimension of 512 in text recognition and 768 for document enhancement. At masking, each input image (with size $64 \times 256 \times 3$ for text recognition and $256 \times 256 \times 3$
for document enhancement) is divided into a set of patches with size $8 \times 8 \times 3$. Similarly as [30], we employ random masking of 75% of the patches. To add blur, we add average blur with random kernel sizes between 1 and 15. In order to add background noise, we add weighted contrasting backgrounds from different text documents. We set the learning rate to $1.5 e^{-4}$ and a cosine scheduler with an AdamW Optimizer. The pre-training datasets are domain-dependant, in handwritten text we used IAM and CVL. In scene text we used cropped words from the dataset presented in [26] as well as the training sets from ICDAR13 [42] and IIIT5K [53]. For document image enhancement we used 203,576 unlabelled document image samples. These samples were taken from the historical document DIBCO benchmarks (2009, 2010, 2013, 2014, 2015, 2016) [59], Publaynet [81], Palm-leaf [10] and IAM Handwriting database. The pre-training was done for 2 epochs in scene text and 100 epochs for the remaining domains.

In the fine tuning stage, we use the same encoder (pre-trained) with a different decoder of 6 layers, 8 attention heads and dimension of 768. In text recognition, we employ Adam optimizer with a learning rate of $1 e^{-4}$ and a cosine scheduler while in document enhancement, we use the same pre-training setting. We fine-tune for 600, 10 and 100 epochs for handwritten, scene text and document image enhancement datasets respectively.

### 4.1 Text Recognition

In this section, we refer to the experiments performed in handwritten and scene-text recognition tasks.

**Datasets.** The experiments are conducted on several publicly available datasets for handwritten and scene-text recognition. In the handwriting recognition scenario, we use the English datasets IAM [51] and CVL [43] with their well defined splits. For scene-text recognition, we employ a modified synthetic dataset [28]. In order to avoid disrupting sequences of characters, vertical and horizontal flips, we employ the version used by [26]. We incorporate additional datasets for testing, namely, ICDAR13 [42] and IIIT5K [53].

**Metrics.** To evaluate the text recognition models, we use the word-level accuracy (Acc). In order to compare the state-of-the-art performance in handwritten recognition, we employ the Character Error Rate (CER) and Word Error Rate (WER) [71, 79]. We also compare same as [1] with the Word-level accuracy up to one edit distance (ED1).

**Evaluating Representations.** In order to evaluate the quality of the learned representations extending commonly used linear-probing settings [78], we employ an extended approach introduced by [1]. As a first step, the encoder is pre-trained with unlabeled data as described in Section 3.1. After that, the encoder’s weights are frozen and a new decoder is trained on top of it with all the labeled data. The used decoder is, as we detailed above, generates the predicted characters in a time-step manner. Since the encoder remains frozen, this scenario is a good proxy that represents the expressivity of the learned visual representations. To this end, Table 1 shows the results of our proposed approach. We compare among self-supervised methods specifically designed for the text recognition task.
Table 1. Representation quality. We evaluate the encoder capability of learning visual representations. This scenario is analogous as the linear probing in self-supervised models. We train a decoder with labelled data on top of a frozen encoder pre-trained on the proposed degradation. The column Seen refers to the number of samples in millions seen during pre-training. Word prediction in terms of Accuracy (Acc) and single edit distance (ED1) in handwritten and text recognition.

| Method    | Encoder | Decoder | Handwritten Text | Scene-Text |
|-----------|---------|---------|------------------|------------|
|           |         |         | IAM Acc | CVL Acc | IIIT5K Acc | IC13 Acc | IAM ED1 | CVL ED1 | IIIT5K ED1 | IC13 ED1 | IAM Seen | CVL Seen | IIIT5K Seen | IC13 Seen |
| simCLR [14] | CNN | CTC | 4.0 | 205.8 | 11.1 | 0.3 | 3.1 | 409.6 | 0.3 | 5.0 | 409.6 |
| seqCLR [1] | CNN | Attn. | 51.9 | 65.0 | 205.8 | 49.2 | 68.6 | 409.6 | 59.3 | 77.1 | 409.6 |
| simCLR [14] | CNN | Attn. | 16.0 | 21.2 | 205.8 | 2.4 | 3.6 | 409.6 | 3.1 | 4.9 | 409.6 |
| seqCLR [1] | CNN | Attn. | 39.7 | 63.3 | 205.8 | 26.7 | 30.6 | 409.6 | 43.5 | 67.9 | 409.6 |
| Ours      | ViT | Transf. | 71.0 | 82.1 | 4.7 | 78.1 | 81.5 | 1.2 | 77.1 | 87.8 | 9.1 | 92.6 | 95.6 | 18.2 |

Better performance achieved by Text-DIAE. As it can be seen from Table 1, the method presented by [1] improves significantly a self-supervised baseline inspired by SimCLR [14]. It is evident that our method greatly outperforms previous state-of-the-art regarding the representation quality obtained, both in handwritten and scene-text. The improvements in term of the accuracy in a handwritten text dataset, IAM, is close to +20 points. Moreover, a bigger improvement gap is obtained when evaluating scene-text. An average gain of +30 points is accomplished in IIIT5K and ICDAR13, proving the generalization of our method to different domains. In our model, the great expressivity of features achieved by the encoder is mainly due to two factors. Firstly, by masking image patches, the encoder learns a strong unigram character distribution (refer to Figure 4), which is not leveraged in previous methods. Secondly, by employing a transformer as encoder, the self-attended embedding in the masking task allows the model to obtain richer representations.

Faster convergence. One of the most important outcomes by employing our method, is that a paramount improvement in convergence is achieved at pre-training. Table 1 shows this effect under the column labelled as “Seen”. It depicts the total number of seen samples that each model requires during the pre-training stage. It is worth highlighting that during pre-training the encoder of our model requires 43 and 166 times less data in IAM and CVL respectively. In scene-text, our model employs only 18.2M samples to yield powerful representations compared to the 409M samples required by previous self-supervised approaches.

Fine-Tuning. In this stage, we evaluate our model considering a semi-supervised setting where the obtained results are depicted in Table 2. Here we use the self-supervised pre-trained encoder as a backbone and train a transformer-based decoder from scratch that predicts the characters in a sequential manner, as illustrated in Fig. 3-Left. In this scenario, the gradients are back-propagated not only to the decoder but also to the encoder. Following the previous work [1], we use 5% and 10% of the labeled dataset by randomly selecting the training samples. As suggested in [14] we perform fine-tuning on all the labelled dataset. In
Table 2. Semi-supervised results. Accuracy obtained by fine-tuning a pre-trained model with varying percentages of the labeled dataset. Under this setting, we back-propagate the gradients through the specific decoder and the pre-trained encoder.

| Method          | Encoder | Decoder | Handwritten Text | Scene-Text |
|-----------------|---------|---------|------------------|------------|
|                 |         |         | IAM 5% 10% 100%  | CVL 5% 10% 100% | HIT5K 100%  | IC13 100% |
| Supervised [1]  | CNN     | CTC     | 21.4 33.6 75.2  | 63.6 75.6 76.1 | 84.3        |
| simCLR [14]     |         |         | 15.4 21.8 65.0  | 62.0 74.1 69.1 | 79.4        |
| seqCLR [1]      |         |         | 31.2 44.9 76.7  | 71.0 77.0 80.9 | 86.3        |
| Supervised [1]  | CNN     | Attention | 25.7 42.5 77.8 | 64.0 72.1 77.2 | 83.8 88.1   |
| simCLR [14]     |         |         | 22.7 32.2 70.7 | 59.0 65.6 75.7 | 77.8 84.9   |
| seqCLR [1]      |         |         | 40.3 52.3 79.9  | 73.1 74.8 77.8 | 82.9 87.9   |
| Ours            | ViT     | Transformer | 22.8 25.3 71.7 | 17.9 19.8 71.9 | 75.7 91.9   |

In order to compare with [1] and since scene-text dataset is synthetic, we evaluate with the complete labeled dataset.

**Text-DIAE has a higher performance in fine-tuning settings.** On the experimentation conducted, we observe that our model exploits data in a more effective manner than previous self-supervised approaches in fine-tuning settings. We infer that the set of degradations proposed yields rich signals that helps the encoder to adapt to the downstream task more efficiently. Our model achieves state-of-the-art in all scenarios when all the labelled datasets are employed. Under semi-supervised settings, our model performs better at the IAM dataset when employing 5% and 10% of the labels. Since CVL contains substantially fewer data samples than IAM, SeqCLR still outperforms our approach in the CVL dataset. However, while employing the full labels of CVL, Text-DIAE outperforms SeqCLR by more than 10 accuracy points.

**More efficient than a supervised baseline.** From table 2, we can also notice the superiority of pre-training our architecture compared to a fully supervised model starting from scratch. This suggest that the self-supervised pre-training of such transformer-based architectures is essential to obtain better results, and beneficial especially in small labeled datasets scenarios, since the unlabeled data is generally easier to obtain for a self-supervised pre-training.

**The effect of fine-tuning after pre-training.** By proposing the degradation invariant optimization at pre-training, our model achieves a significant gain in recognition on handwritten text datasets. An average of 10 points of accuracy are gained after fine-tuning (refer to Table 1 and 2). Finally, it is important to note that our model reaches state-of-the-art in the handwritten text recognition task, even comparing to specifically designed supervised approaches. The results on the IAM dataset are shown in Table 3, which measures the performance of a model in terms of word and character error rate, WER and CER respectively.

**Ablation Studies.** The results of experimentation regarding the effect of each degradation as pretext task at pre-training is given in Table 4. Firstly, among the
three proposed degradations, masking is the most crucial to be applied in both tasks, handwritten and scene text recognition. When an input word is masked, and in order to properly reconstruct it, the model has to learn a character level distribution. This by itself provides with a strong prior compared to denoising or deblurring an image. Additionally, adding blur in scene-text imagery improves the representations learned by the model shown by the results. Lastly, adding noise does not result in an improvement in text recognition tasks. However, as it is shown in the next section, the combination of the 3 degradation produce a richer encoder in document enhancement. Therefore, we can safely assume that each degradation has a task-dependent impact on the representations learned depending on the similarity of them when compared to the final downstream task and input data distribution.

**Qualitative Results.** In Figure 4 we show the reconstructed images at pre-training stage for handwritten and scene-text samples. It is important to note the complexity of the reconstruction task even for humans. Even though high masking percentages are employed (75%), our model learns to properly adapt to handwritten styles and fonts found in scene-text. As can be appreciated, although sometimes our model’s reconstruction does not match with the ground truth images, it can still reconstruct the most probable and plausible English words (e.g. see “school” vs “sand” in 4th row in handwritten examples). Another interesting outcome is also noticed for scene-text example where “xperia” is reconstructed correctly while the last character “a” is selected from another font, demonstrating the model’s capability. Minor reconstruction errors are found such as that the model eventually learns to overcome at fine-tuning stage.

### 4.2 Document Image Enhancement

In this subsection, we provide the experiments to validate the effectiveness of Text-DIAE in two significant document image enhancement benchmark tasks - binarization and deblurring.

**Datasets.** We have employed the datasets proposed in the DIBCO 2011 [36], 2017 [60] and H-DIBCO 2012 [36] and 2018 [58] challenges for printed and handwritten degraded document binarization, to get the final validation and
Fig. 4. Qualitative results of pre-training samples. The scenario on the left refers to handwritten text, while scene-text is depicted on the right. On each scenario, from left to right, the original, masked and reconstructed images are depicted.

Table 5. SOTA results. Comparison of the proposed Text-DIAE compared to previous state-of-the-art approaches on the different DIBCO and H-DIBCO Benchmarks

| Method       | 2011  | 2012  | 2017  | 2018  |
|--------------|-------|-------|-------|-------|
|              | PSNR↑ | FM↑   | Fps↑  | DRD↓  |
| Savoula et. al. [61] | 15.60 | 82.10 | -     | 8.50  |
| Kang et. al. [40]    | 19.90 | 95.50 | -     | 1.80  |
| Zhao et al. [80]     | 20.30 | 93.80 | -     | 1.80  |
| DocEnTr [67]         | 20.81 | 94.17 | 96.15 | 1.63  |
| Ours                | 21.29 | 95.01 | 96.86 | 1.48  |

evaluation of Text-DIAE after pre-training procedure. The same self-supervised settings have been applied for document deblurring benchmark proposed in [35].

Metrics. For comparison, we adapted the performance evaluation metrics for DIBCO benchmarks in document image binarization task as proposed in [56]. The metrics principally comprise Peak signal-to-noise ratio (PSNR), F-Measure (FM), pseudo-F-measure ($F_{ps}$) and Distance reciprocal distortion metric (DRD). To better understand the quantitative results, we briefly explain their significance in the task. PSNR evaluates the similarity between the ground-truth and predicted output in terms of the amount of noise. While FM computes the harmonic mean of precision and recall, $F_{ps}$ provides a more accurate pixel-based evaluation by weighing the distance between the foreground (text) and background boundary pixels. DRD [47] measures the visual distortion of every pixel in the image.

For document deblurring task, we measure the performance of our model using the PSNR metric as done in [35]. Also, for a qualitative evaluation of content recovery after the enhancement, we test the performance of an open-source Tesseract-OCR on the binarized and deblurred images, with the hypothesis of if the textual content is well preserved, OCR should perform better.

Performance Analysis on Binarization. As shown in Table 5, the Text-DIAE outperforms the previous state-of-the-art approaches on majority of the standard metrics for document binarization task. Specifically, the quantitative comparison of results demonstrate that Text-DIAE achieves an optimal gain in PSNR, FM, $F_{ps}$ and DRD performance surpassing the all previous arts. The
Fig. 5. Qualitative results of binarized samples: We show the results of Text-DIAE on the document image binarization task. Given a degraded input example from DIBCO 2017, our model performs significantly better qualitatively compared to previous approaches.

Table 6. SOTA results: Quantitative evaluation with state-of-the-art methods on the deblurring dataset.

| Method         | PSNR  |
|----------------|-------|
| CNN-Baseline   | 19.36 |
| Pix2Pix-HD     | 19.89 |
| DE-GAN         | 20.37 |
| DocEnTr        | 21.28 |
| Ours           | 23.58 |

Table 7. Ablations of the degradations as pre-training objectives. Results in document image binarization on DIBCO 2018 obtained by each pretext task in terms of PSNR.

|        | Lmask | Lblur | Lnoise | PSNR  |
|--------|-------|-------|--------|-------|
| ✗ ✗ ✗  |       |       |        | 18.75 |
| ✓ ✗ ✗  |       |       |        | 19.65 |
| ✗ ✓ ✗  |       |       |        | 18.98 |
| ✗ ✗ ✓  |       |       |        | 19.82 |
| ✗ ✓ ✓  |       |       |        | 19.34 |
| ✓ ✗ ✓  |       |       |        | 19.45 |
| ✓ ✓ ✓  |       |       |        | 19.95 |

largest performance improvement is obtained over the H-DIBCO 2012 while the least performance gain is obtained in the H-DIBCO 2018. One of the major concerns which degraded historical documents face is the show-through effect, which appears when ink impressions from one side of the document start appearing on the other side, making it almost impossible to read as shown in Figure 5. The enhanced Text-DIAE output illustrates that it not only resolves the show-through but also sharpens and smoothens the edges of the foreground text approximately to the ground-truth level.

Performance Analysis on Deblurring. In Table 6 we show a quantitative comparison and superiority of Text-DIAE over supervised techniques [35,67,69,75] on the document deblurring benchmark. A substantial gain in PSNR by +2 points on a logarithmic scale is obtained over DocEnTr [67], which signifies the greater quality of deblurred images generated by Text-DIAE. There are two different kinds of blurring which appear in documents: motion blur owing to the sudden rapid camera movement and out-of-focus blur which emerges when light fails to converge in the image. In Fig. 6, we show an interesting qualitative case study of a motion blurred document image. We assess the performance of deblurring by running the Tesseract-OCR engine [65] over the blurred, ground-
Fig. 6. Qualitative results of deblurred samples. The document image on the left refers to the originally captured blurred image, followed by the ground-truth, and the deblurred results from the DocEnTr and our Text-DIAE model towards right. The correctly predicted OCR output is shown in "Green" font while the inaccurate ones are depicted in "Red" and recognition performance in terms of CER.

5 Conclusion

In this work, we have presented a Text-Degradation Invariant Auto-Encoder (Text-DIAE) framework designed for representation learning. The main take-home lesson is the capability of learning richer representations through pretext degradation tasks. Self-supervised learning can immensely boost the performance of text recognition and document image enhancement without any requirement of labeled data. Notably, we show that Text-DIAE does not share the limitations of contrastive or sequential approaches and is more effective at learning rich representations while seeing significantly less data points. Extensive experimentation during fine-tuning demonstrate that Text-DIAE surpasses previous supervised and self-supervised state-of-the-art in handwritten text recognition and document image enhancement, while outperforming previous self-supervised approaches in scene-text recognition. We hypothesize that Text-DIAE performs complex variable reconstructions during pre-training, which helps to learn meaningful visual concepts from the latent representation space. In future work, we
consider integration of more self-supervised schemes for document image analysis and recognition downstream tasks.

Acknowledgement

This work has been partially supported by the Swedish Research Council (grant 2018-06074, DECRYPT), the Spanish projects RTI2018-095645-B-C21, CERCA Program / Generalitat de Catalunya, the FCT-19-15244, the Catalan projects 2017-SGR-1783, PhD Scholarship from AGAUR (2021FIB-10010) and (2019-FIB01233) and UAB (B18P0073). DocPRESERV project (Swedish STINT grant).
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