COLLEGE OF
ENGINEERING, ARCHITECTURE AND TECHNOLOGY

Deep Learning for Recognizing and Converting Handwritten Scientific Equations into LaTeX

Deep Learning (ECEN 5060)

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Outline

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- Problem
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Introduction

- As engineers, we often want to fast-track our handwritten notes into digital format for various purposes. But can we digitalize handwritten equations directly?
- …Hence, the motivation for this project.

What if we could extend the problem and get our hand-written equations converted to LaTex version directly?

Problem

Develop a machine learning based system that accurately recognizes and converts handwritten mathematical expressions/scientific equations into LaTeX format using deep learning techniques.

Dataset

- CROHME 2019 (Competition on Recognition of Handwritten Mathematical Expressions)
- Contains approximately 12,000 HMEs from previous CROHME competitions (2014-2019)
- Format:
  - Greyscale Images: Sized 1000x1000 pixels with 5 pixels of padding.
  - SymLG annotations: SymLG is a structured representation of HMEs that captures both individual symbols and their spatial relationships.
- Annotations are used to create a vocabulary split.
- Train/test/validation split: 8,835 / 2,186 / 1,147 (images and captions each)

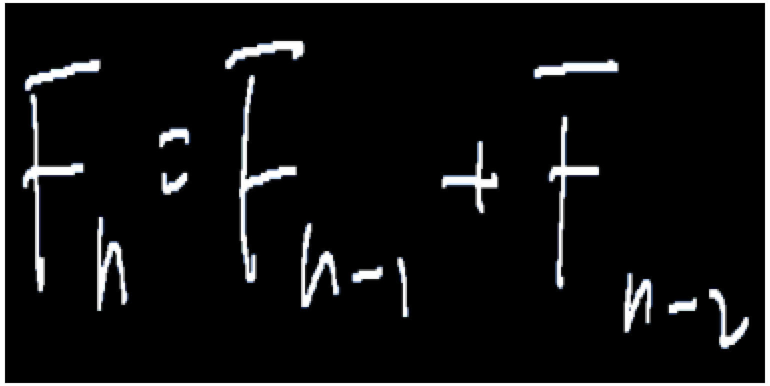
Methodology

Pre-processing

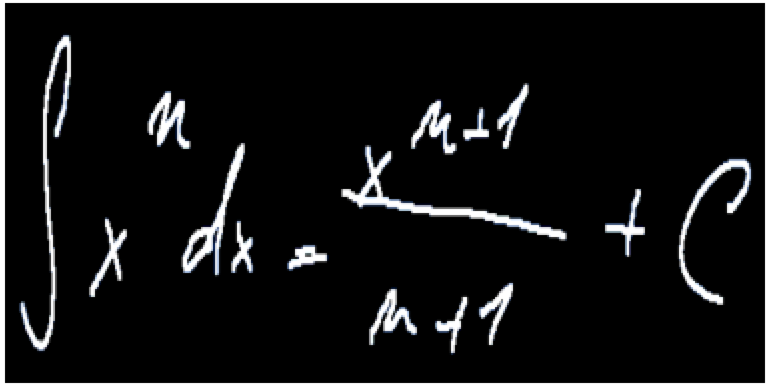
- Tokenizing / creating a unified vocabulary
- Implemented CROHMEDataset to load images and their corresponding tokenized labels.
- Data augmentation:
  - Resizing to 100 x 100
  - Random rotation
  - Color jitter by varying brightness and contrast
  - Normalizing with mean = standard deviation = 0.5
  - Converted images to PyTorch tensors and normalized to [0,1].

Methodology

GT: F _ { n } = F _ { n - 1 } + F _ { n - 2 }

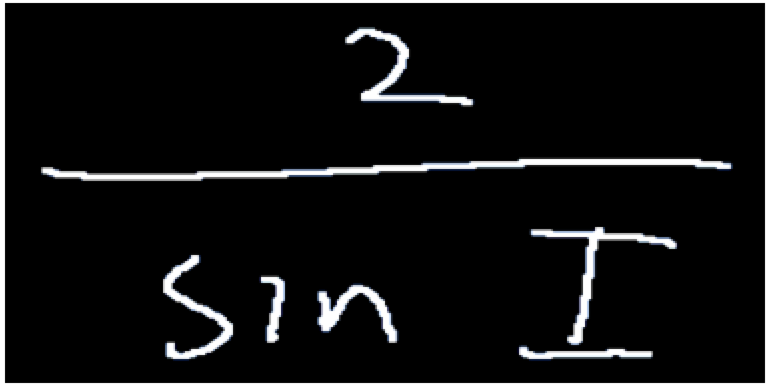


GT: \int x ^ { n } d x = \frac { x ^ { n + 1 } } { n + 1 } + C

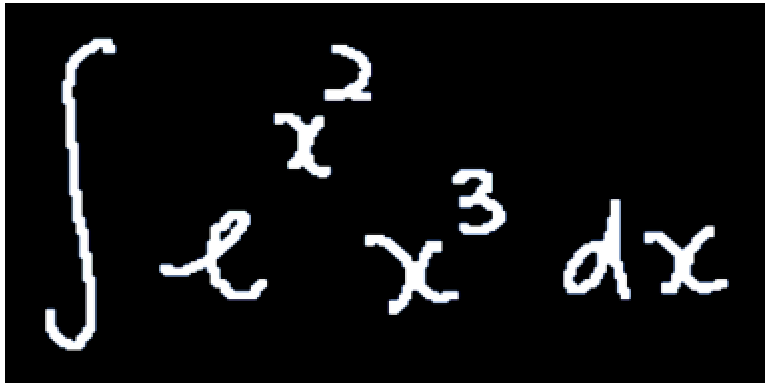


GT: c _ { t }

GT: \frac { 2 } { \sin I }



GT: \int e ^ { x ^ { 2 } } x ^ { 3 } d x



GT: ([R _ { y }])

Methodology

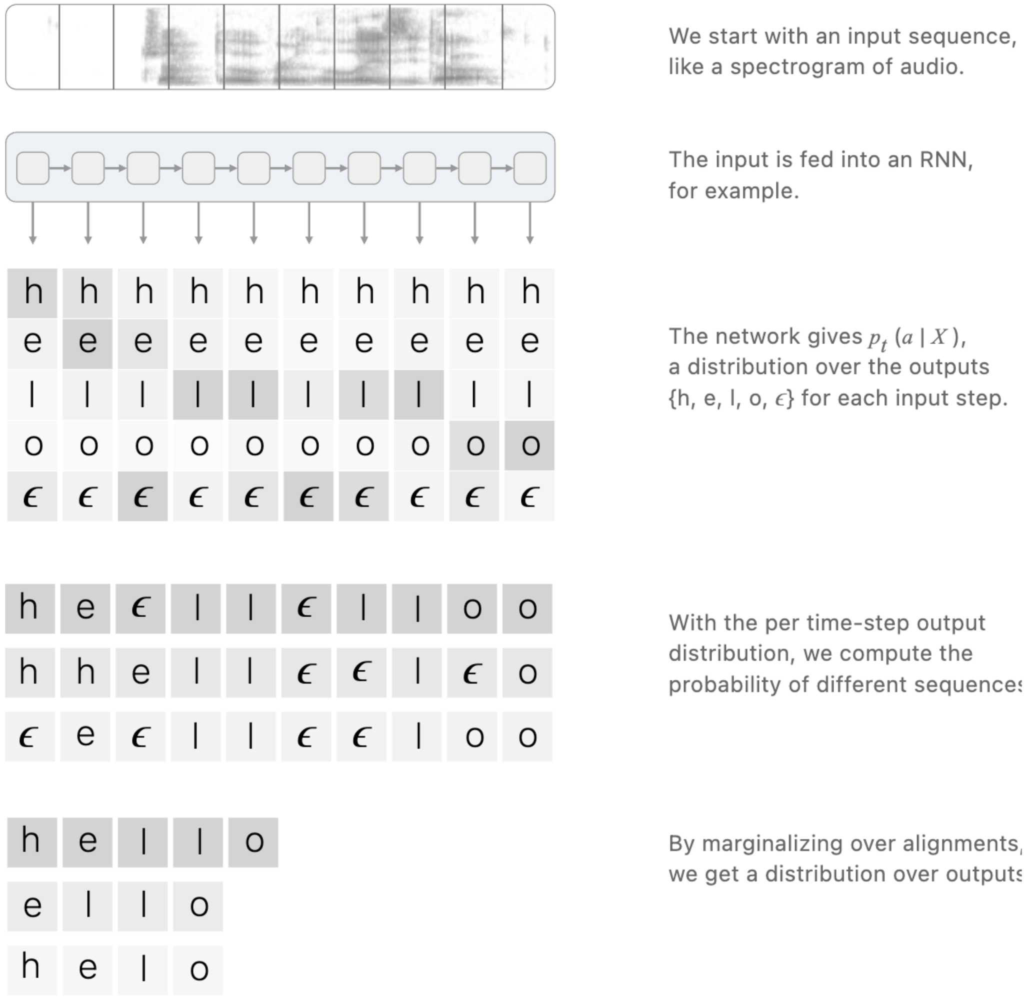
Baseline Model

- Using a CNN-RNN
- Pre-trained ResNet18
- Freezing the early layers of the ResNet to reduce computation time.
- Adding Batch Normalization and Dropout layers for regularization and preventing overfitting.
- Enhancing the LSTM layers to improve temporal sequence handling.

```
def __init__(self, num_classes):
    super(CRNN, self).__init__()
    resnet = models.resnet18(pretrained=False)
    state_dict = torch.load("/kaggle/input/resnet18/resnet18-f37072fd.pth")
    resnet.load_state_dict(state_dict)

    # Freeze first few layers to avoid overfitting
    for param in list(resnet.children())[:5]:
        for p in param.parameters():
            p.requires_grad = False

    # Extract CNN layers up to layer3
    self.cnn = nn.Sequential(
        *list(resnet.children())[:-3],                  # Keep until layer3
        nn.BatchNorm2d(256),                            # Add BatchNorm after last conv layer
        nn.Dropout2d(p=0.3)                             # Dropout after batchnorm
    )

    # Bidirectional LSTM with dropout
    self.rnn = nn.LSTM(
        input_size=256,
        hidden_size=256,
        num_layers=2,
        dropout=0.5,                 # Dropout between LSTM layers
        bidirectional=True,
        batch_first=True
    )

    self.dropout_fc = nn.Dropout(p=0.3)                # Dropout before final classification
    self.fc = nn.Linear(512, num_classes)

def forward(self, x):
    x = self.cnn(x)  # (B, 256, H, W)
    x = nn.functional.adaptive_avg_pool2d(x, (1, x.size(3)))  # (B, 256, 1, W)
    x = x.squeeze(2)  # (B, 256, W)
    x = x.permute(0, 2, 1)  # (B, W, 256)
    x, _ = self.rnn(x)
    x = self.fc(x)
    return x
```

Loss function

- CTC Loss [2]
  - Enables models to learn alignments between input sequences and output label sequences without requiring explicit frame-level annotations.
  - It allows for flexible spacing and repeated characters, while handling intermediate blank tokens.

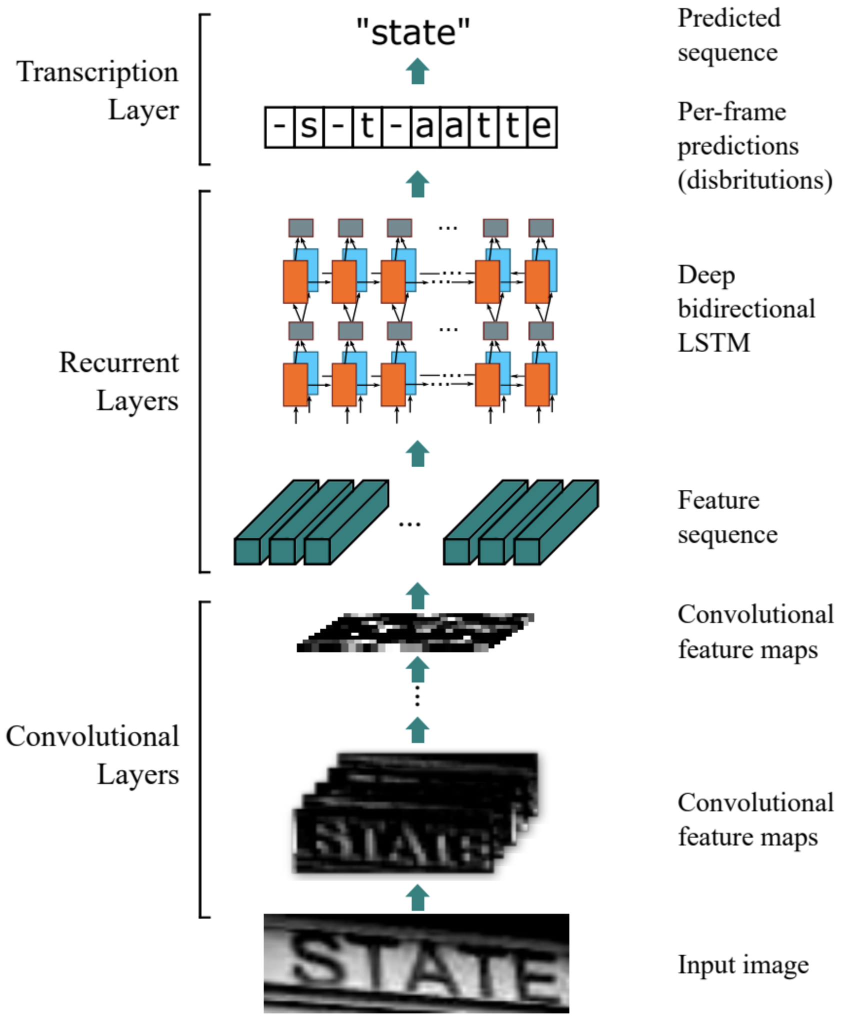


Evaluation Metric

- **Levenshtein distance:** a string metric that measures how many **single-character edits** are needed to change one string into another. These edits include:
  - Insertion
  - Deletion
  - Substitution
- Character Error Rate (CER): Levenshtein distance / Total number of characters
- Word Error Rate (WER): Levenshtein distance (words) / Total number of words

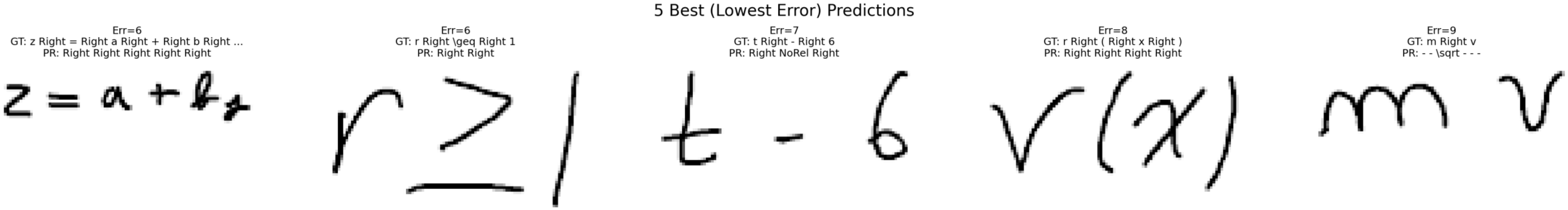
Methodology – 1st iteration

- CRNN framework from [1]
  - Convolution layer: extract features from images
  - Recurrent layer: makes prediction for each frame of the feature sequence (bi-directional)
  - Transcription layer: translates per-frame predictions into labeled sequence
- Feature maps are "sliced" to keep the height, helps distinguish stacked symbols like fractions or superscripts



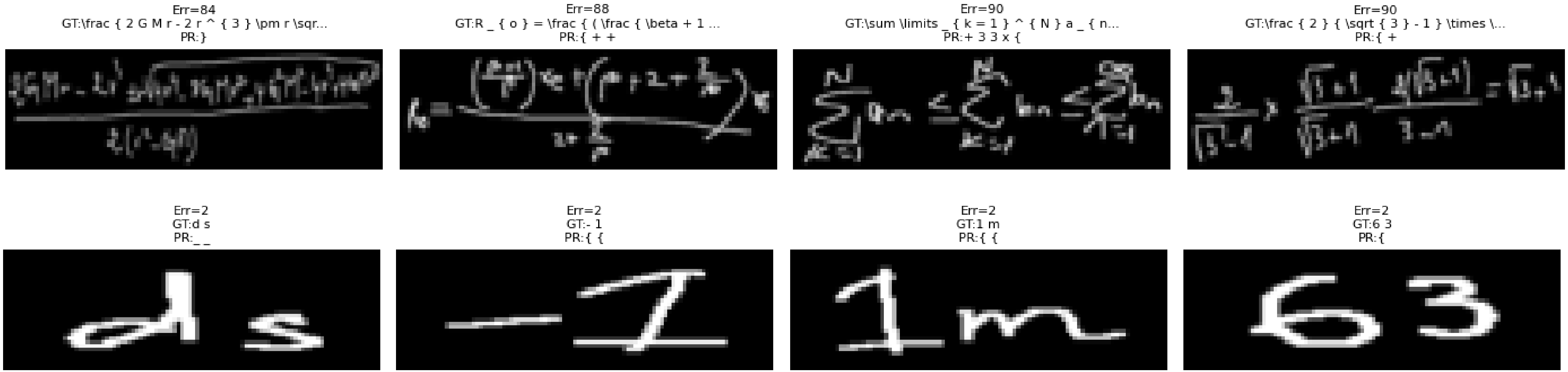
Methodology – 1st iteration results

- Image is resized to 32 x 300 (unlike paper, which uses varying width)
- Train and Validation WER: 19.98% and 21.66%
- However, predictions were spammed with "Right", inflating the accuracy
- Indicators such as "Right", "Below", "Inside"… are unnecessary due to the CRNN framework



Methodology – 2nd iteration

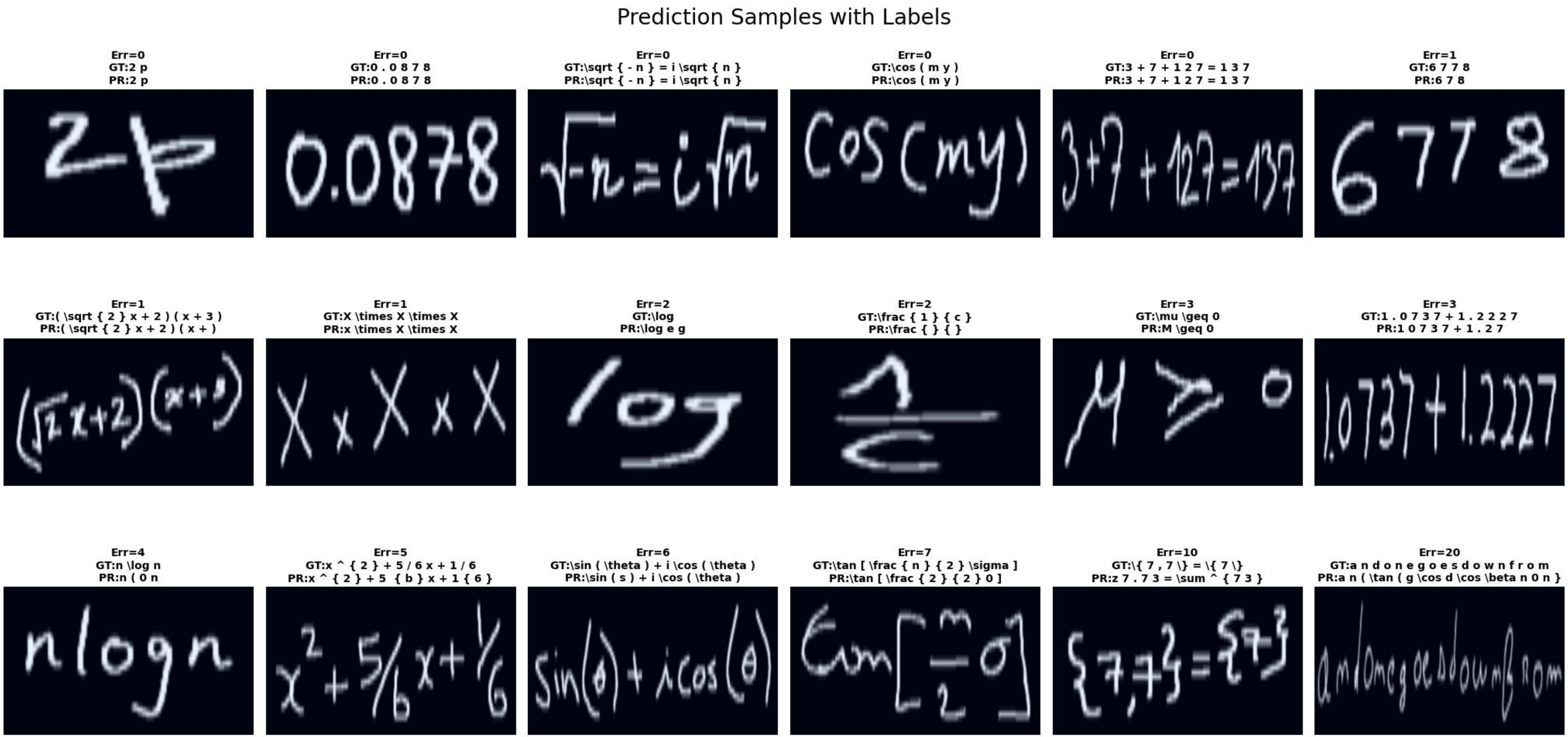
- Modified the vocabulary to exclude structural / relationship indicators
- Model's predictions were still very bad even after hyperparameter optimization (Train and validation WER: 43.29% and 37.14%)



Methodology – 3rd iteration

- Greedy decoding:
  - At each timestep, selects the single most probable token
  - Does not consider the **long-term sequence likelihood**. A locally optimal token may lead to poor global predictions.
- Beam decoding:
  - Maintains the top-k most likely sequences at each timestep (e.g., top 5 partial predictions).
  - Common math structures (fractions, subscripts, braces) can be preserved due to global consistency.
- Due to the nature of CTC loss, beam decoding is especially effective in the proposed framework

Methodology – 3rd iteration results



Methodology

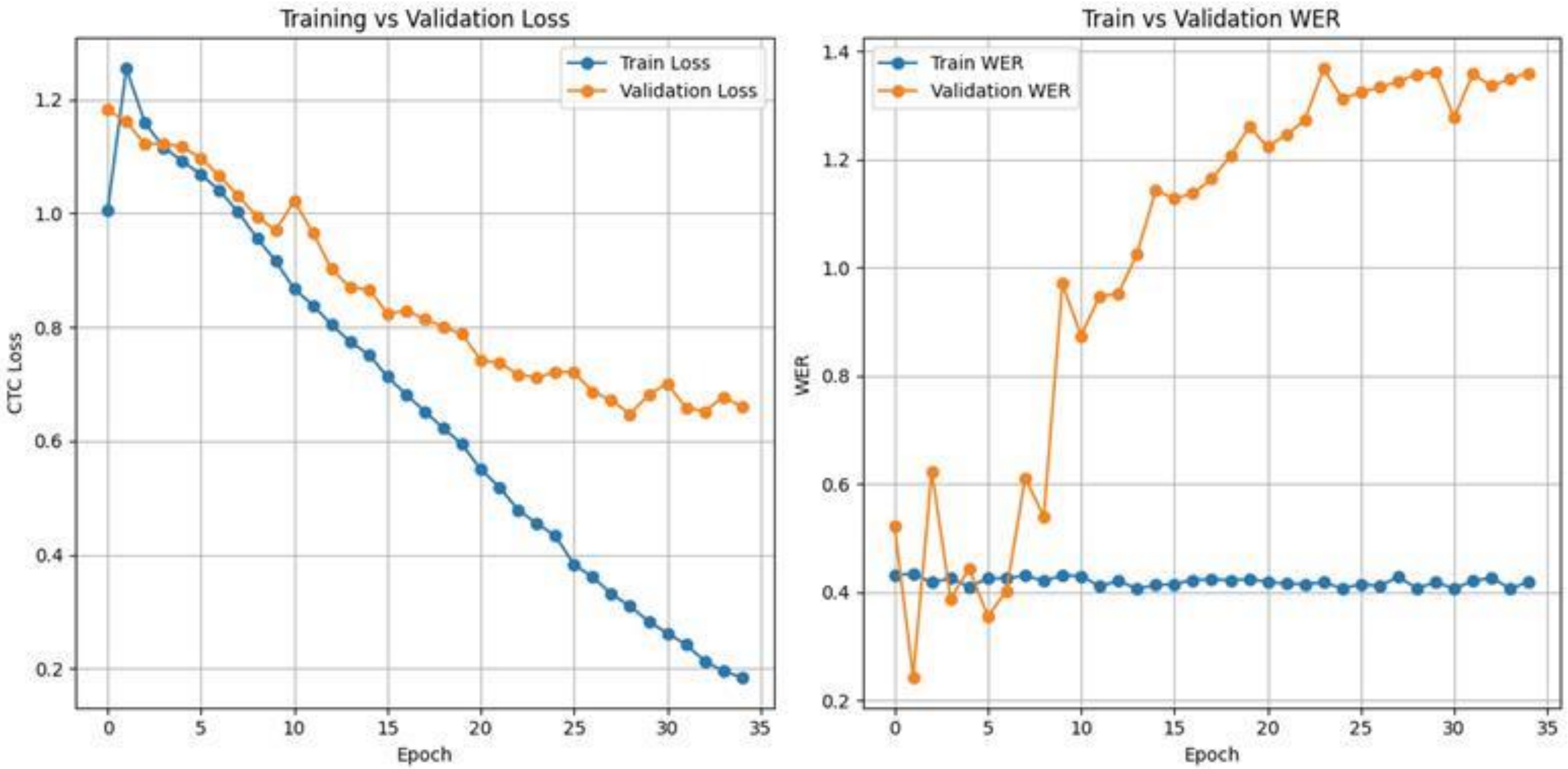
Post-processing

GroundTruth	Prediction	Error
k N	k | N	1
1 2	1 | 2	1
P a	p | { | a | }	6
1 9	7 | 9	2
2 6	2 | 6	1
1 m	1 | m	1
N m	N	1
H z	H | { | z | }	5
k g	k	1
m v	m | v	1

Notice something?

Final Results

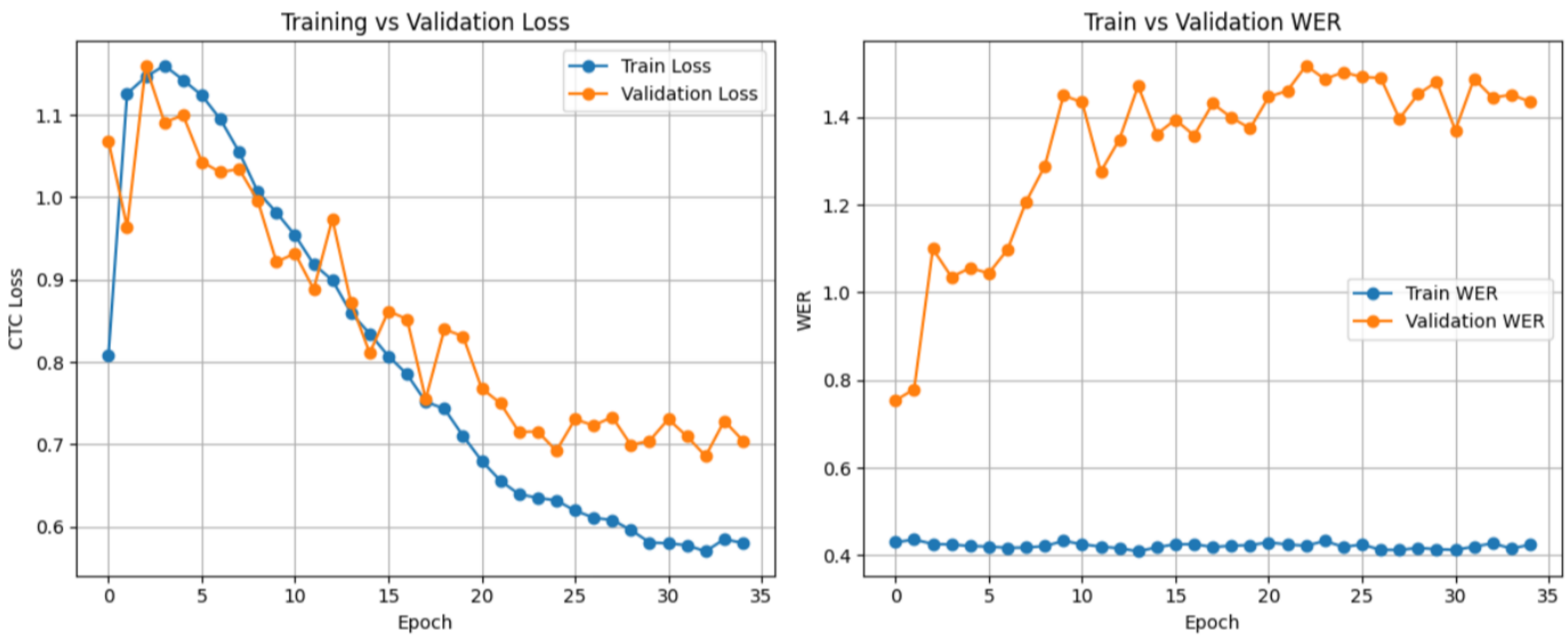
Training loop/Intermediate Results



Baseline model – Iteration 1

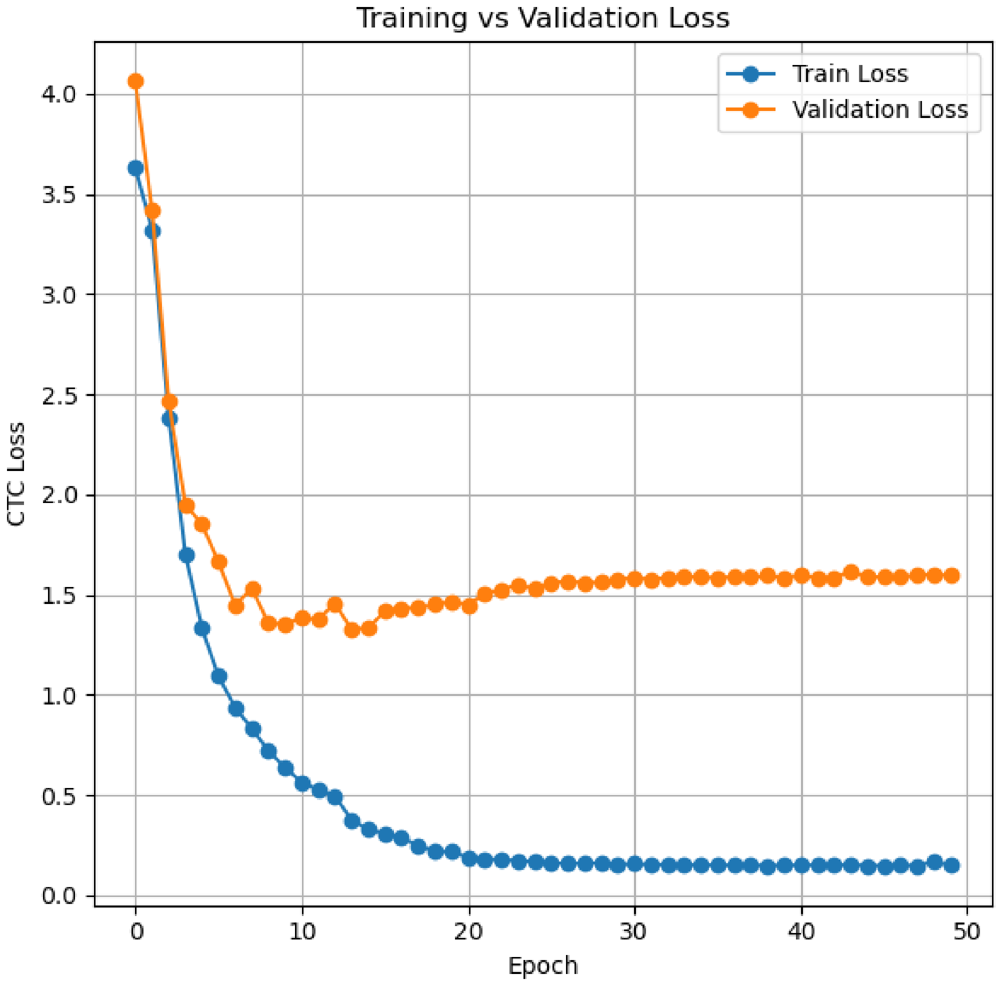
Final Results

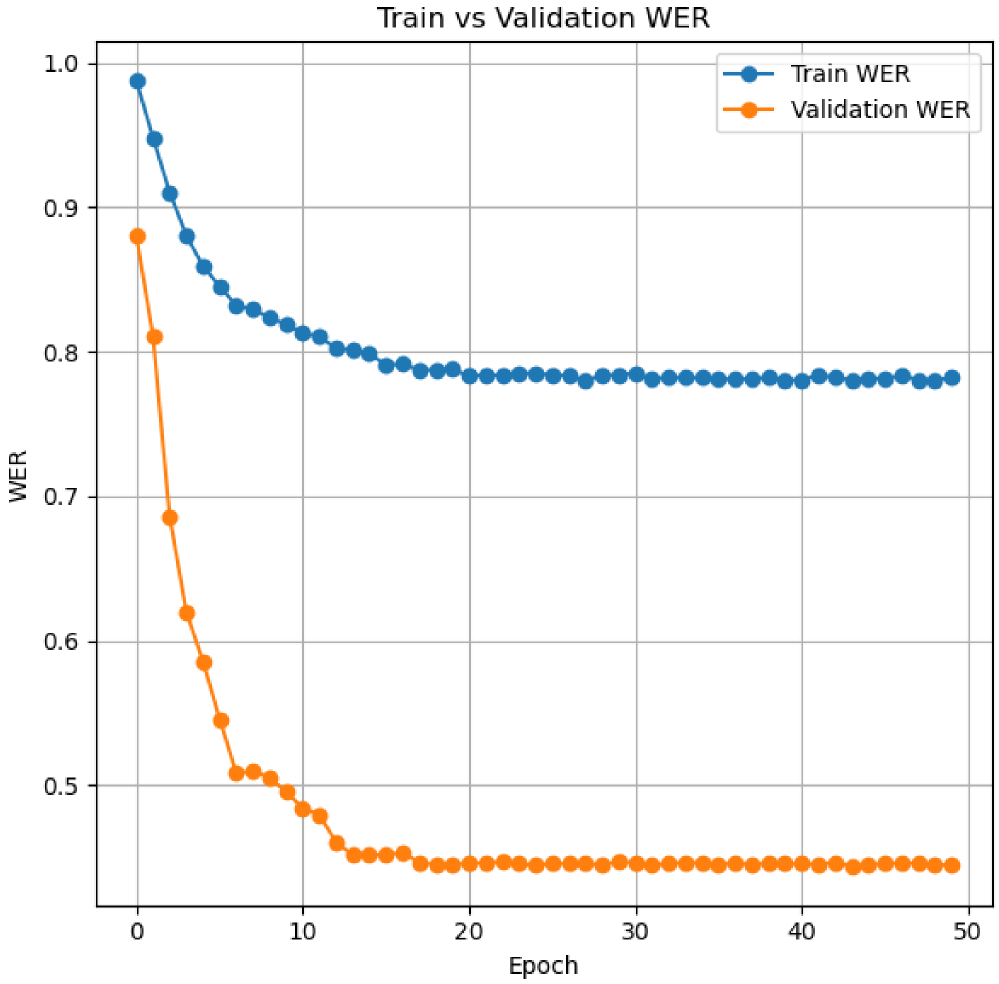
Training loop/Intermediate Results



Baseline model – Iteration 2

Final Results





Final Model Architecture and Parameters

Component	Hyperparameter	Value / Setting
Input	Image Size	(3, 32, 300)
CNN Backbone	Architecture	VGG16
RNN	Type	2-layer Bidirectional LSTM
	Hidden Size	256
	Dropout (between layers)	0.5
Fully Connected Layer	Input / Output Size	512 (256 × 2) / 110 tokens
	Dropout	0.3
Loss	Loss Function	CTC
Optimizer	Type	Adam
	Learning Rate	5e-4
Scheduler	Type	ReduceLROnPlateau
	Factor and Patience	0.5 (halves LR on plateau), 2
Decoding	Beam Width	10
Training	Epochs	50

Post Processing

- Due to the garbage token insertion, the WER were inflated
- After preprocessing, we split the predictions by length, and compare the original and cleaned WER
  - Split was done by finding the median expression length value
  - We see a significant improvement in overall WER, especially for short expressions

Expression Length	**Original WER**	**Cleaned WER**
Short (≤ 14 tokens)	0.7639	0.2385
Long (> 14 tokens)	0.5344	0.3936

Limitations

- CTC loss suffers with long sequences, as evident from WER
- CTC assumes the output sequence is *monotonically aligned* with the input (left-to-right), which doesn't always hold for math expressions
- The model treats output as a flat sequence of tokens, thus it can't handle hierarchical or spatial relationships
- Even with beam search, the model makes decisions at the token level, which means it can still miss globally optimal expression sequences.

Conclusion

- Developed a deep learning pipeline to recognize and convert handwritten mathematical expressions from images into LaTeX format
- Implemented a CRNN-based model with CTC loss for sequence prediction.
- Iteratively refined the system by adjusting model architecture, vocabulary, and decoding strategies (greedy → beam search).
- Integrated post-processing to remove garbage tokens, significantly improving WER rates, especially for shorter sequences

Future Work

- Attempt a Transformer based model – does it out perform our work?
- Experimenting with deeper trained models.
- Incorporate additional data augmentation strategies, such as elastic distortions or random cropping, to make the model more robust to various writing styles and formats.
- Integrate the proposed mechanism into a mobile/web application to enable wide-spread use.

References

1. Baoguang Shi, Xiang Bai, and Cong Yao. “An End-to-End Train- able Neural Network for Image-Based Sequence Recognition and Its Application to Scene Text Recognition”. In: IEEE Transactions on Pattern Analysis and Machine Intelligence 39.11 (2016), pp. 2298– 2304.
2. Hannun, "Sequence Modeling with CTC", Distill, 2017.

THANK YOU

Questions?