



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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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

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)

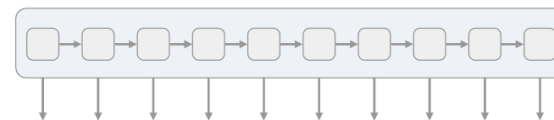
def forward(self, x):
    x = self.cnn(x)  # (B, 256, H, W)
    x = nn.functional.adaptive_avg_pool2d(x, (1, x.size(3)))  # (B, 256, 1, W)
    x = x.squeeze(2)  # (B, 256, W)
    x = x.permute(0, 2, 1)  # (B, W, 256)
    x, _ = self.rnn(x)
    x = self.fc(x)
    return x
```

Loss function

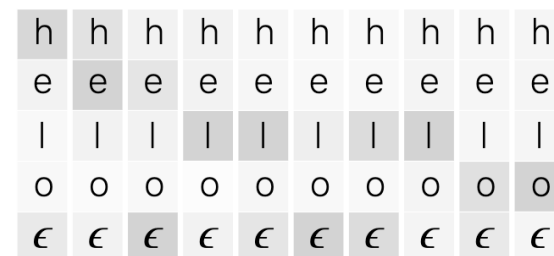
- CTC Loss
 - Enables models to learn alignments between input sequences and output label sequences without requiring explicit frame-level annotations.
 - It allows for flexible spacing and repeated characters, while handling intermediate blank tokens.



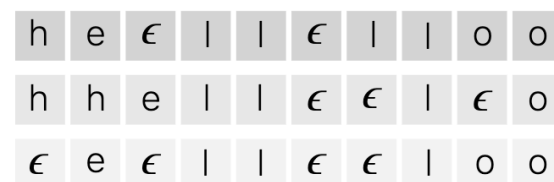
We start with an input sequence, like a spectrogram of audio.



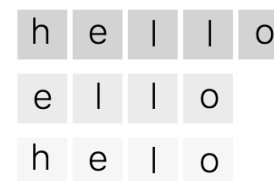
The input is fed into an RNN, for example.



The network gives $p_t(a | X)$, a distribution over the outputs $\{h, e, l, o, \epsilon\}$ for each input step.



With the per time-step output distribution, we compute the probability of different sequences:



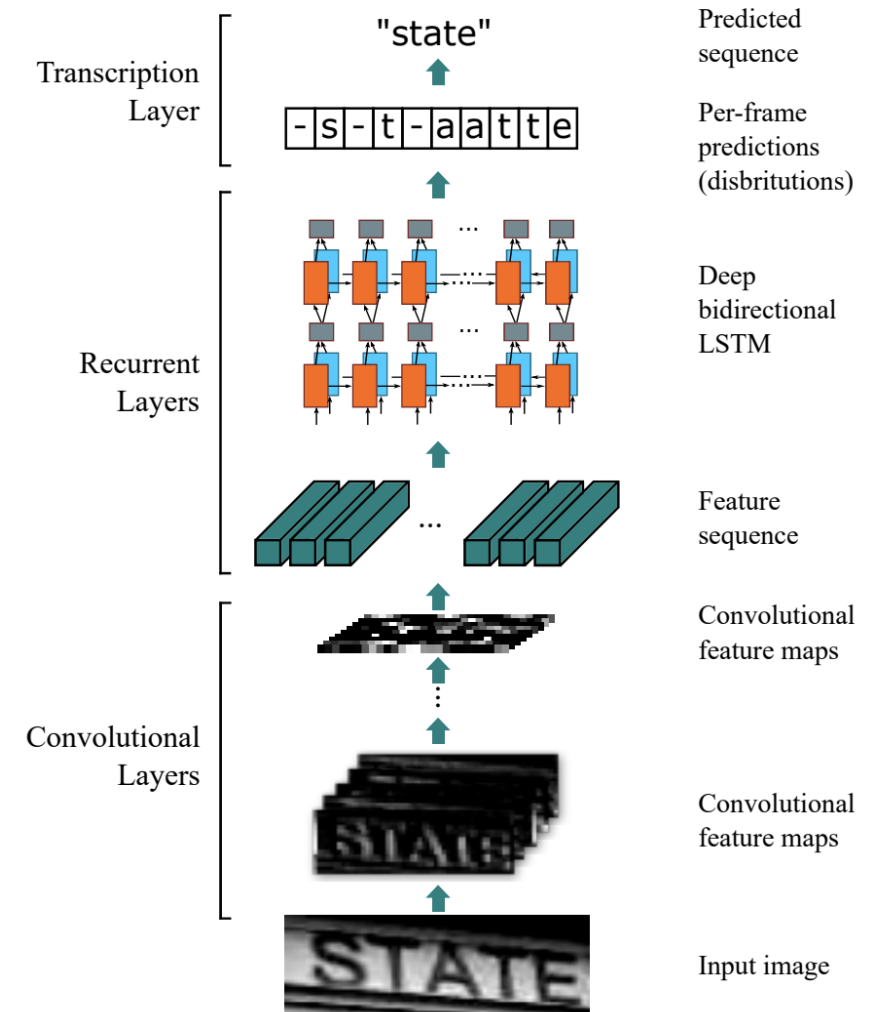
By marginalizing over alignments, we get a distribution over outputs

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): $\text{Levenshtein distance} / \text{Total number of characters}$
- Word Error Rate (WER): $\text{Levenshtein distance (words)} / \text{Total number of words}$

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

- 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

5 Best (Lowest Error) Predictions

Err=6
GT: z Right = Right a Right + Right b Right ...
PR: Right Right Right Right Right

$z = a + b$

Err=6
GT: r Right \geq Right 1
PR: Right Right

$r \geq 1$

Err=7
GT: t Right - Right 6
PR: Right NoRel Right

$t - 6$

Err=8
GT: r Right (Right x Right)
PR: Right Right Right Right

$v(x)$

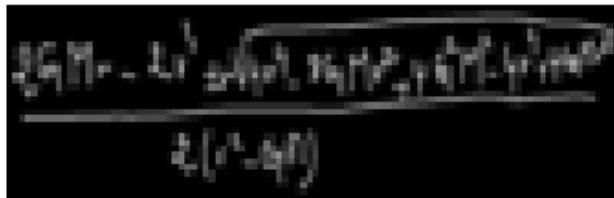
Err=9
GT: m Right v
PR: - - \sqrt - - -

$m \sqrt$

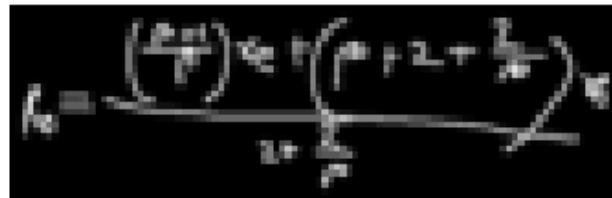
Methodology – 2nd iteration

- 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%)

Err=84
GT:\frac { 2 G M r - 2 r ^ { 3 } } { \pm r \sqrt { r ... }
PR:}



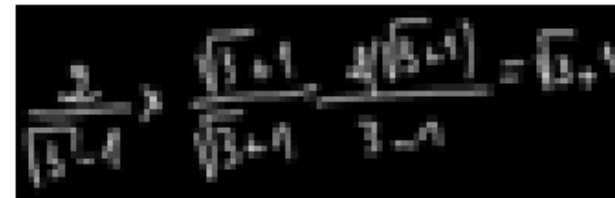
Err=88
GT:R _ { o } = \frac { (\frac { \beta + 1 ... } { \beta + 1 ... }
PR: { + +



Err=90
GT:\sum \limits _ { k = 1 } ^ { N } a _ { n ... }
PR: + 3 3 x {



Err=90
GT:\frac { 2 } { \sqrt { 3 + 1 } } \{ \sqrt { 3 } - 1 \} \times \sqrt { ... }
PR: { +



Err=2
GT:d s
PR: _ _



Err=2
GT:- 1
PR: { {



Err=2
GT:1 m
PR: { {



Err=2
GT:6 3
PR: { {

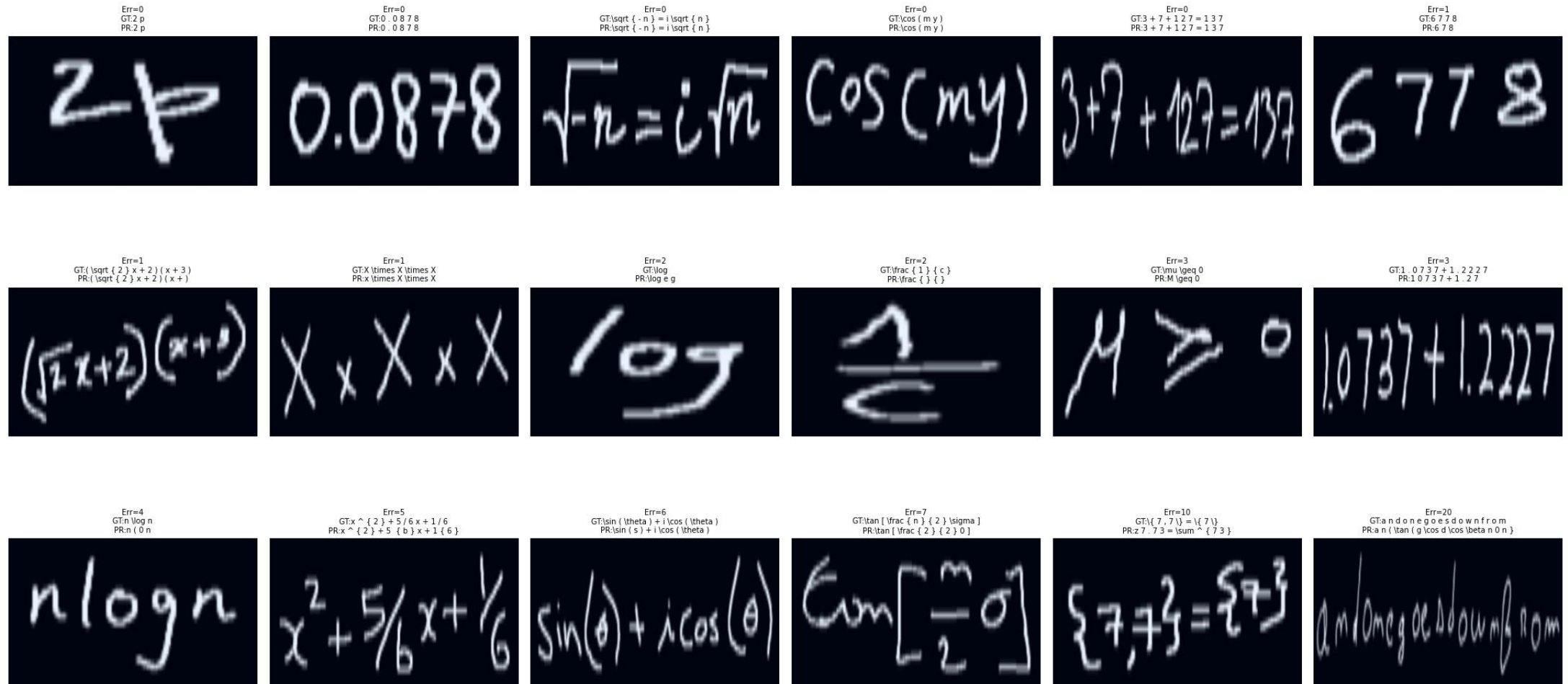


Methodology – 3rd iteration

- 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

Prediction Samples with Labels



Methodology

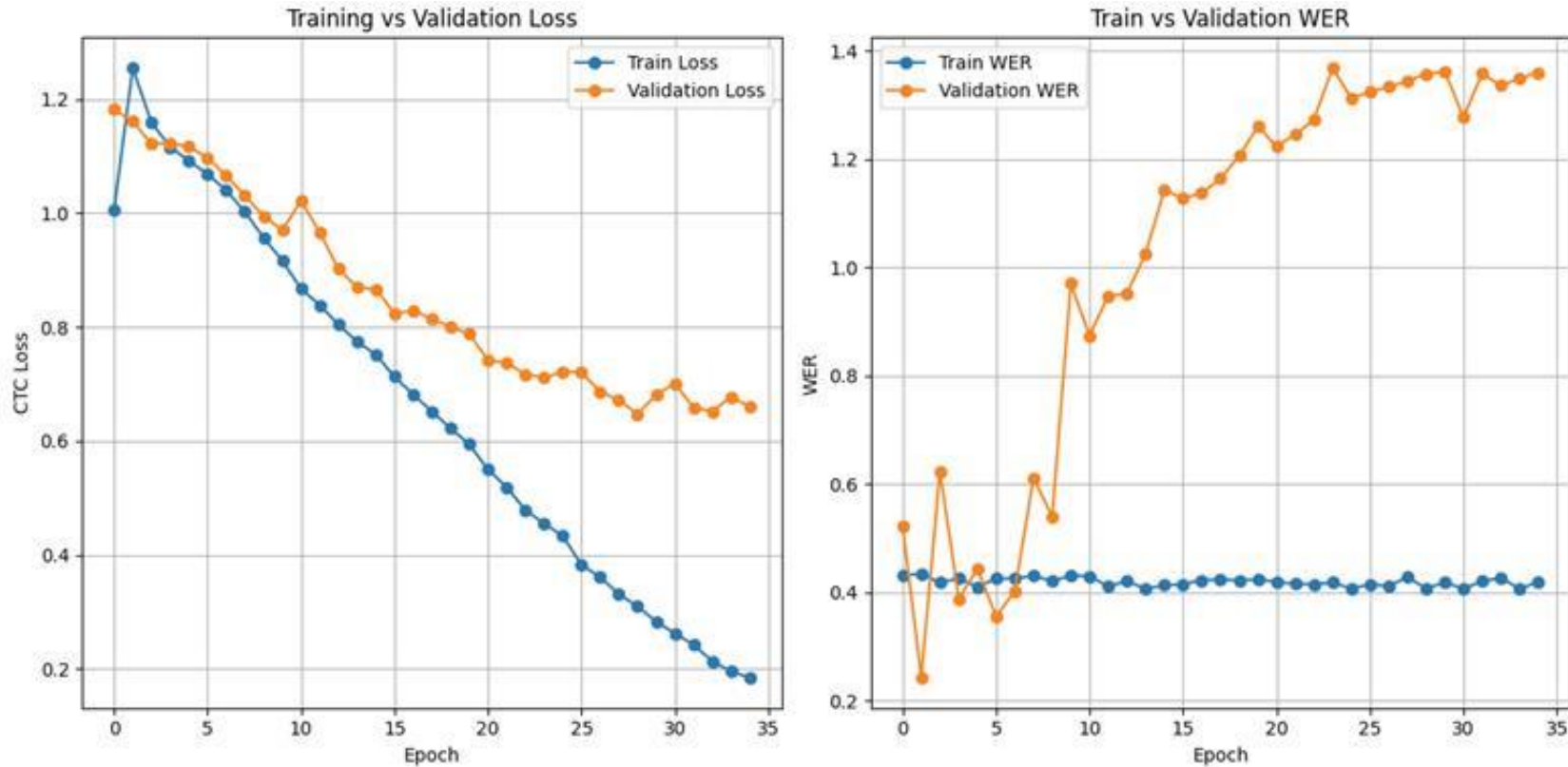
Post-processing

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

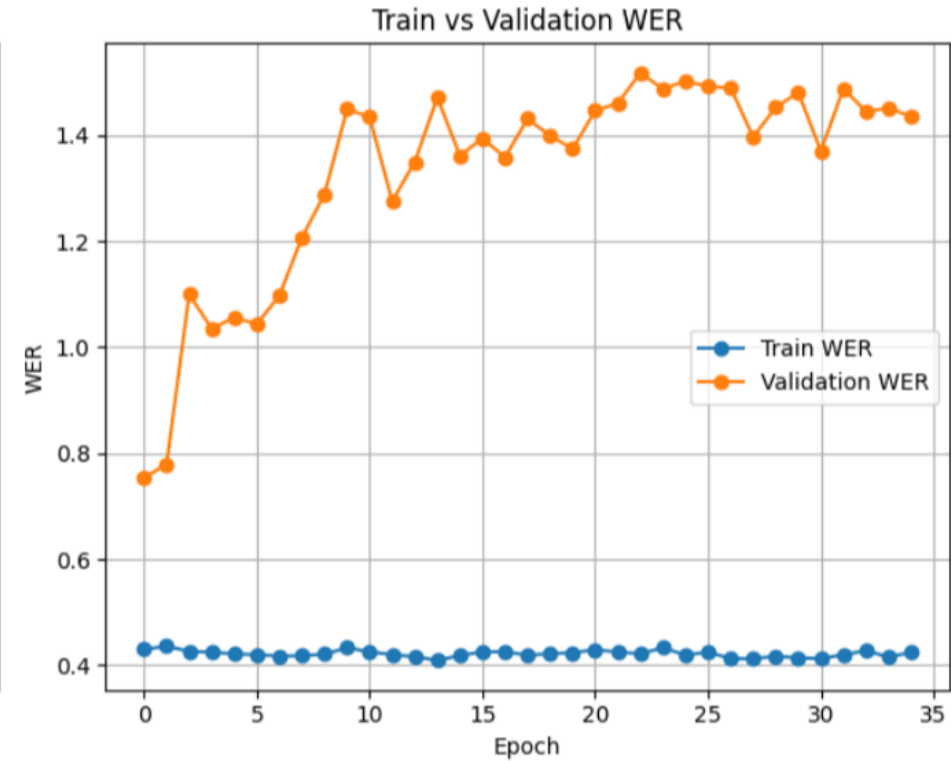
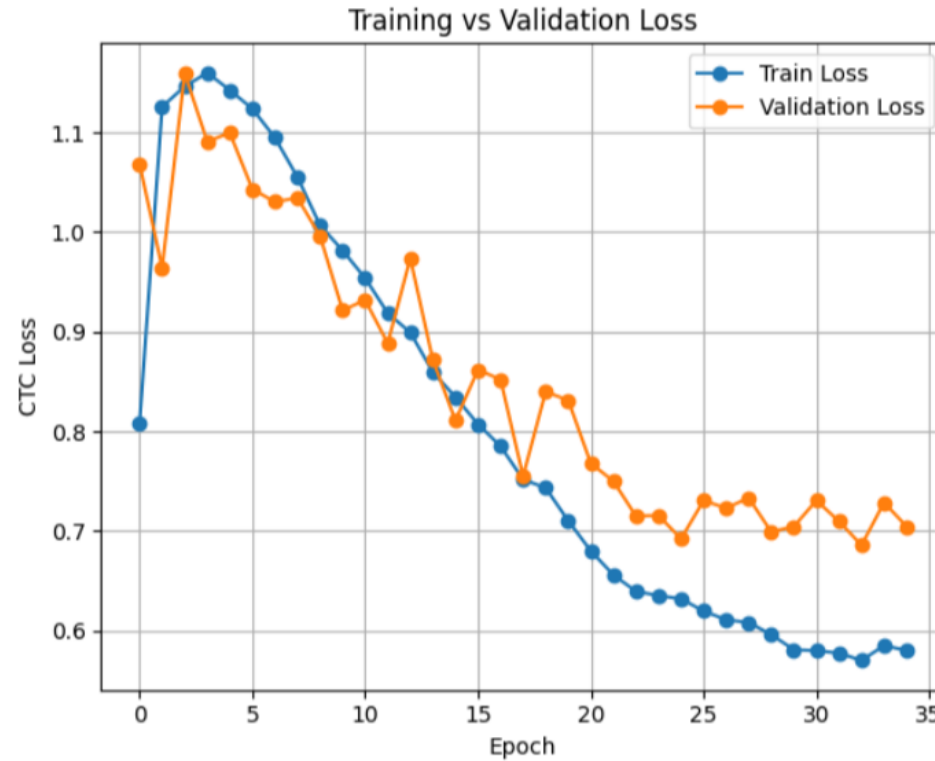
Training loop/Intermediate Results



Baseline model – Iteration 1

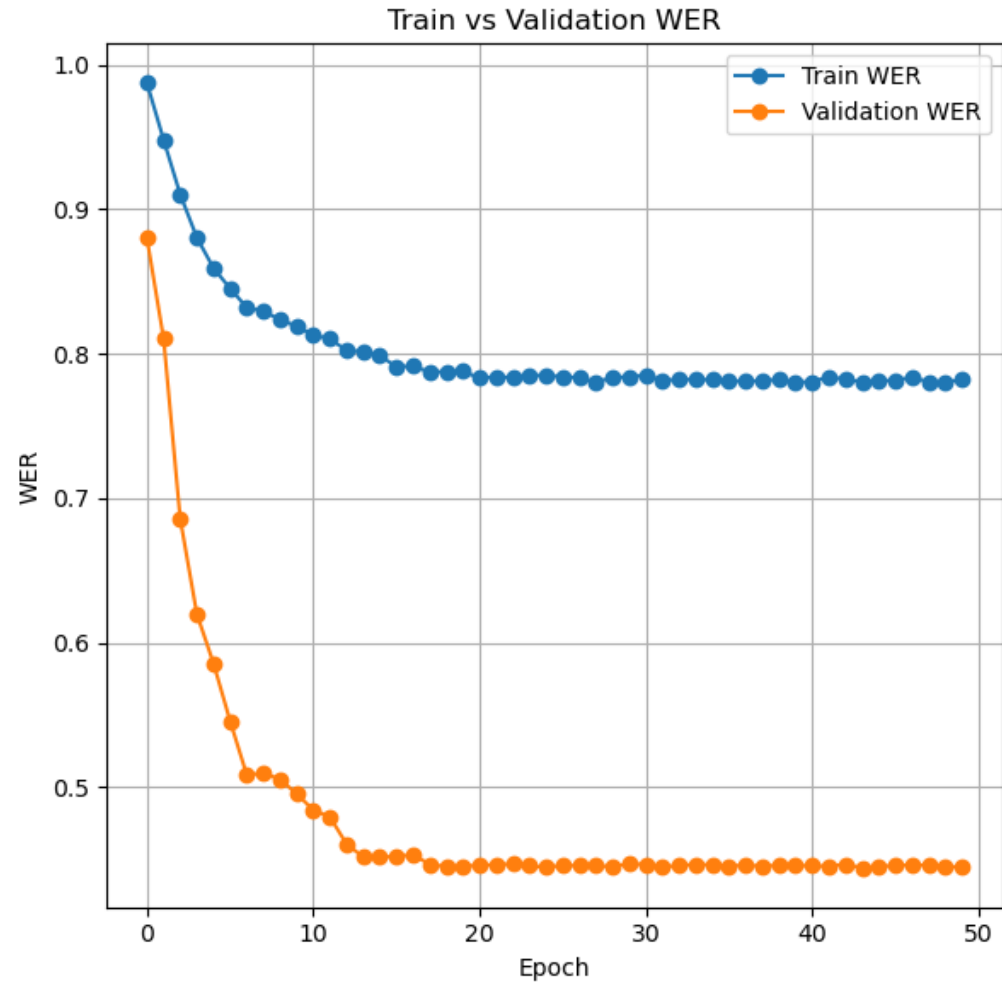
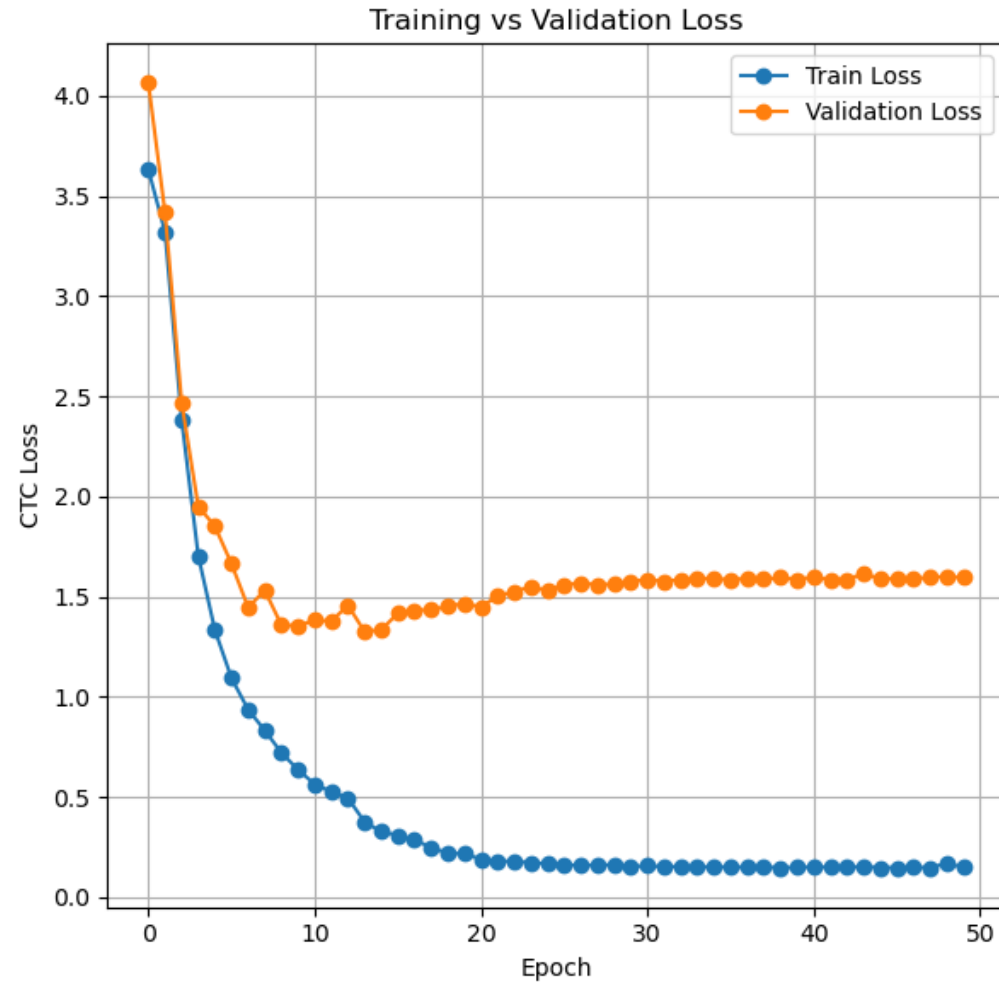
Final Results

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 (if used)	10 (optional)
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

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?

