Report

Word-Level Handwritten OCR using IAM Dataset

Team Members

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1. Problem Description

The goal of this project is to solve a **word-level handwritten Optical Character Recognition (OCR)** problem. Given an image containing a **single handwritten word**, the task is to predict its **textual transcription**. This is a challenging problem due to large variations in handwriting styles, character spacing, word length, and image quality.

2. Dataset Description

We use the IAM Handwriting Database (word-level), accessed via a publicly available **Kaggle dataset**. The dataset provides handwritten word images along with ground-truth transcriptions and follows the original IAM annotation format.

the handwritten word structure.

- Annotation file: words_new.txt
- Only samples with status = ok are used
- Missing or corrupted images are automatically filtered out
- The dataset is limited to word-image folders from **A to E**, as later folders are not visually available

Dataset Split

The dataset is split using CSV files:

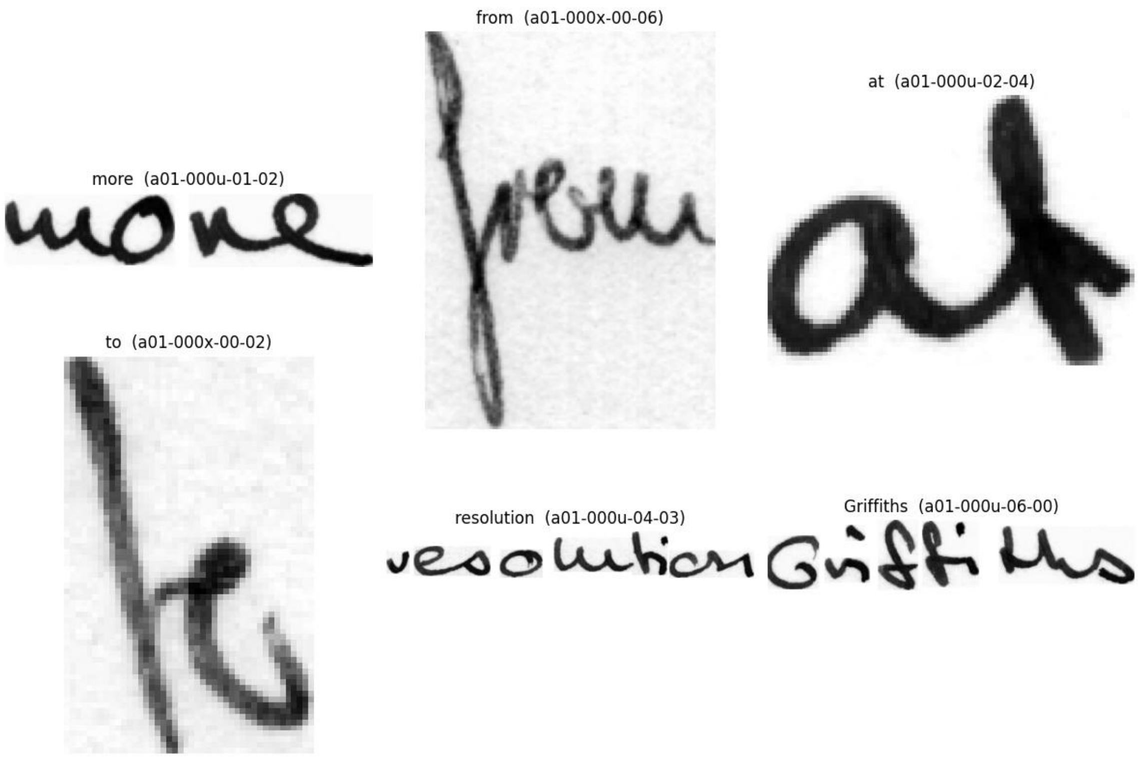
- splits/train.csv
- splits/val.csv
- splits/test.csv

Split ratios:

- **Train:** 80%
- **Validation:** 10%
- **Test:** 10%

The final **test set contains 3825 word images**.

Samples:



3. Preprocessing

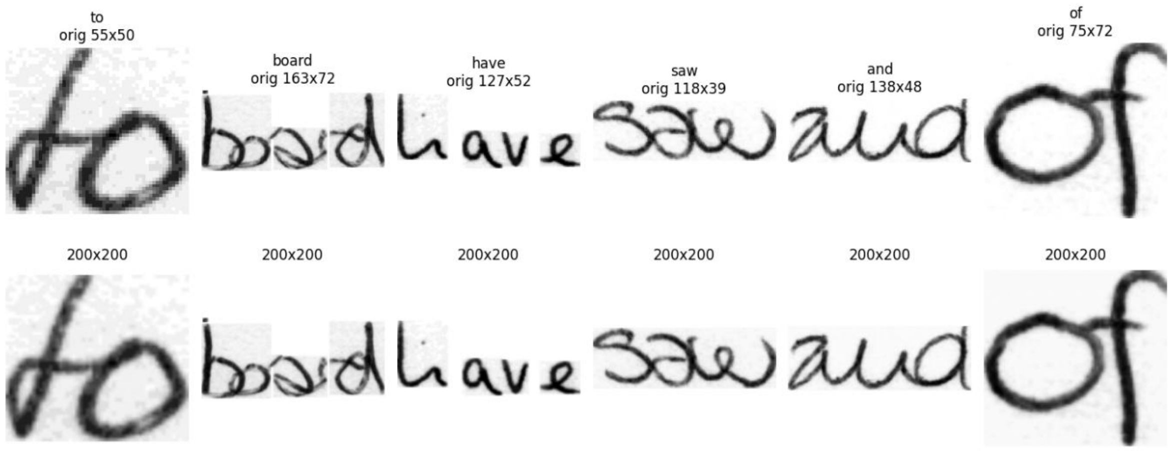
Each word image is processed as follows:

- Converted to **grayscale**
- Resized to **200×200 pixels**
- Aspect ratio preserved, padded and centered
- Pixel values normalized to [0, 1]

Data Augmentation

To improve generalization, light augmentation is applied **only to the training set**:

- For data augmentation, RandomAffine transformations with small rotation and translation ranges were applied (e.g., rotations up to ±5 degrees and small translations), in order to increase robustness without distorting



4. Model Architecture

The OCR system follows a **CNN–RNN–CTC** pipeline.

CNN Backbone

- **ResNet18**, pretrained on ImageNet
- First convolution layer adapted from 3-channel to **1-channel input**

Sequence Modeling

- Feature maps are converted into sequences
- **2-layer Bidirectional LSTM** is used to model character dependencies

Output

- Linear projection layer to character logits
- **CTC Loss** for alignment-free training
- **Greedy decoding** during inference

Architecture flow:

ResNet18 → Feature Maps → Sequence Extraction → BiLSTM → Linear → CTC

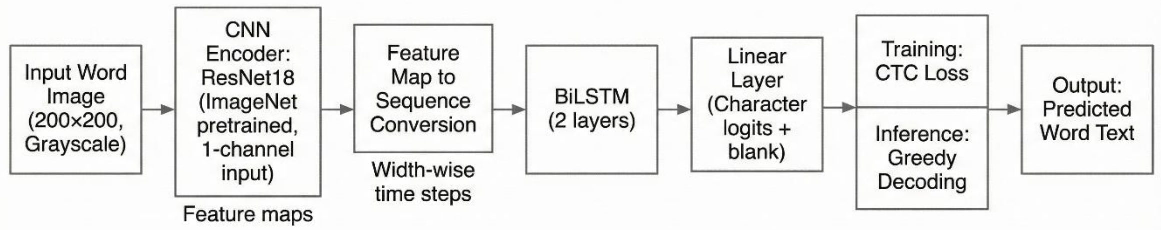


Figure: CNN–BiLSTM–CTC pipeline used for word-level handwritten OCR.

5. Model Analysis

- Backbone: ResNet18
- Sequence model: 2× BiLSTM
- Total parameters: **16 million**:
  - Model file size: **61 MB**
  - The model size fits comfortably in GPU memory
  - Number of parameters is dominated by the CNN backbone
- Suitable for word-level OCR without excessive computational cost

6. Training Procedure

Training is performed using the following setup:

- **Optimizer:** AdamW, chosen for its better regularization properties compared to Adam
- **Learning rate:** 1e-4
- **Scheduler:** ReduceLROnPlateau
- **Batch size:** 32

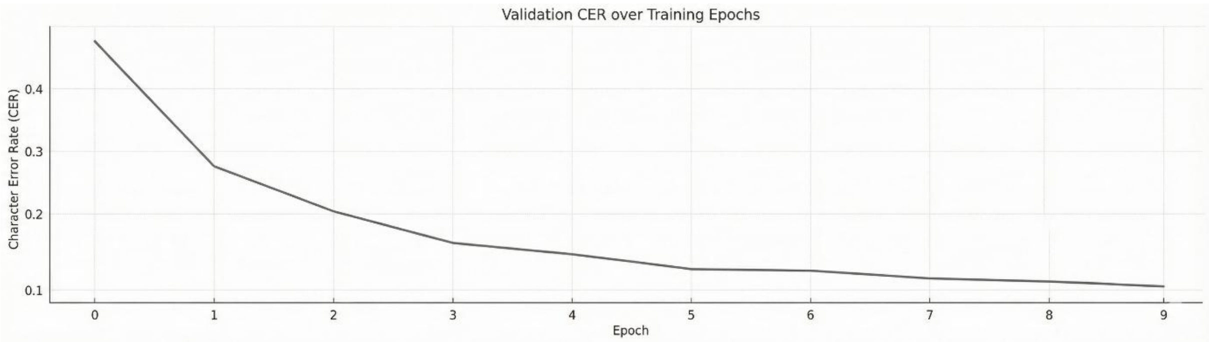
- **Gradient clipping** enabled to stabilize training
- Best model selected based on **lowest validation CER**

Training and validation metrics are logged per epoch.

Commands to Run

The training and evaluation pipeline can be executed by running the notebook:

IAM_Word_Level_OCR.ipynb



Training complete. Best CER: 0.1079

7. Hyperparameters and Explanation

Hyperparameter	Value	Explanation
Image size	200×200	Standardized input size while preserving details
Batch size	32	Balanced between stability and memory usage
Learning rate	1e-4	Stable convergence for pretrained backbone
Optimizer	AdamW	Better regularization than Adam
Scheduler	ReduceLROnPlateau	Adapts learning rate based on validation CER
Epochs	10	Enough to converge without overfitting

8. Loss and Evaluation Metrics

Loss

- **CTC Loss** is used to handle variable-length predictions without explicit alignment.

Metrics

- **CER (Character Error Rate)**
- **WER (Word Error Rate)**
- **Word Accuracy**

At least two metrics (CER and WER) are used as required.

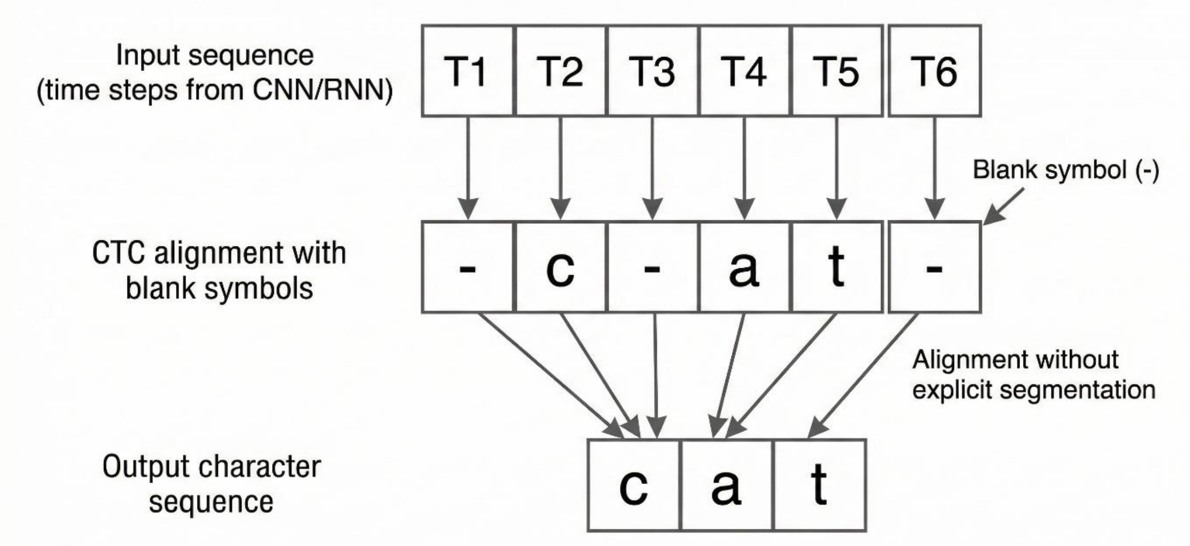


Illustration of Connectionist Temporal Classification (CTC) loss for sequence alignment in OCR.

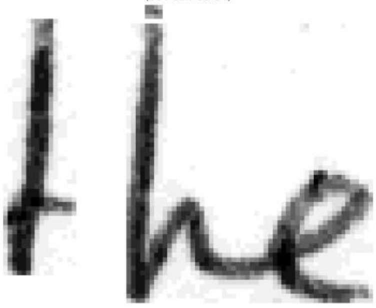
9. Results

Test Set Results (Best Model)

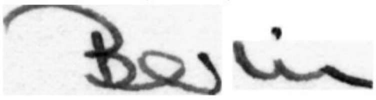
- **Test CER:** 0.1166
- **Test WER:** 0.3354
- **Test Word Accuracy:** 0.6646
- **Test samples:** 3825

The model shows consistent performance on both validation and test sets.
Errors mostly occur on longer words or visually ambiguous characters.

GT: the
Pred: the
(b04-054-03-04)

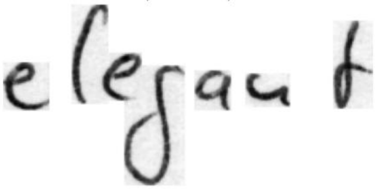


GT: Berlin
Pred: Berlin
(a05-089-07-02)

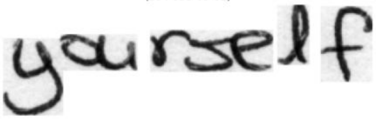


GT: NATO
Pred: 1T0
(a02-020-05-08)

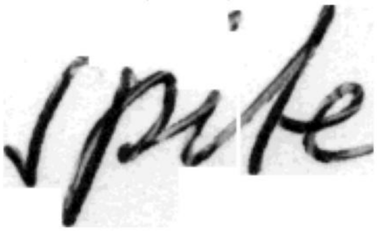
GT: elegant
Pred: elegant
(e01-059-04-04)



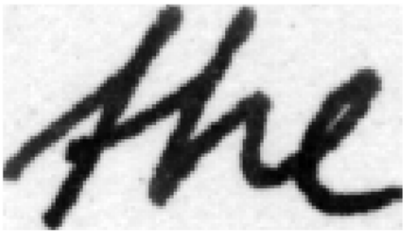
GT: yourself
Pred: yarself
(d04-053-09-01)



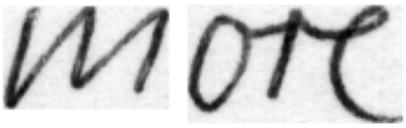
GT: spite
Pred: spite
(b05-088-01-07)



GT: the
Pred: the
(c03-087d-04-01)



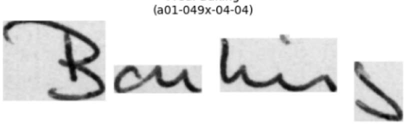
GT: more
Pred: more
(c03-087c-06-01)



GT: city
Pred: city
(c02-030-02-04)

GT: of
Pred: of
(b05-062-03-09)

GT: Banking
Pred: Baking
(a01-049x-04-04)



GT: to
Pred: to
(a03-011-04-05)

10. Training and Inference Time

- Training time: ~30 minutes for 10 epochs on NVIDIA GPU
- Inference time: ~5ms per image (batch size 32)

11. Comparison of Models

Only one main architecture is used in this project.
The choice of ResNet18 + BiLSTM provides a good balance between accuracy and computational cost for word-level OCR.

12. Libraries and Tools

A full list of libraries is provided in requirements.txt, including:

- PyTorch
- torchvision
- NumPy
- matplotlib
- Pillow (PIL)
- TensorBoard

13. TensorBoard Experiment Tracking

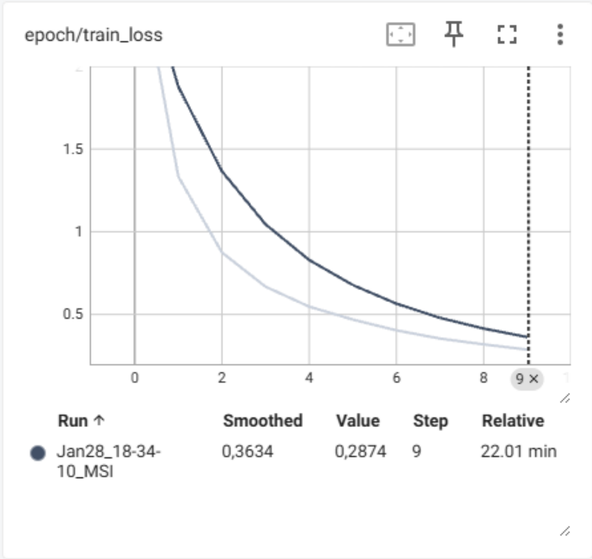
Training metrics were logged using TensorBoard for monitoring loss and error rates.

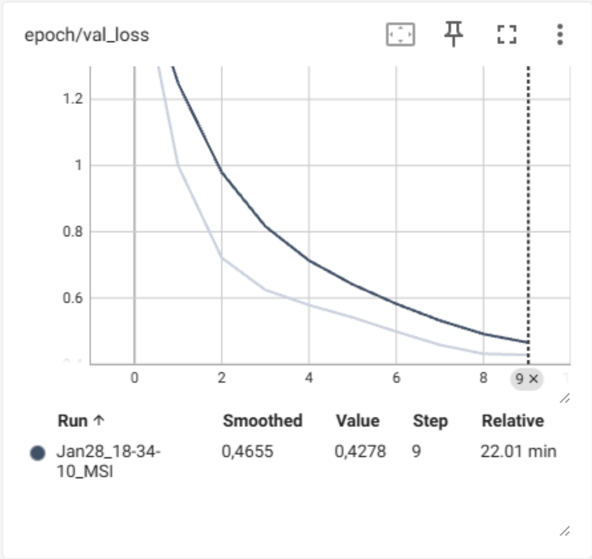
Logged Metrics:

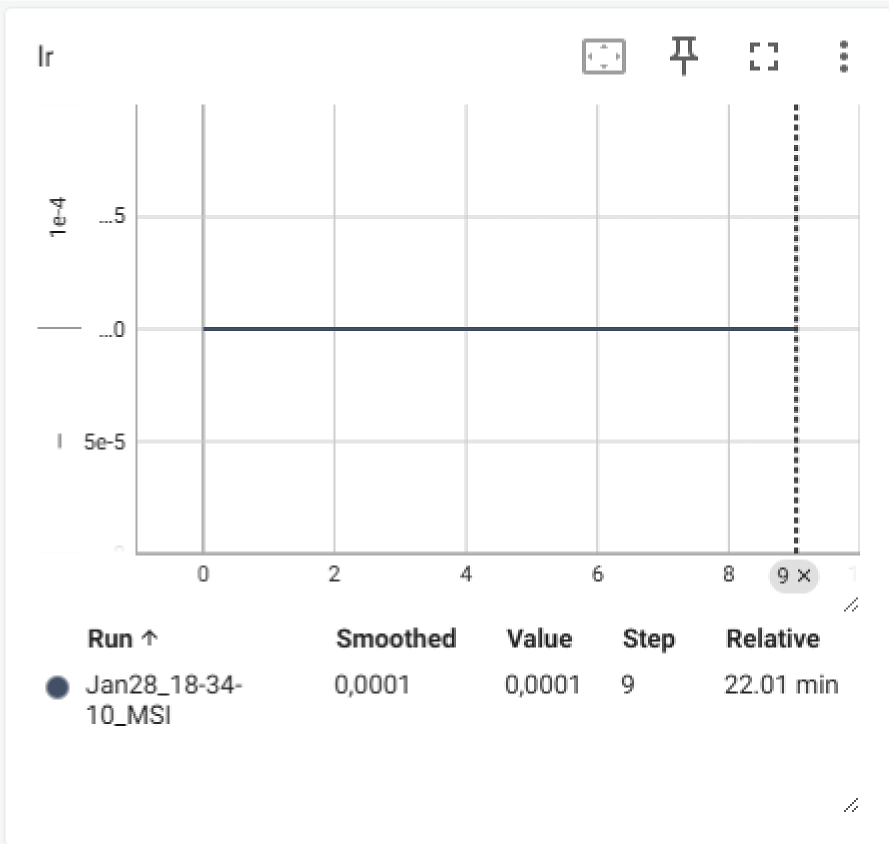
- Training loss (per batch and per epoch)
- Validation loss
- Validation CER and WER
- Learning rate changes

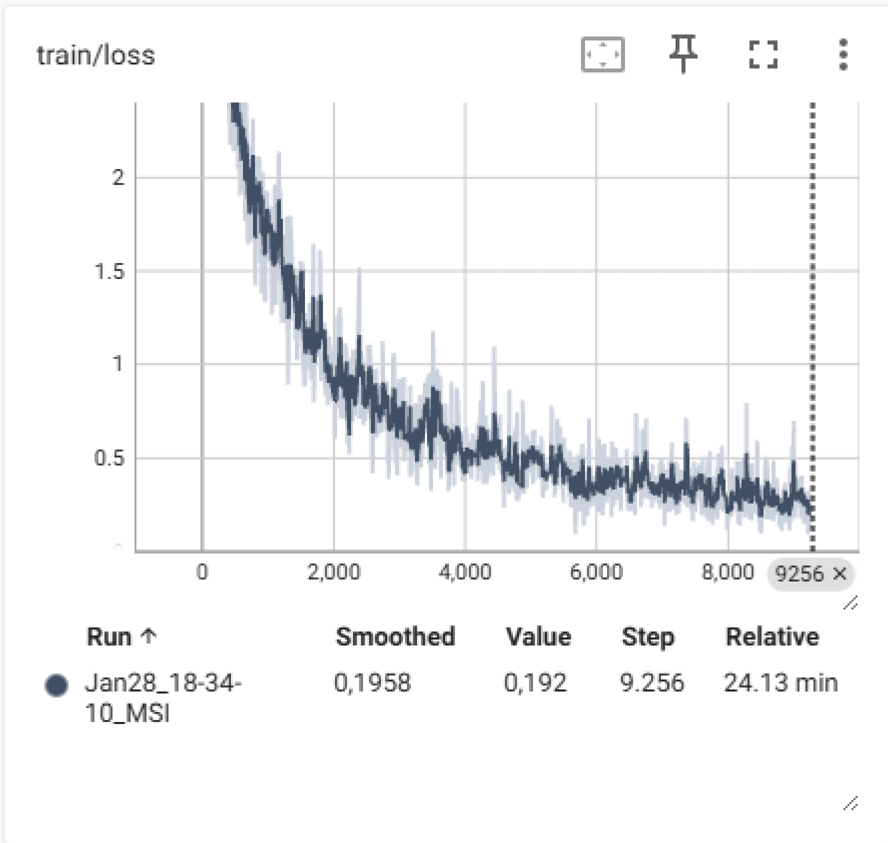
Analysis:

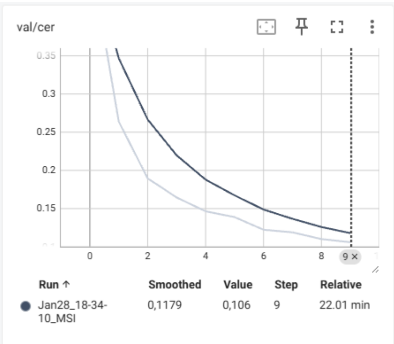
- Training loss decreased steadily over epochs
- Validation CER dropped from ~0.45 to ~0.11, showing good convergence
- Learning rate was reduced automatically when validation loss plateaued
- No significant overfitting observed (validation loss follows training loss)

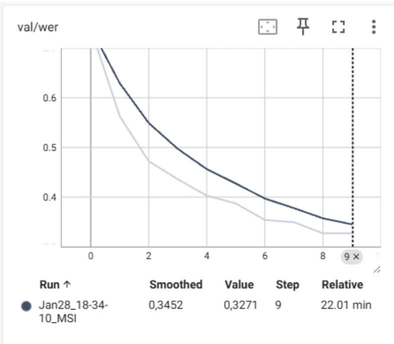

epoch/train_loss
1.5
1
0.5
0
2
4
6
8
9
Run
Smoothed
Value
Step
Relative
Jan28_18-34-10_MSI
0,3634
0,2874
9
22.01 min

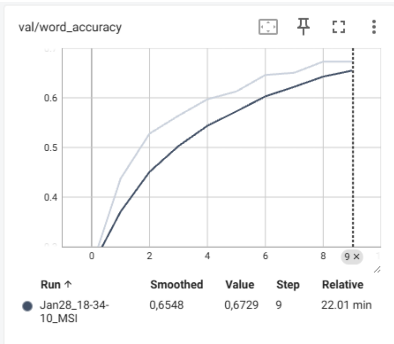

epoch/val_loss
1.2
1
0.8
0.6
0
2
4
6
8
9
Run
Smoothed
Value
Step
Relative
Jan28_18-34-10_MSI
0,4655
0,4278
9
22.01 min


lr
1e-4
...5
...0
5e-5
0
2
4
6
8
9
Run
Smoothed
Value
Step
Relative
Jan28_18-34-10_MSI
0,0001
0,0001
9
22.01 min









14. Runtime Environment

- Python 3
- GPU-enabled environment recommended
- Experiments conducted using standard deep learning libraries

15. Completed Items Table

OCR of handwritten text	2 point
pre-trained model on the different problem (transfer-learning)	1 point
Adaptive hyperparameters	1 point
Data augmentation	1 point
Tensorboard	1 point

16. GitHub Repository

Link to GitHub repository:
https://github.com/BarisAI/Computer-Vision-OCR-of-handwritten-text

17. Bibliography

- Marti, U.-V., & Bunke, H. “The IAM-database: an English sentence database for offline handwriting recognition.”
- Graves, A. et al. “Connectionist Temporal Classification.”
- He, K. et al. “Deep Residual Learning for Image Recognition.”
- Kaggle Dataset:

  IAM Handwriting Word Database. Available at:

  https://www.kaggle.com/datasets/nibinv23/iam-handwriting-word-database