ABSTRACT

Convolutional Neural Networks (CNN) have shown promising results for the task of Handwritten Text Recognition (HTR) but they still fall behind Recurrent Neural Networks (RNNs)/Transformer based models in terms of performance. In this paper, we propose a CNN based architecture that bridges this gap. Our work, *Easter* 2.0, is composed of multiple layers of 1D Convolution, Batch Normalization, ReLU, Dropout, Dense Residual connection, Squeeze-and-Excitation module and make use of Connectionist Temporal Classification (CTC) loss. In addition to the *Easter* 2.0 architecture, we propose a simple and effective data augmentation technique 'Tiling and Corruption (TACo)' relevant for the task of HTR/OCR. Our work achieves state-of-the-art results on IAM handwriting database when trained using only publicly available training data. In our experiments, we also present the impact of TACo augmentations and Squeeze-and-Excitation (SE) on text recognition accuracy. We further show that *Easter* 2.0 is suitable for few-shot learning tasks and outperforms current best methods including Transformers when trained on limited amount of annotated data. Code and model is available at: [https://github.com/kartikgill/Easter2](https://github.com/kartikgill/Easter2)
In the context of handwritten text recognition, very few works have used entirely convolutional architectures devoid of any recurrence \cite{1,4,5}. Some recent works\cite{2,15} combine CNNs with a gating mechanism to compensate for the dependency on LSTM cells, known as Gated Convolutional Neural Networks (GCN). GCN architectures have been shown to outperform fully convolutional architectures yet they lag behind RNN/Transformer based architectures such as \cite{7,8,9}.

Recurrent Neural Networks (RNN) work well for large variety of tasks including Handwritten Text Recognition (HTR). LSTM based models can handle long term context in sequences but at the cost of long learning times and potentially a huge number of parameters. Work by Voigtlaender et. al. \cite{12} uses multi-dimensional LSTM to learn dependencies over both axis (horizontal and vertical), which makes them even slower. The most common architectures have a combination of CNN and RNN, where CNN is used for feature extraction from images and RNN is used for modeling sequential context \cite{16,3}. Works by Michael and Labahn et. al. \cite{10} and Kang and Toledo et. al. \cite{17} improve CNN+LSTM architectures with use of various attention mechanisms. While some works such as \cite{10,18,19,20} have also experimented with sequence-to-sequence approaches.

Recent progress in tasks associated with text recognition has achieved state-of-the-art (SOTA) results using Transformer-based architectures \cite{8,9,7}. Some of these works use a CNN-based backbone with self-attention as encoders to understand images\cite{9}. Li and Lv et. al. \cite{9} use pre-trained Computer Vision (CV) and Natural Language Processing (NLP) models to improve Transformer-based encoder-decoder architecture to achieve SOTA results on IAM handwriting dataset without an external language model. This approach leverages a large sized synthetic training set and multiple pre-trainings with a large number of training parameters.

We believe that the biggest challenge in developing an HTR system is not modeling but obtaining sufficient amounts of high quality training data. In this paper we address this problem by presenting a method that achieves encouraging results with very less amount of training samples. We also propose a CNN based architecture, \textit{Easter2.0}, that is data efficient, parameter-efficient, compute-efficient, latency-efficient and is easy to understand and deploy. Our model utilizes multiple layers of 1D Convolution, Batch Normalization, ReLU, Dropout, Dense Residual Connections, a Squeeze-and-Excitation (SE)\cite{13} module and make use of Connectionist Temporal Classification (CTC) loss\cite{21}. The SE module improves access to global context for our proposed CNN architecture. \textit{Easter2.0} has advantages from both worlds, i.e., speed and parameter efficiency of CNN and access to global context similar to RNN/Transformers (using the SE module). The contributions of this paper are summarized as follows:

1. We propose \textit{TACo}, a simple and novel data augmentation technique for Handwritten Text Recognition with experimental results to prove it’s effectiveness.

2. We present \textit{Easter2.0}, a novel CNN based architecture for the task of end-to-end handwritten text line recognition that utilizes only 1D Convolutions with dense residual connections and a squeeze-and-excitation module.
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Figure 2: Easter 2.0 Architecture: (Left) Block type-A has 1-DCNN, Batch Norm, ReLU and Dropout layers. (Middle) Block type-C has 1-DCNN followed by a Softmax layer. (Right) Block type-B has repetitions of type-A blocks with Dense Residual Connections and SE module.

Figure 3: 1D Squeeze-and-Excitation module applies a sequence of steps starting with average pooling on local features followed by two fully connected layers to get context vector. The context vector is multiplied element wise with local features.

3. Easter 2.0 is recurrence-free, parameter efficient, fast and simple convolutional architecture that achieves state-of-the-art results on IAM handwritten test set when trained using only publicly available data (IAM-Train set).

2 Tiling and Corruption Augmentation (TACo)

We introduce a simple and effective augmentation technique for the task of handwritten text line recognition. TACo augmentations help the model to learn useful features and achieve good results even on very small training sets.

Tiling refers to cutting the input image into multiple small tiles of equal size ($T_w$). After tiling, a fraction ($C_p$) of the tiles is replaced with corrupted ones as part of the corruption step ($C_p$ is a hyper-parameter used to set the corruption probability). Finally, tiles are stitched back together in the same order to get the augmented image (see figure 4). Tile width $T_w$ is sampled from a uniform distribution from $\frac{H}{10}$ to maximum tile width parameter $T_{max}$ (where $H$ is height of input image). TACo augmentations can be applied on an input image across height($H$), width($W$) or both. The TACo augmentation algorithm is presented in algorithm 1. 

Algorithm 1: Tiling and Corruption (TACo)

1: \textbf{procedure} APPLYTACo(img)
2: \hspace{2em} H, W ← Shape of img
3: \hspace{2em} Tw ← sample from uniform distribution \([H, T_{\text{max}}]\)
4: \hspace{2em} tiles ← cut and return a list of image tiles each with width = Tw
5: \hspace{2em} for \(i = 1 \rightarrow \text{length}(\text{tiles})\) do
6: \hspace{4em} \(p \leftarrow \text{random floating point number from range}[0.0, 1.0)\) \hspace{1em} \(\triangleright\) using pseudo-random number generator
7: \hspace{4em} \text{if} \(p \leq C_p\) then
8: \hspace{6em} tiles\([i] \leftarrow \text{a corrupt tile of width}(Tw)\) \hspace{1em} \(\triangleright\) \(C_p:\) Corruption Probability\hspace{1em} \(\triangleright\) tile replacement
9: \hspace{2em} augmented_img ← join back tiles in the same order
10: \textbf{return} augmented_img

Figure 4: TACo augmentation examples. \textit{(Top)} Example of Vertical Tiling (across width) and Corruption with random noise. \textit{(Bottom)} Shows Horizontal Tiling (across height) and Corruption with random noise.

3 Model Architecture

The architecture of \textit{Easter}2.0 is inspired by the design of \textit{Easter}1 which is a fully convolutional architecture with only 1D convolutions. However, there are some key differences in our proposed \textit{Easter}2.0 architecture. \textit{Easter}2.0 makes use of dense residual connections and a squeeze-and-excitation module to introduce global context into local features. Sections 3.1 to 3.3 describe components of our model in more detail and section 3.4 describes the final configuration of \textit{Easter}2.0.

3.1 Convolution Blocks

\textit{Easter}2.0 has overall 14 layers and each layer represents one of the 3 types of convolution blocks A, B or C as shown in figure 2. Block type-A is composed of a standard 1D convolutional layers followed by layers of batch normalization, ReLU and dropout. Block type-B has \(R\) repetitions of Block type-A with a residual connection. The residual connection is first projected through a \(1 \times 1\) convolution to balance the number of channels followed by a batch normalization layer. The output of this batch normalization layer is then added to the output of SE layer in the last convolution block, just before the layers of ReLU and Dropout (see figure 2). The SE layer is only present in the last convolution block of Block type-B, just after the batch normalization layer(see figure 2). Block type-C is only used as the last layer of our model. Block type-C regulates size of output via \(1 \times 1\) convolution layers and is followed by a softmax layer to calculate the distribution of probabilities over the characters of given vocabulary.

Figure 5: TACo augmentation examples of IAM-Handwritten-lines. \textit{(Top)} Example with only Vertical TACo. \textit{(Center)} Represents Horizontal TACo. \textit{(Bottom)} An example of hybrid (Vertical + Horizontal) TACo.
Table 1: *Easter*2.0 configuration. The kernel size is for the window size across width and convolutions are across height.

| Block ID | Block type | Conv layers | #Output Channels | Kernel Size | Other | Dropout |
|----------|------------|-------------|------------------|-------------|-------|---------|
| B1, B2   | A          | 1           | 128              | 3           | stride=2 | 0.2     |
| B3       | B          | 3           | 256              | 5           | dense residual | 0.2     |
| B4       | B          | 3           | 256              | 7           | dense residual | 0.2     |
| B5       | B          | 3           | 256              | 9           | dense residual | 0.3     |
| B6       | A          | 1           | 512              | 11          | dilation=2 | 0.4     |
| B7       | A          | 1           | 512              | 1           | -       | 0.4     |
| B8       | C          | 1           | #Vocab           | 1           | -       | -       |

3.2 Dense Residual Connections

*Easter*2.0 utilizes dense residual connections as shown in the Block type-B of figure 2. The dense residual connections\(^2\) are obtained by adding the output of a convolution block to the inputs of all following blocks of type-B as shown in the figure 2. We found dense residual connections to be performing better than normal residual connections at the cost of small increase in training parameters (more details in the experiments section).

3.3 Squeeze-and-Excitation

We use a 1-D version of squeeze-and-excitation module to introduce global context as depicted in figure 3. SE module squeezes the local features into a single global context vector of weights and broadcasts this context back to each local feature vector through element-wise multiplication of context weights with features. We present experimental study on how SE module improves the model performance. Checkout the pseudo-code for our SE module implementation\(^2\) which is very similar to the works of Hu and Shen et. al.\(^1\) and Han and Zhang et. al.\(^1\).

```
Algorithm 2 Squeeze-and-Excitation-1D(SE)
1: procedure ADD_GLOBAL_CONTEXT(data, filters)
2:     x ← GlobalAveragePooling1D on data
3:     x ← FullyConnected (units=\(\frac{\text{filters}}{8}\)) on x  \(\triangleright\) Bottleneck
4:     x ← ReLU on x
5:     x ← FullyConnected (units=\(\text{filters}\)) on x
6:     weights ← Sigmoid on x
7:     final_data ← Element-wise Multiplication (weights, data)  \(\triangleright\) context broadcasted
8: return final_data
```

3.4 Configuration

*Easter*2.0 has a total 14 blocks of convolution layers. Table 1 summarizes the architectural details. First two layers are type-A blocks (B1 and B2) with kernel width of 3 and a stride of 2. Next 3 blocks are type-B blocks (B3 to B5) with kernel widths of 5, 7 and 9 respectively with dense residual connections. Blocks B6 and B7 are again type-A blocks with kernel widths of 11 and 1 respectively. Block B6 has a dilation rate of 2. Block B8 is a type-C block. All blocks except B8, have dropout layers.

4 Experiments

4.1 Dataset

The biggest challenge for OCR/HTR tasks is obtaining good quality labelled dataIAM handwriting database\(^2\) is a popular benchmark for comparing HTR models. Recent studies have utilised synthetic/INTERNAL datasets in addition to IAM-Training set to obtain SOTA results on IAM-Test set. Curation and usage of such synthetic datasets presents difficulties in reproducibility. We only make use of publicly available datasets for our experiments.
4.1.1 IAM

The IAM handwritten dataset is composed of 1,539 scanned form pages from 657 writers. It corresponds to handwritten English text images also available as grayscaled images. There are 79 characters in the alphabet. We only focus on the line level dataset. IAM-A has about 6,482,976 and 2,915 lines for training, validation and test datasets respectively. IAM-B has about 6,161,940 and 1,861 lines for training, validation and test datasets respectively.

4.1.2 Long-Lines

Long line samples are obtained by randomly choosing two training images and stacking them horizontally (with a small white background image in between) to form a long line and labels are concatenated with a space. This introduces examples with long lengths, multiple handwritings, strokes, etc.

4.2 Training Details

The experiments are carried out with Tensorflow toolkit with a weighted Connectionist Temporal Classification (w-CTC) (similar to [1]) as loss function. We have used Adam optimizer with an initial learning rate of $10^{-3}$ and a batch size of 32 with early stopping criteria.

4.3 Evaluation

We use case-sensitive Character Error Rate ($CER$) as evaluation metric to compare results in our experiments. We also provide model parameters from our experiments. The $CER$ is computed as the Levenshtein distance which is the sum of the character substitutions ($Sc$), insertions ($Ic$) and deletions ($Dc$) that are needed to transform one string into the other, divided by the total number of characters in the groundtruth ($Nc$). Formally,

$$CER(\%) = \frac{(Sc + Ic + Dc)}{Nc} \times 100$$

4.4 Results

In this section, we present results for different experiments based on different configurations discussed so far.

1. **Effect of Residual Connections:** Residual connections improve training when networks are deep. Table 2 shows the effect of residual connections on performance. We found out that dense residual connections outperform normal residual connections by a good margin.

2. **Effect of Normalization:** In our study, we evaluate performance of our model with 2 normalization techniques: batch normalization [25] and layer normalization [26] and also without normalization. Experiment results are shown in Table 3. We found that batch normalization outperforms layer normalization. Both normalization techniques help model train faster and achieve better results than the case without normalization.

3. **Effect of Squeeze-and-Excitation:** The squeeze-and-excitation module introduces the global context into convolutions. We found that adding SE to our network improves the model performance with a small increase in parameters. Table 2 shows the accuracy improvements when SE module is applied to Easter2.0 with dense as well as normal residual connections.

4. **Effect of TACo Augmentations:** TACo being a simple augmentation technique improves the model performance considerably. Table 4 shows that TACo improves $CER$ irrespective of the type of corruption applied to certain parts of the image. We finally went ahead with random-noise as a type of corruption in rest of our experiments.

5. **Effect of Tile Width:** We experimented with different values of maximum tile widths ($T_{max}$) while applying TACo augmentations (check section 2). In our experiments, we found out that TACo improves Easter2.0 irrespective of tile widths (see Table 5). Model achieves best results when $T_{max}=H$ (H is height of input image).

6. **Effect of Input Length:** Our experiments suggest that Easter2.0 works well irrespective of input length and thus a good option for recognizing longer sequences. Figure 6 shows the $CER$ analysis wrt. the input length on IAM-offline test set.

7. **Few-shot Training:** Easter2.0 is ideal for few-shot training and produces state-of-the-art (SOTA) results with very small amount of annotated data. Table 6 shows some experiments that we conducted with limited
Table 2: Effects of Residual Connections and SE module evaluated in terms of case-sensitive Character Error Rate (CER) on IAM-Test set. This experiment uses IAM-B partition (see section 4.1.1)

| Residual Type | SE layer | CER(%) | #param |
|---------------|----------|--------|--------|
| -             | -        | 10.47  | 5.8M   |
| Normal        | -        | 10.24  | 5.9M   |
| Dense         | -        | 9.18   | 6.1M   |
| Normal        | ✓        | 8.95   | 6.0M   |
| Dense         | ✓        | 8.90   | 6.1M   |

Table 3: Effect of Normalization choices evaluated in terms of case-sensitive Character Error Rate (CER) on IAM-Test set. This experiment uses IAM-A partition (see section 4.1.1)

| Normalization Type | CER(%) |
|--------------------|--------|
| -                  | 11.42  |
| Layer Norm         | 9.05   |
| Batch Norm         | 8.73   |

number of training samples. We found out that Easter2.0 outperforms SOTA works including Transformers[7] when training data is small (see tables 6 and 7). As obtaining large amount of good quality annotated data is a challenge in many recognition tasks, Our solution can be a choice in such scenarios. External language model can improve our model further however we have only presented greedy decoding results in this paper.

8. Comparison with the State-of-the-Art: Table 7 compares current state-of-the-art results on IAM-Test set. Easter2.0 beats previous SOTA results with a good margin when only publicly available data is used for training. Many state-of-the-art (SOTA) solutions use pre-trainings and large internal/synthetic datasets to boost model accuracy. As everyone has their own way to collect synthetic/internal data, it makes the model comparison unfair. To avoid this bias, we train Easter2.0 only with publicly available IAM-offline training set (6,482 lines). We present SOTA results on IAM-test set having 2,915 lines (see table 7). However, when synthetic/Internal data is allowed Diaz et al.[8] and TrOCR[9] achieve SOTA results on IAM-Test set with CER 2.75 and 2.89 respectively.

Table 4: Effect of TACo augmentation-variations evaluated in terms of case-sensitive Character Error Rate (CER) on IAM-Test set. This experiment uses IAM-B partition (see section 4.1.1)

| Corruption Type | Vertical | Horizontal | CER(%) |
|-----------------|----------|------------|--------|
| -               | -        | -          | 8.90   |
| Black           | ✓        | -          | 7.80   |
|                 | ✓        | ✓          | 8.21   |
| White           | ✓        | -          | 8.29   |
|                 | ✓        | ✓          | 8.09   |
| Mean            | ✓        | -          | 7.78   |
|                 | ✓        | ✓          | 7.77   |
| Random          | ✓        | -          | 7.76   |
|                 | ✓        | ✓          | 7.72   |
| Miscellaneous   | ✓        | -          | 8.32   |
Table 5: Effect of \textit{TACo}-Tile width evaluated in terms of case-sensitive Character Error Rate (CER) on IAM-Test set. This experiment uses IAM-A partition (see section 4.1.1)

| Corrumpion | Tile Width | CER(\%) |
|------------|------------|---------|
| -          | -          | 10.71   |
| random, vertical | $H/2$   | 8.92    |
| random, vertical | $H$     | 8.73    |
| random, vertical | $2 \times H$ | 9.33  |
| random, vertical | $4 \times H$ | 9.37  |

Table 6: Few-shot training and results comparison with SOTA solutions evaluated in terms of case-sensitive Character Error Rate (CER) on IAM-Test set. This experiment uses IAM-A partition (see section 4.1.1)

| Method                  | CER (%) | Time (s) | #param (M) |
|-------------------------|---------|----------|------------|
| Seq2Seq\[7\]            | 20.61   | 338.7    | 37         |
| Transformer w/CNN\[7\]  | 73.81   | 202.5    | 100        |
| \textit{Easter}2.0 (Ours) | 38.90   | 51       | 6.1        |
| \textit{Easter}2.0 + Long-Lines\[4.1.2\] | -       | 6.21     | 6.1        |

Figure 6: Effect of Input Length on model performance (in terms of CER).

Table 7: Comparison with previous solutions using case-sensitive CER on IAM-Test set (line-level test set with greedy decoding). These results use IAM-A partition (see section 4.1.1)

| Training Data | Model                  | Architecture | External LM | CER(\%) | #param(M) |
|---------------|------------------------|--------------|-------------|---------|-----------|
| IAM (6k)      | Ingle et al., 2019\[2\] | GRCL         | No          | 14.1    | 10.6      |
|               | Chaudhary et al., 2021\[1\] | FCN/CTC     | No          | 9.8     | 28        |
|               | Kang et al., 2020\[7\]  | Transformer w/ CNN | No  | 7.62    | 100       |
|               | Wang et al. \[27\]      | DAN, FCN/GRU | No          | 6.4     | -         |
|               | \textit{Easter}2.0 (Ours) | 1DCNN-SE/ CTC | No   | 6.21    | 6.1       |
| Synthetic + IAM | Kang et al., 2020 \[7\] | Transformer w/ CNN | No  | 4.67    | 100       |
|               | Bluche and Messina, 2017\[3\] | GCRNN / CTC | Yes         | 3.2     | -         |
|               | TrOCR(LARGE) 2021\[9\]  | Transformer   | No          | 2.89    | 558       |
| Internal + IAM | Michael et al., 2019\[10\] | LSTM/LSTM w/Attn | No  | 4.87    | -         |
|               | Ingle et al., 2019\[2\]  | GRCL         | No          | 4.0     | 10.6      |
|               | Diaz et al., 2021\[8\]  | Transformer w/ CNN | No  | 2.96    | -         |
|               | Diaz et al., 2021\[8\]  | S-Attn / CTC | Yes         | 2.75    | -         |
5 Conclusion

In this paper, we proposed a convolutional architecture for the task of handwritten text recognition that utilizes only 1D convolutions, dense residual connections and a SE module. We also proposed a simple and effective data augmentation technique-TACo useful for OCR/HTR tasks. We have presented experimental study on components of Easter2.0 architecture including dense residual connections, normalization choices, SE module, TACo variations and few-shot training. Our work achieves SOTA results on IAM-Test set when training data is limited, also Easter2.0 has very small number of trainable parameters compared to other solutions. The proposed architecture can be used in search of smaller, faster and efficient OCR/HTR solutions when available annotated data is limited.

References

[1] Kartik Chaudhary and Raghav Bali. Easter: Simplifying text recognition using only 1d convolutions. Proceedings of the Canadian Conference on Artificial Intelligence, 6 2021. https://caiac.pubpub.org/pub/fm5sy88o.

[2] R Reeve Ingle, Yasuhsia Fuji, Thomas Deselaers, Jonathan Baccash, and Ashok C Popat. A scalable handwritten text recognition system. In 2019 International Conference on Document Analysis and Recognition (ICDAR), pages 17–24. IEEE, 2019.

[3] Théodore Bluche and Ronaldo Messina. Gated convolutional recurrent neural networks for multilingual handwriting recognition. In 2017 14th IAPR international conference on document analysis and recognition (ICDAR), volume 1, pages 646–651. IEEE, 2017.

[4] Raymond Ptucha, Felipe Petroski Such, Suhas Pillai, Frank Brockler, Vatsala Singh, and Paul Hutkowski. Intelligent character recognition using fully convolutional neural networks. Pattern recognition, 88:604–613, 2019.

[5] Mohamed Yousef, Khaled F Hussain, and Usama S Mohammed. Accurate, data-efficient, unconstrained text recognition with convolutional neural networks. Pattern Recognition, 108:107482, 2020.

[6] François Chollet. Xception: Deep learning with depthwise separable convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1251–1258, 2017.

[7] Lei Kang, Pau Riba, Marçal Rusiñol, Alicia Fornés, and Mauricio Villegas. Pay attention to what you read: Non-recurrent handwritten text-line recognition. arXiv preprint arXiv:2005.13044, 2020.

[8] Daniel Hernandez Diaz, Siyang Qin, Reeve Ingle, Yasuhsia Fuji, and Alessandro Bissacco. Rethinking text line recognition models. arXiv preprint arXiv:2104.07787, 2021.

[9] Minghao Li, Tengchao Lv, Lei Cui, Yijuan Lu, Dinei Florencio, Cha Zhang, Zhoujun Li, and Furu Wei. Trocr: Transformer-based optical character recognition with pre-trained models. arXiv preprint arXiv:2109.10282, 2021.

[10] Johannes Michael, Roger Labahn, Tobias Grüning, and Jochen Zöllner. Evaluating sequence-to-sequence models for handwritten text recognition. In 2019 International Conference on Document Analysis and Recognition (ICDAR), pages 1286–1293. IEEE, 2019.

[11] Vu Pham, Théodore Bluche, Christopher Kermorvant, and Jérôme Louradour. Dropout improves recurrent neural networks for handwriting recognition. In 2014 14th international conference on frontiers in handwriting recognition, pages 285–290. IEEE, 2014.

[12] Paul Voigtlaender, Patrick Doetsch, and Hermann Ney. Handwriting recognition with large multidimensional long short-term memory recurrent neural networks. In 2016 15th International Conference on Frontiers in Handwriting Recognition (ICFHR), pages 228–233. IEEE, 2016.

[13] Jie Hu, Li Shen, and Gang Sun. Squeeze-and-excitation networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 7132–7141, 2018.

[14] Wei Han, Zhengdong Zhang, Yu Zhang, Jiahui Yu, Chung-Cheng Chiu, James Qin, Anmol Gulati, Ruoming Pang, and Yonghui Wu. Contextnet: Improving convolutional neural networks for automatic speech recognition with global context. arXiv preprint arXiv:2005.03191, 2020.

[15] Denis Coquent, Clément Chatelain, and Thierry Paquet. Recurrence-free unconstrained handwritten text recognition using gated fully convolutional network. In 2020 17th International Conference on Frontiers in Handwriting Recognition (ICFHR), pages 19–24. IEEE, 2020.

[16] Curtis Wigington, Seth Stewart, Brian Davis, Bill Barrett, Brian Price, and Scott Cohen. Data augmentation for recognition of handwritten words and lines using a cnn-lstm network. In 2017 14th IAPR International Conference on Document Analysis and Recognition (ICDAR), volume 1, pages 639–645. IEEE, 2017.
[17] Lei Kang, J Ignacio Toledo, Pau Riba, Mauricio Villegas, Alicia Fornés, and Marçal Rusinol. Convolve, attend and spell: An attention-based sequence-to-sequence model for handwritten word recognition. In *German Conference on Pattern Recognition*, pages 459–472. Springer, 2018.

[18] Théodore Bluche. Joint line segmentation and transcription for end-to-end handwritten paragraph recognition. *Advances in Neural Information Processing Systems*, 29:838–846, 2016.

[19] Arindam Chowdhury and Lovekesh Vig. An efficient end-to-end neural model for handwritten text recognition. *arXiv preprint arXiv:1807.07965*, 2018.

[20] Jorge Sueiras, Victoria Ruiz, Angel Sanchez, and Jose F Velez. Offline continuous handwriting recognition using sequence to sequence neural networks. *Neurocomputing*, 289:119–128, 2018.

[21] Alex Graves, Santiago Fernández, Faustino Gomez, and Jürgen Schmidhuber. Connectionist temporal classification: labelling unsegmented sequence data with recurrent neural networks. In *Proceedings of the 23rd international conference on Machine learning*, pages 369–376, 2006.

[22] Jason Li, Vitaly Lavrukhin, Boris Ginsburg, Ryan Leary, Oleksii Kuchaiev, Jonathan M Cohen, Huyen Nguyen, and Ravi Teja Gadde. Jasper: An end-to-end convolutional neural acoustic model. *arXiv preprint arXiv:1904.03288*, 2019.

[23] U-V Marti and Horst Bunke. The iam-database: an english sentence database for offline handwriting recognition. *International Journal on Document Analysis and Recognition*, 5(1):39–46, 2002.

[24] Martín Abadi, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Geoffrey Irving, Michael Isard, et al. Tensorflow: A system for large-scale machine learning. In *12th {USENIX} symposium on operating systems design and implementation ({OSDI} 16)*, pages 265–283, 2016.

[25] Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In *International conference on machine learning*, pages 448–456. PMLR, 2015.

[26] Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E Hinton. Layer normalization. *arXiv preprint arXiv:1607.06450*, 2016.

[27] Tianwei Wang, Yuanzhi Zhu, Lianwen Jin, Canjie Luo, Xiaoxue Chen, Yaqiang Wu, Qianying Wang, and Mingxiang Cai. Decoupled attention network for text recognition. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 12216–12224, 2020.
A APPENDIX- Easy Examples

Figure 7 shows some clean examples (From IAM-Offline Test partition) that were easy for model. In these examples, Easter2.0 doesn’t make any mistake and recognises full sentence correctly.

Figure 7: Examples where model doesn’t make any mistake
Figure 8: Examples where model makes mistakes

B APPENDIX- Difficult Examples

Figure 8 shows some difficult examples (From IAM-Offline Test partition) where model makes mistakes. Sometimes these mistakes are due to noisy input, and sometimes even label is incorrect. We didn’t explicitly correct any labels for our experiments.