Text-DIAE: A Self-Supervised Degradation Invariant Autoencoder for Text Recognition and Document Enhancement

Mohamed Ali Souibgui*1, Sanket Biswas*1, Andres Mafia*1, Ali Furkan Biten*1, Alicia Fornés1, Yousri Kessentini2, Josep Lladós1, Lluis Gomez1, Dimosthenis Karatzas1

1 Computer Vision Center, Universitat Autònoma de Barcelona, Barcelona, Spain
2 Digital Research Center of Sfax, SM@RTS Laboratory, Sfax, Tunisia

Abstract
In this paper, we propose a Text-Degradation Invariant Auto Encoder (Text-DIAE), a self-supervised model designed to tackle two tasks, text recognition (handwritten or scene-text) and document image enhancement. We employ a transformer-based architecture that incorporates three pretext tasks as learning objectives to be optimized during pre-training without the usage of labelled data. Each of the pretext objectives is tailored for the final downstream tasks. We conduct several ablation experiments that confirm the design choice of the selected pretext tasks. Importantly, the proposed model does not exhibit limitations of previous state-of-the-art methods based on contrastive losses, while at the same time requiring substantially fewer data samples to converge. Finally, we demonstrate that our method surpasses the state-of-the-art 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 https://github.com/dali92002/SSL-OCR.

1 Introduction
In recent times, self-supervised learning paradigms have gained a lot of attention due to its ability of benefiting from massive unlabelled data which is easily accessible from different sources. However, applying these approaches remain quite limited in the domains of optical character recognition (OCR), handwritten text recognition (HTR) and document image enhancement, which motivate us to tackle the problem in this study.

Common computer vision pipelines using self-supervised frameworks employ a pretext-task (e.g. relative position prediction of patches (Doersch, Gupta, and Efros 2015), contrastive views (Chen et al. 2020), image inpainting (Pathak et al. 2016), etc.) to learn visual representations for solving down-stream tasks like classification, object detection and so on. Current self-supervised paradigms (Caron et al. 2021; Chen et al. 2020; Chen, Xie, and He 2021) have adapted transformers (Vaswani et al. 2017) to learn visual representations from unlabelled images which are semantically meaningful. More recently, generative self-supervised approaches (He et al. 2021; Bao, Dong, and Wei 2021; Dong et al. 2021) 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 (HTR) (Aberdam et al. 2021; Bhunia et al. 2021; Liu et al. 2022) and Scene-Text Recognition (STR) (Aberdam et al. 2021; Zhang et al. 2022) and image enhancement (Liang et al. 2022). 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.

For humans, reading text in noisy scenarios is possible because of the ability to reconstruct the degraded regions and predicting the missing/blurry content (Howard et al. 1998; Dehaene 2014). 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 order to endow this human-specific skill to our models, we present in this paper a new self-supervised framework called Text-Degradation Invariant Auto-Encoders (Text-DIAE) inspired by the principle of denoising autoencoders (Vincent et al. 2008). 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 specifically tackle two different downstream tasks: text recognition (HTR and STR) and document image enhancement (document binarization, document deblurring). As a consequence, the choice of the proxy tasks have been realized to learn useful representations for solving these specific downstream tasks using unlabeled data.

The benefits of employing such approach are: we do not define sequences at the feature level. Rather, by employing a transformer-based (Vaswani et al. 2017) approach, similar to BERT (Devlin et al. 2018) 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 (Kolesnikov, Zhai, and Beyer 2019; Zhang, Isola, and Efros 2016) and follows the scheme of (Aberdam et al. 2021) in text recognition task. 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. The essential findings and novelties of our work are based on the following interesting deductions:

• The impact and combination of pretext tasks depends on the downstream task.
• The closer the association between a pretext task and a downstream task, the better is the model performance.
• By employing Text-DIAE, we achieve faster convergence and use order of magnitude lesser data during pre-training than the contrastive-learning based approaches.

To add on top of this, this is the first work to our knowledge that investigates different self-supervised pretext tasks for multiple significant downstream tasks in text recognition (HTR-word level, STR) and document image enhancement (document binarization, deblurring) while achieving state-of-the-art performance with 43 and 45 times lesser data for HTR and STR, respectively.

2 Related Work

Self-Supervised Learning. Due to extensive efforts on labelled data requirements of supervised models, this learning paradigm emerges as a way of exploiting the structured information contained in data itself. Self-Supervised learning aims to obtain rich representations of an input modality by designing pretext tasks that are used as auxiliary signals that are informative for a given downstream task. Initial approaches relied on auto-encoders (Vincent et al. 2008) trained to remove artificially added noise from an image. Later, several approaches introduced other pretext tasks that provide rich signals to train a network as a feature extractor. Some pretext tasks employed were image colorization (Zhang, Isola, and Efros 2016), jigsaw puzzle solving (Noroozi and Favaro 2016), patch ordering (Doersch, Gupta, and Efros 2015), rotation prediction (Gidaris, Singh, and Komodakis 2018) among others. Recent approaches rely on extensive image augmentation to maximize the agreement among paired samples and contrast with all possible negative samples (Chen et al. 2020; He et al. 2020; Zbontar et al. 2021; Caron et al. 2021).

More recently, generative approaches like Masked Auto-encoders (MAE) (He et al. 2021) are introduced to predict a masked latent representation of patches. Similar ideas have been also explored in other recent works like BEiT (Bao, Dong, and Wei 2021) and PeCo (Dong et al. 2021) which adopt a discrete variational autoencoder (VAE) to generate discrete visual tokens from the original image. Motivated by these works, we expand this generative learning framework to tackle text recognition and document enhancement tasks.

Text Recognition. Ample research in text recognition has been conducted, resulting in handwritten (HTR) (Sonkusare and Sahu 2016; Memon et al. 2020) and scene-text (STR) (Shi, Bai, and Yao 2016; Long, He, and Yao 2021; Chen et al. 2021) recognition pipelines. Most common approaches that tackle text recognition are using supervised methodologies that employ an encoder-decoder mechanism (Cheng et al. 2017; Shi, Bai, and Yao 2016; Shi et al. 2016; Litman et al. 2020; Kang et al. 2020a) based on a Connectionist Temporal Classification (CTC) (Graves et al. 2006) network or an Attention-based (Cheng et al. 2017; Shi et al. 2016) decoder. Recently, approaches that focus on semi-supervised and self-supervised learning have been explored (Soubgui et al. 2021) with domain adaptation techniques on STR (Kang et al. 2020b) and HTR (Zhang et al. 2019). Under the unsupervised paradigm, (Gupta, Vedaldi, and Zisserman 2018) 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, (Aberdam et al. 2021) proposes a self-supervised sequence-to-sequence model that separates consecutive text features to be later used in a contrastive loss similar to (Chen et al. 2020). Analogously, (Zhang et al. 2022) and (Liu et al. 2022) improve the features obtained from a contrastive loss by concatenating characters and by perceiving spatial strokes respectively. Nevertheless, these methods require large batches, and rely on a sequential definition of features that can produce misaligned characters or n-grams contained in different words.

Document Image Enhancement. 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, show-through, faint characters, contrast variations and so on. The work from (Calvo-Zaragoza and Gallego 2019; Kang, Iwana, and Uchida 2021) maps images from the degraded domain to the enhanced one using end-to-end CNN-based autoencoders. Other techniques (Soubgui and Kessentini 2020; Soubgui, Kessentini, and Fornés 2020; Jemni et al. 2022) 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 (Soubgui et al. 2022) to capture high-level global features using self-attention for binarizing degraded documents. Regarding document deblurring, a benchmark was formulated by (Hradiš et al. 2015) where a CNN was trained to reconstruct enhanced images from blurry inputs that consist of a combination of camera-driven motion blurred and defocused images of text documents. Lately, (Soubgui and Kessentini 2020) improved the baseline performance using a similar c-GAN based approach in a binarization task.

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. 1. 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 $z_T$:

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

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 (Dosovitskiy et al. 2021) backbone. Given an input image $I_d$, it is first split into a set of $N$ patches, $I_d^p = \{I_d^1, I_d^2, ..., I_d^N\}$. Then, these patches are embedded with a trainable linear projection layer $E$. Text-DIAE uses a distinct linear projection layer for every defined pre-text 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 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 1. Each of these blocks are preceded by a LayerNorm (LN) (Ba, Kiros, and Hinton 2016) and followed by a residual connection:

$$z_0 = E(I_d^p) + E_{pos}$$
$$z'_l = \text{MSA}(\text{LN}(z_{l-1})); z_{l-1}, l = 1, ... L$$
$$z_l = \text{MLP}(\text{LN}(z'(l)) + z'_l), l = 1, ... L$$
$$z_T = \text{LN}(z_L)$$

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 $I_r = \{I_r^1, I_r^2, ..., I_r^N\}$ 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.

$$z'_l = \text{MSA}(\text{LN}(z_{l-1})); z_{l-1}, l = 1, ... L$$
$$z_l = \text{MLP}(\text{LN}(z'(l)) + z'_l), l = 1, ... L$$
$$I_r = \text{Linear}(z_L)$$

3.2 Fine-Tuning

Our fine tuning process is illustrated in Fig. 2 where we perform two different downstream tasks; text recognition and document image enhancement.

Text Recognition. Text recognition aims to transform an image into a 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 (Vaswani et al. 2017) as seen in Fig. 2-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 $t - 1$. 

Figure 1: 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.
**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: $L_{mask}$, $L_{blur}$ and $L_{noise}$. Each of these losses is a mean squared error (MSE) between the reconstructed image $I_r$ (from the masked, blurred or noisy image) and its ground-truth version $I_{gt}$. Thus, the overall loss for our pre-training stage is:

$$L_{pt} = \lambda_1 L_m (I_r, I_{gt}) + \lambda_2 L_b (I_r, I_{gt}) + \lambda_3 L_n (I_r, I_{gt})$$

During our experimentation, the best results were obtained with setting $\lambda_1 = \lambda_2 = \lambda_3 = 1$.

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.

#### 4.1 Text Recognition

**Evaluating Representations.** In order to evaluate the quality of the learned representations, and extending commonly used linear-probing settings (Zhang, Isola, and Efros 2016), we employ a similar approach as introduced by (Aberdam et al. 2021). 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 decoder, as 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.

**Better performance.** As it can be seen from Table 1, the seqCLR method presented by (Aberdam et al. 2021) improves significantly a self-supervised baseline inspired by SimCLR (Chen et al. 2020). In the recently released approach PerSec by (Liu et al. 2022), they slightly improve over the seqCLR. It is evident that our Text-DIAE model greatly outperforms all the aforementioned state-of-the-art approaches regarding the representation quality obtained, both in handwritten and scene-text. The improvements in terms 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 3), which is not leveraged in previous methods. Secondly, by distorting and recovering the image, we make the model learn richer representations to detect and recover the text into a clean and readable state. Thus, the model is learning the most valuable features that lead to the best recognition performance.

**Faster convergence.** One of the most important outcomes

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**Figure 2:** 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).
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 | CVL | IIIT5K | IC13 |
| simCLR (Chen et al. 2020) | CNN     | CTC     | 4.0 | 16.0 | 205.8 | 1.8 | 11.1 | 205.8 | 0.3 | 3.1 | 409.6 | 0.3 | 5.0 | 409.6 |
| seqCLR (Aberdam et al. 2021) | CNN     | CTC     | 39.7 | 63.3 | 205.8 | 66.7 | 77.0 | 205.8 | 35.7 | 62.0 | 409.6 | 43.5 | 67.9 | 409.6 |
| PerSec (Liu et al. 2022) | CNN     | CTC     | –   | –   | –   | –   | –   | –   | –   | –   | –   | –   | –   | –   |
| PerSec (Liu et al. 2022) | ViT     |         | –   | –   | –   | –   | –   | –   | –   | –   | –   | –   | –   | –   |
| simCLR (Chen et al. 2020) | CNN     | Attn.   | 16.9 | 21.2 | 205.8 | 26.7 | 77.1 | 205.8 | 50.7 | 61.1 | 409.6 | 43.5 | 67.9 | 409.6 |
| seqCLR (Aberdam et al. 2021) | CNN     | Attn.   | 51.9 | 65.0 | 205.8 | 74.5 | 77.1 | 205.8 | 59.3 | 77.1 | 409.6 | 59.3 | 77.1 | 409.6 |
| PerSec (Liu et al. 2022) | CNN     | Attn.   | –   | –   | –   | –   | –   | –   | –   | –   | –   | –   | –   | –   |
| PerSec (Liu et al. 2022) | ViT     |         | –   | –   | –   | –   | –   | –   | –   | –   | –   | –   | –   | –   |
| Ours                | ViT     | Transf. | 71.0 | 82.1 | 4.7  | 78.1 | 81.5 | 12.1 | 77.1 | 87.8 | 9.1  | 92.6 | 95.6 | 18.2 |

Table 2: Semi-supervised learning 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 | CVL | IIIT5K | IC13 |
| Supervised (Aberdam et al. 2021) | CNN     | CTC     | 21.4 | 33.6 | 75.2  | 48.7 | 63.6 | 75.6 | 76.1 | 84.3 |
| simCLR (Chen et al. 2020) | CNN     | CTC     | 15.4 | 21.8 | 65.0  | 52.1 | 62.0 | 74.1 | 69.1 | 79.4 |
| seqCLR (Aberdam et al. 2021) | CNN     | CTC     | 31.2 | 44.9 | 76.7  | 66.0 | 71.0 | 77.0 | 80.9 | 86.3 |
| PerSec (Liu et al. 2022) | ViT     |         | –   | –   | –   | –   | –   | –   | 80.8 | 85.2 | 89.2 |
| Supervised (Ours) | ViT     | Transf. | 22.8 | 25.3 | 71.7  | 17.9 | 19.8 | 71.9 | 75.7 | 91.9 |

by employing our method, is that a **paramount** improvement in convergence is achieved during 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 lesser data in IAM and CVL respectively when compared to the seqCLR and simCLR. 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. 2-Left. In this scenario, the gradients are back-propagated not only to the decoder but also to the encoder. Following the previous work (Aberdam et al. 2021), we use 5% and 10% of the labeled dataset by randomly selecting the training samples. As suggested in (Chen et al. 2020) we perform fine-tuning on all the labelled dataset. In order to compare with (Aberdam et al. 2021) and since scene-text dataset is synthetic, we evaluate with the complete labeled dataset.

**Higher performance in fine-tuning settings.** Our model exploits data in a more efficient manner than previous self-supervised methods in fine-tuning setting. We infer that the set of degradations proposed yields rich signals, helping 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 used except in IAM where the PerSec is slightly better. Under semi-supervised settings, our model performs better at the IAM dataset when employing 5% and 10% of the labels than simCLR and seqCLR. 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 all the methods by a large margin.

**More efficient than a supervised baseline.** From table 2,
representations learned depending on the similarity of them.

In document enhancement, therefore, we can safely assume that each degradation has a task-dependent impact on the combination of the nition tasks. However, as it is shown in the next section, the effect of adding noise does not result in an improvement in text recog-
nance in 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 hand-
written examples). Another interesting outcome is also noticed for scene-text example where “xperia” is reconstructed correctly while the last character “a” is selected from an-
other 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

Performance Analysis on Binarization. As shown in Ta-
ble 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 com-
parison of results demonstrate that Text-DIAE achieves an optimal gain in PSNR, FM, \( F_{ps} \) and DRD performance surpassing the all previous arts. The largest performance im-
provement 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 docu-
ments face is the show-through effect, which appears when ink impressions from one side of the document start appear-
ing on the other side, making it almost impossible to read as shown in Appendix. The enhanced Text-DIAE output illus-
trates that it not only resolves the show-through but also sharpens and smoothens the edges of the foreground text ap-
proximately 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 (Hradiš et al. 2015; Wang et al. 2018; Souibgui and Kessentini 2020; Souibgui et al. 2022) on the document deblurring benchmark. A substan-
tial gain in PSNR by +2 points on a logarithmic scale is obtained over DocEnTr (Souibgui et al. 2022), 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 sud-

Table 3: SOTA results. Quantitative evaluation with state-of-the-art methods on the IAM word level dataset.

| Method                  | IAM CER | IAM WER | IC13 CER | IC13 WER | Avg. CER | Avg. WER |
|-------------------------|---------|---------|----------|----------|----------|----------|
| Bluche et al. (Bluche 2015) | 7.3     | 24.7    | 16.00    |          |          |          |
| Bluche et al. (Bluche 2016) | 7.9     | 24.6    | 16.25    |          |          |          |
| Sueiras et al. (Sueiras et al. 2018) | 8.8     | 23.8    | 16.30    |          |          |          |
| ScrabbleGAN (Fogel et al. 2020) | -       | 23.6    | -        |          |          |          |
| SSDAN (Zhang et al. 2019) | 8.5     | 22.2    | 15.35    |          |          |          |
| SeqCLR (Aberdam et al. 2021) | 9.5     | 20.1    | 14.80    |          |          |          |
| PerSec (Liu et al. 2022) | -       | 18.2    | -        |          |          |          |
| Ours | 9.3     | 20.0    | 14.65    |          |          |          |

Table 4: Ablations of the pre-training objectives. Results in handwritten and scene-text recognition obtained by each pretext task. The performance is measured in terms of Word and Character error rates (WER and CER).

| \( L_{mask} \) | \( L_{blur} \) | \( L_{noise} \) | IAM CER | IAM WER | Avg. CER | Avg. WER |
|---------------|----------------|-------------|--------|--------|---------|---------|
| ✓             | x              | x           | 9.3    | 20.0   | 14.65   | 4.5     |
| ✓             | ✓              | x           | 12.3   | 24.8   | 18.5    | 4.2     | 8.0     | 6.10    |
| ✓             | ✓              | ✓           | 11.1   | 23.3   | 17.2    | 4.8     | 8.6     | 6.70    |
| ✓             | ✓              | ✓           | 11.4   | 23.8   | 17.6    | 5.1     | 9.3     | 7.20    |
5 Conclusion

This work demonstrates 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 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 fewer data points. We hypothesize that Text-DIAE performs complex variable reconstructions during pre-training, which helps to learn meaningful visual concepts from the latent representation space. We also provide the community the following insights to work on: 1) Designing new pretext tasks that are similar to downstream tasks. 2) The effect/trade-off of combination of various pretext tasks on the downstream tasks. 3) A need for a holistic approach to combine all the tasks into a single model.
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