Comparative Analysis of Initial Model vs. Adam Optimized Model in Symbol Detection

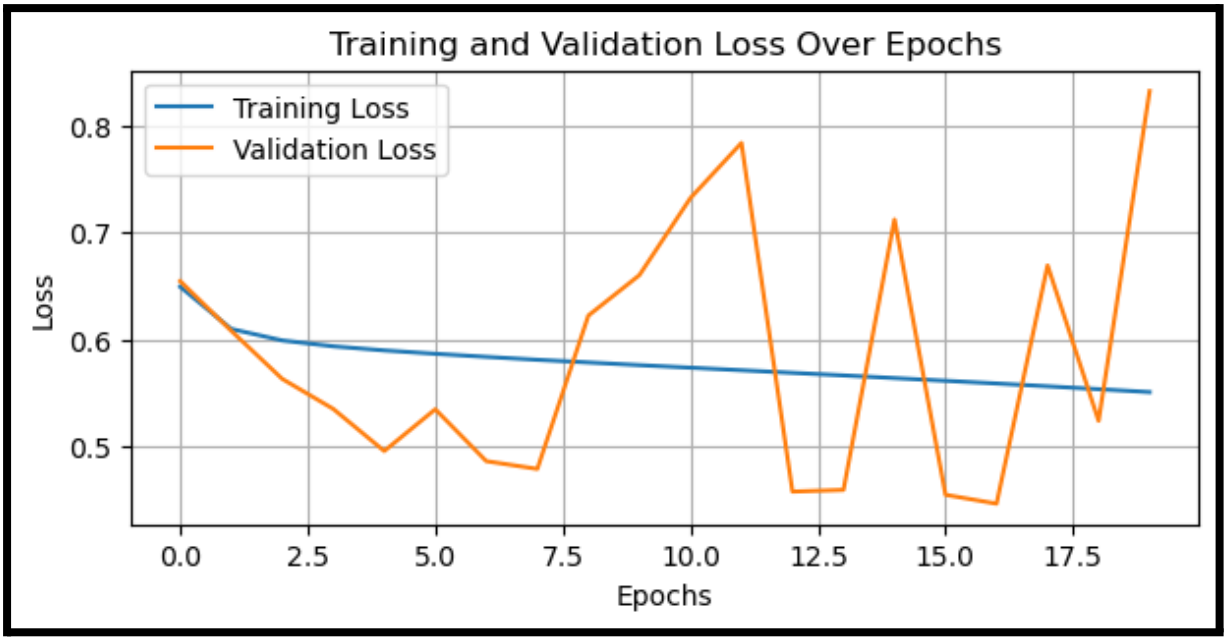
Introduction:

This analysis explores the performance differences between two neural network configurations developed for a symbol detection task. The focus is on the Bit Error Rate (BER), a critical metric for assessing the accuracy of symbol detection in communication systems. Two different optimizer configurations were evaluated: an initial model setup and a subsequent optimization using the Adam optimizer.

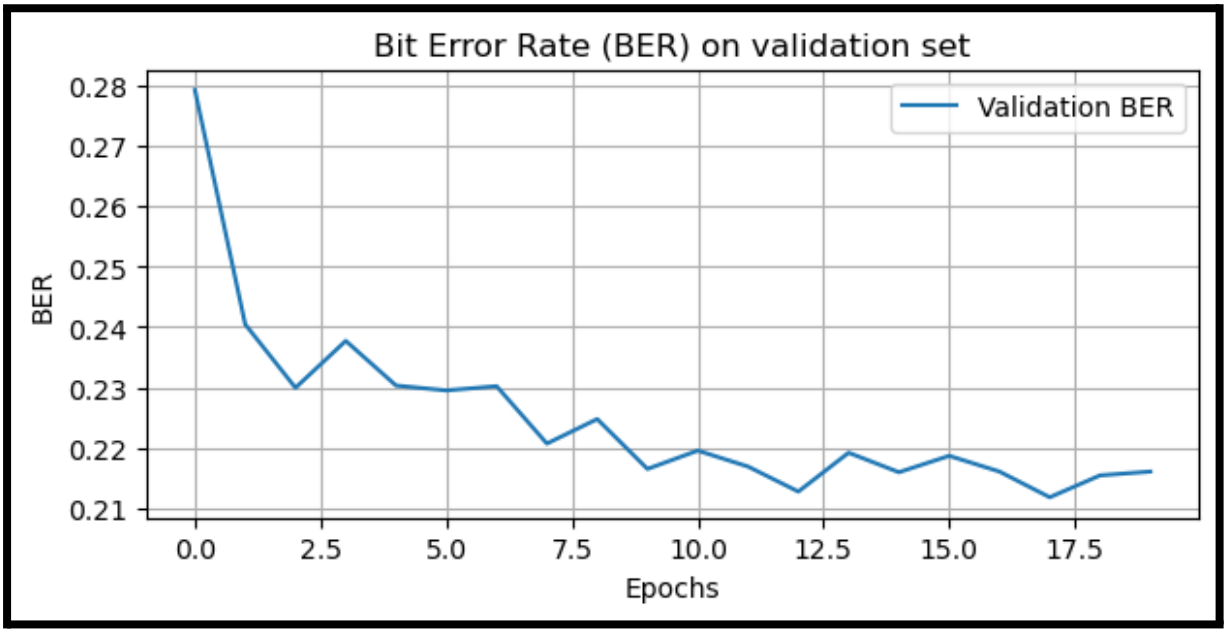
Initial Model Configuration and Results:

- Optimizer: The initial model likely employed a straightforward optimization approach, such as SGD, without adaptive learning rate adjustments.
- Performance Metrics at Epoch 20:
    - Training Loss: 0.5513
    - Validation Loss: 0.8324
    - Validation BER: 0.2160

The initial model's performance serves as a baseline for evaluating the impact of optimizer choice on the model's ability to accurately detect symbols. The relatively higher BER and validation loss suggest room for significant improvement, particularly in optimizing the model to better generalize from training to unseen data.



fig=Training and Validation Loss Over Epochs

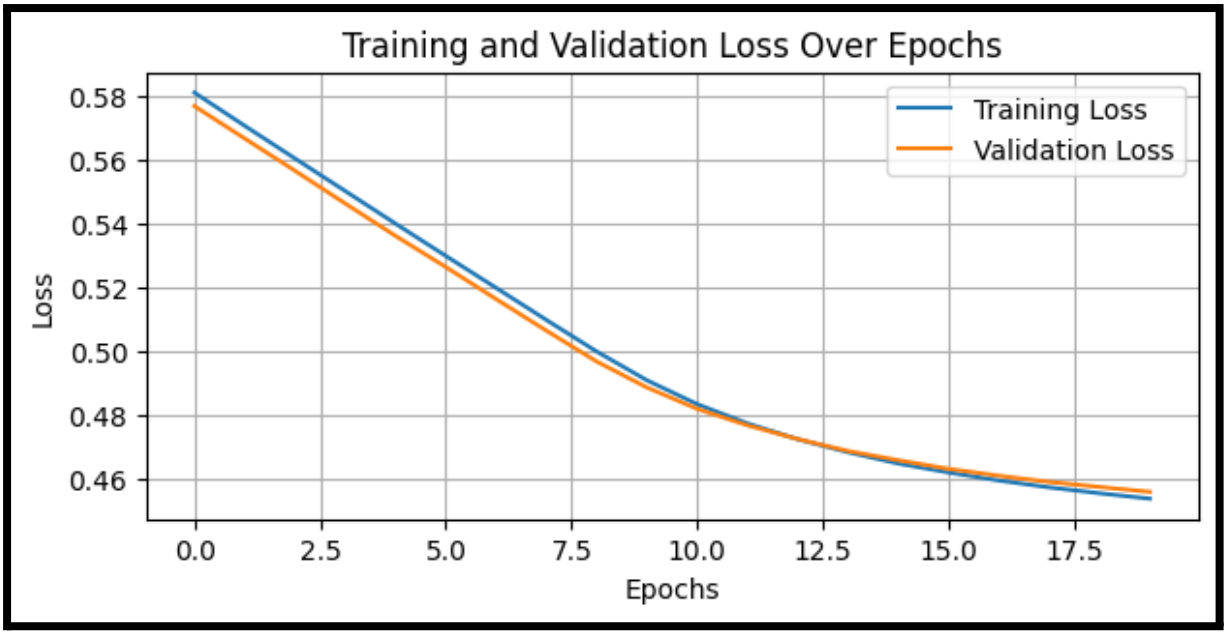


fig=Bit Error Rate(BER) on validation set

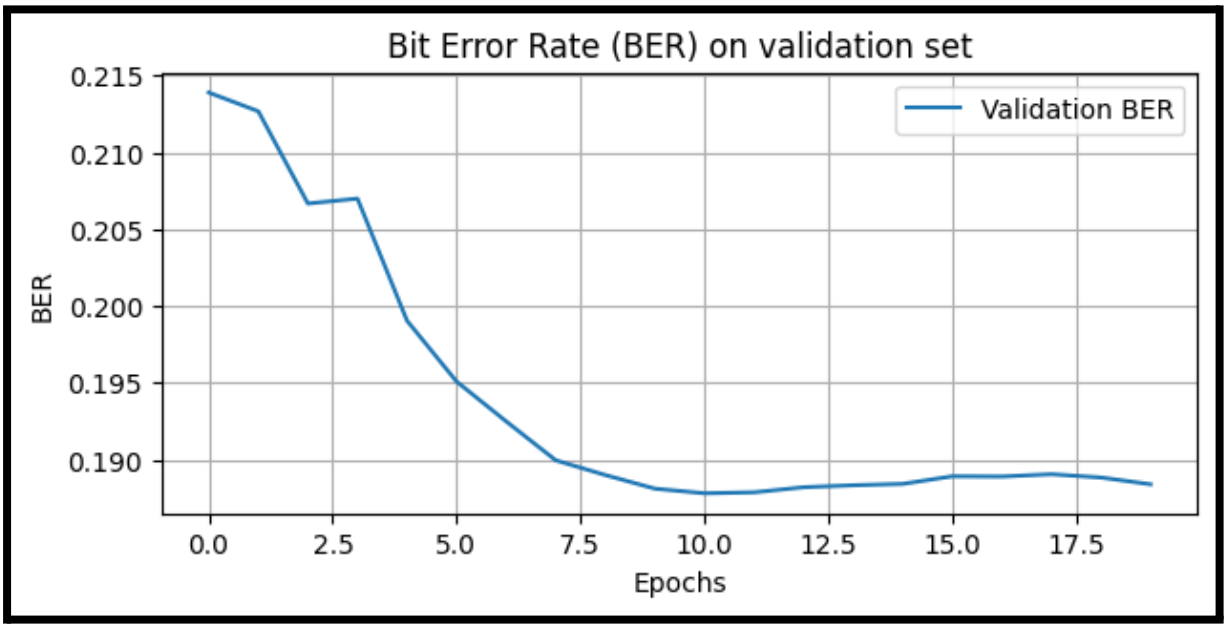
Adam Optimized Model Configuration and Results:

- Optimizer: Transitioning to the Adam optimizer introduced adaptive learning rate adjustments, leveraging moment estimates to optimize the training process dynamically.
- Performance Metrics at Epoch 20:
    - Training Loss: 0.4536
    - Validation Loss: 0.4557
    - Validation BER: 0.1884

The adoption of the Adam optimizer led to noticeable improvements across all evaluated metrics. Not only did the model achieve a lower BER, indicating more accurate symbol detection, but it also displayed a significant reduction in both training and validation loss. This underscores the effectiveness of Adam in handling the complexities associated with the symbol detection task.



fig=Training and Validation Loss Over Epochs(Adam)



fig=Bit Error Rate(BER) on validation set

Detailed Comparison:

BER Reduction: The reduction in BER from 0.2160 with the initial model to 0.1884 with the Adam-optimized model highlights the latter's superior performance in accurately detecting symbols under the same training conditions. This improvement is critical for communication systems where even minor enhancements in BER can lead to significant increases in the quality of the transmitted signal.
Loss Improvements: The drastic reduction in validation loss from 0.8324 to 0.4557 with the Adam optimizer demonstrates its capability to enhance model generalization. This is indicative of a model that not only learns well but also performs more consistently when exposed to new, unseen data.
Convergence Efficiency: While specific convergence rates are not provided, the substantial improvements in loss and BER with the Adam optimizer suggest a more efficient training process. Adam's adaptive learning rates likely contributed to faster convergence towards a more optimal set of model parameters.
Overall Model Performance: The comparison clearly illustrates the advantages of utilizing advanced optimization techniques like Adam for deep learning tasks in communication systems. The optimizer plays a crucial role in navigating the model towards optimal performance, as evidenced by the significant improvements in both BER and loss metrics.

Conclusion:

The comparative analysis between the initial and Adam-optimized models for the symbol detection task clearly demonstrates the impact of optimizer selection on model performance. The Adam optimizer's adaptive learning rate mechanism provided substantial benefits, including reduced BER and lower validation loss, highlighting its suitability for complex tasks such as symbol detection. This case study reinforces the importance of careful hyperparameter tuning and optimizer selection in the development of neural network models for communication systems.

GitHub Link= https://github.com/kapilgulani/DEEP-LEARNING