EEE598 – VLSI Design Automation

Project 2: Report, Phase -2

Choice of Model:
The ML model used for training is **Unet** generated by [2], a fully convolutional CNN model designed for image segmentation tasks. The model takes a set of input images and generates an output image. The 2D distributions of Current Map, Voltage Source Map, and PDN Density Map are passed as input features, and the model predicts a 2D distribution of the IR Drop. As suggested in [1], Unet with a pre-convolution layer could give higher accuracy considering IR Drop estimation.

Features used to train the model:
The features used to train the model are:

- Current Map
- Voltage Source Map
- PDN Density Map

The label that is predicted is the **IR Drop Map.**

Steps taken to increase the accuracy of the model:
Initially, the model was trained with fewer Epochs, and the Accuracy of the predicted IR drop was lower; therefore, the number of Epochs was increased. Two kinds of data sets were considered, one considering the IR drop label without convolution, where the zeros were predominant in the heatmap, and another with a convolution approach to smooth the label data. Training the Unet model with non-convoluted data for 300 epochs resulted in an average F1 Score of 0.15%. The actual and predicted IR Drop Maps are shown in Figure 1.

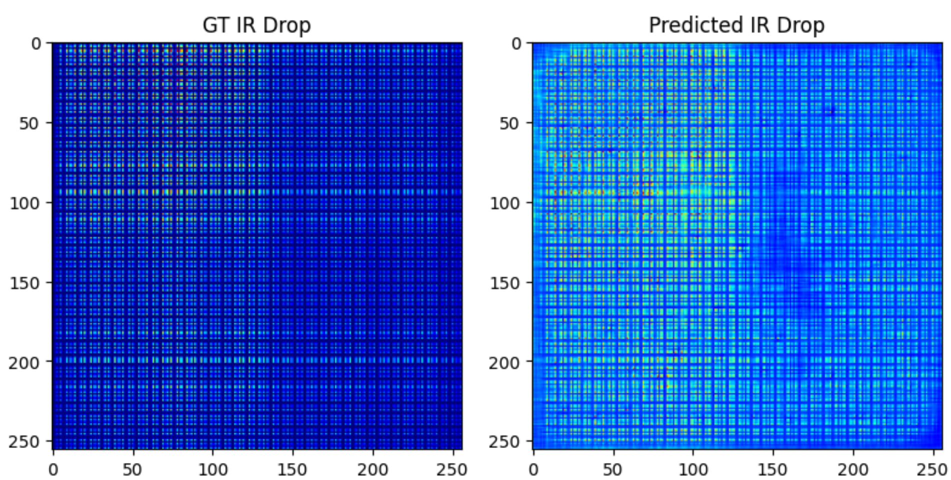

Fig.1. Prediction in the Non-convoluted Dataset for one of the test cases

After smoothing the IR Drop label and including the pre-convolution layer as suggested in [1], the average F1 Score of the model increased to 2.4%. The prediction result is as shown in Figure 2.

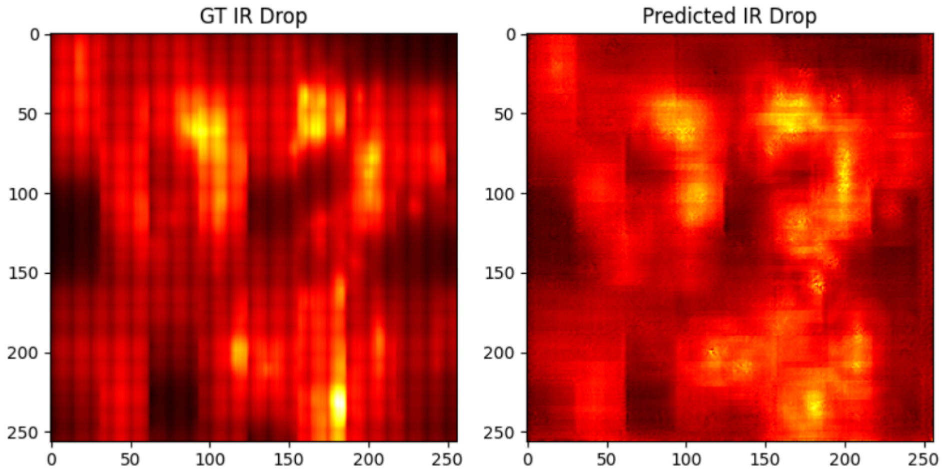

Fig.2. Prediction in the convoluted Dataset for one of the test cases

Later, because the datapoints were limited, all the datapoints provided for training were augmented as suggested in [1].
Argumentation techniques used:

1. Flipping the Feature and the Label data vertically
2. Flipping the Feature and the Label data horizontally
3. Rotating the Features and label by 90 degrees
4. Rotating the Features and label by 180 degrees
5. Rotating the Features and label by 270 degrees

Although the augmentation techniques suggested in [1] were not efficient in our case, they did slightly increase the average F1 score. The resulting average F1 score is 3.9. The picture of the prediction after adding augmented data is shown in Figure 3.

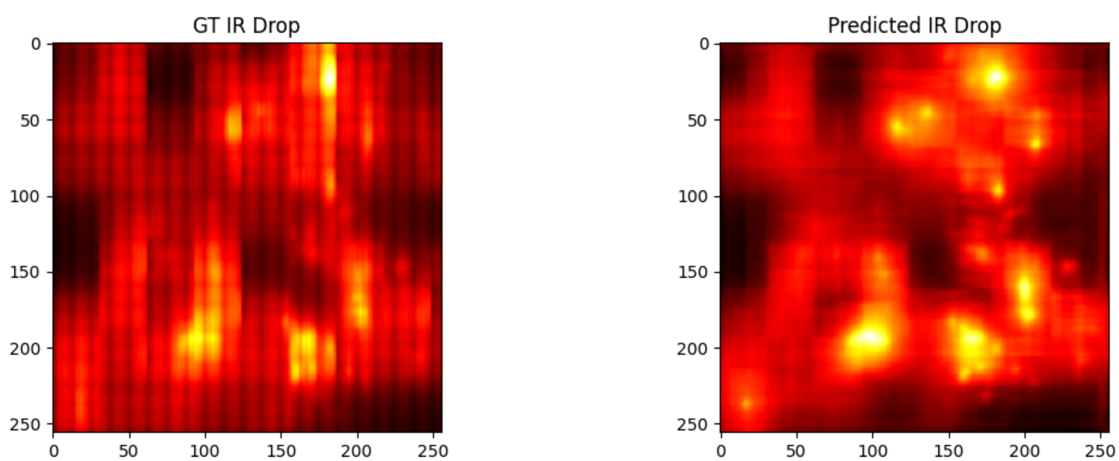

Fig.3. Prediction in the augmented Dataset for one of the test cases

Plot of Converging loss during training

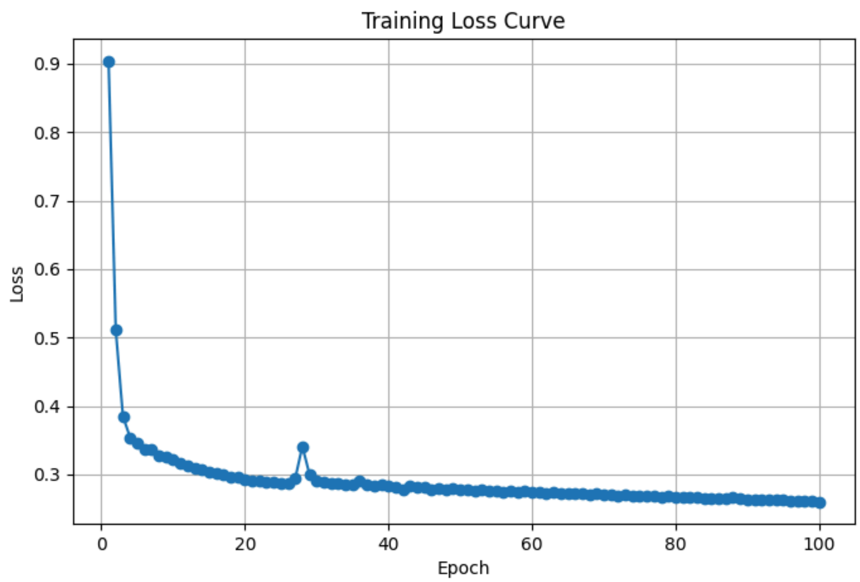

Fig.4. Plot showing the convergence of loss during Training for the augmented dataset for 100 epochs

Evaluation Metrics for all the test cases

Table 1. Evaluation Metrics for the ML Model

Testcase Name	F1 Score	MAE	Runtime
testcase1.sp	0.39	0.42	1.35s
testcase2.sp	0.0	0.43	1.28s
testcase3.sp	0.0	0.28	50.45s
testcase4.sp	0.0	0.43	50.64s
testcase5.sp	0.0	0.29	13.94s
testcase6.sp	0.0	0.33	13.77s
testcase11.sp	0.0	0.40	0.92s
testcase12.sp	0.0	0.71	0.94s
testcase17.sp	0.0	0.43	7.76s
testcase18.sp	0.0	0.48	7.59s

Predicted IR Drop Map versus the actual IR Drop Map for all the testcase files:

<u>testcase1.sp</u>

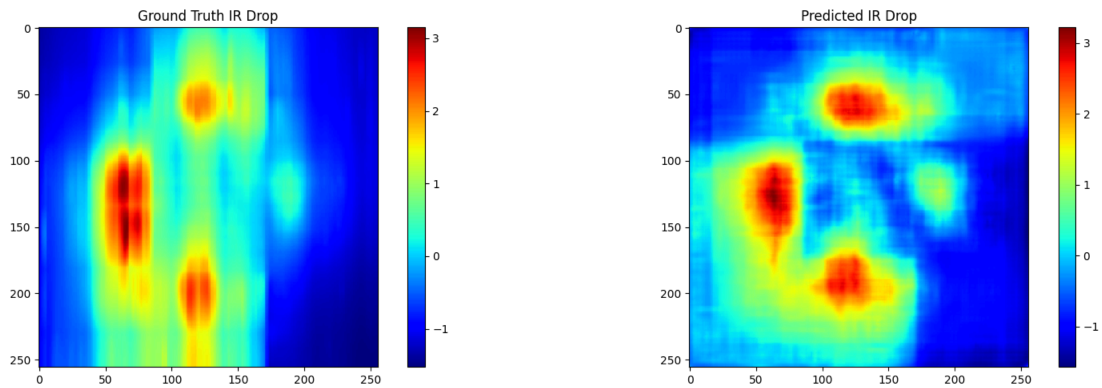

Fig.5. Actual vs Predicted IR drop for testcase1

<u>testcase2.sp</u>

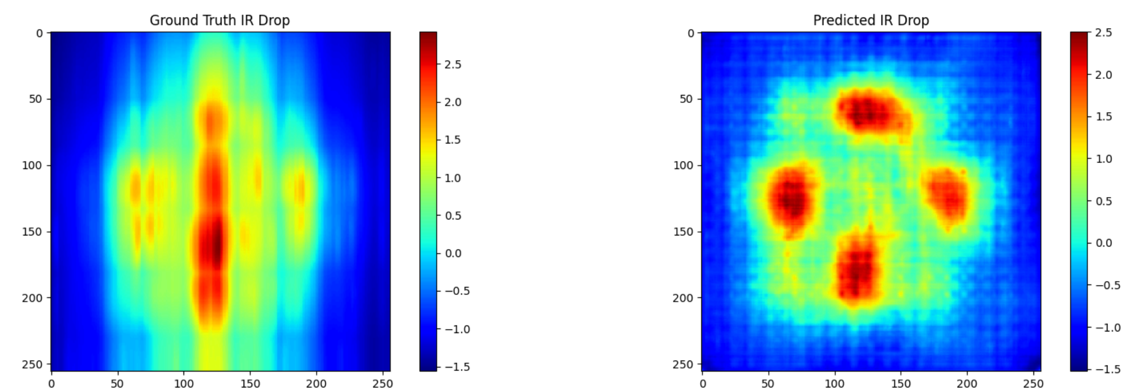

Fig.6. Actual vs Predicted IR drop for testcase2

<u>testcase3.sp</u>

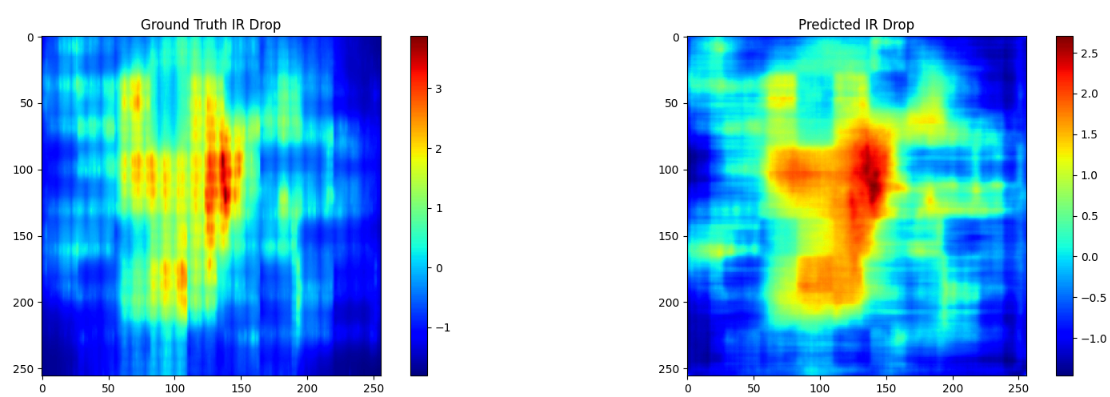

Fig.7. Actual vs Predicted IR drop for testcase3

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testcase4.sp

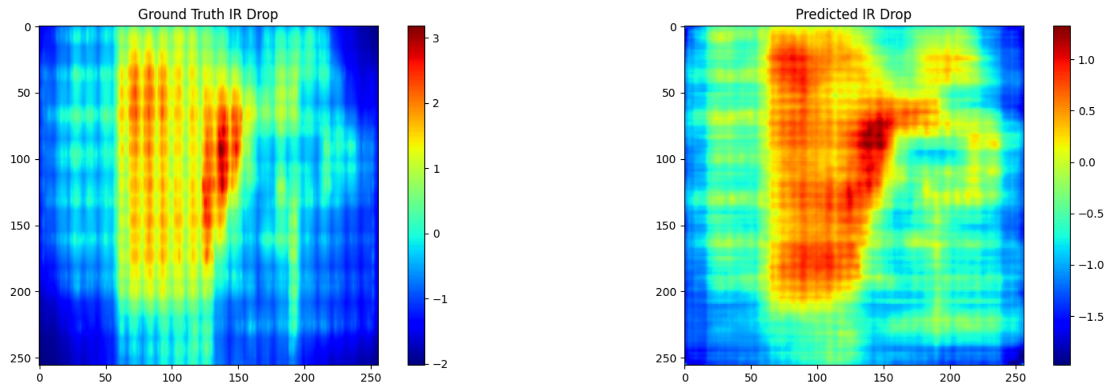

Fig.8. Actual vs Predicted IR drop for testcase4

testcase5.sp

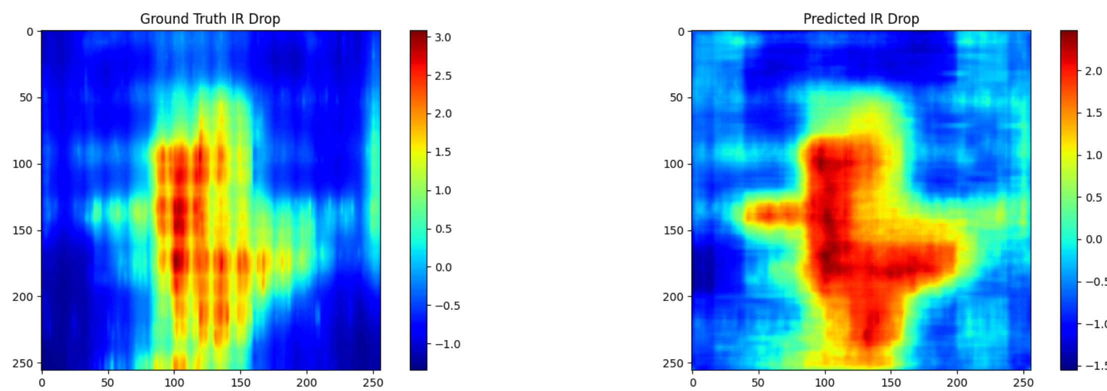

Fig.9. Actual vs Predicted IR drop for testcase5

testcase6.sp

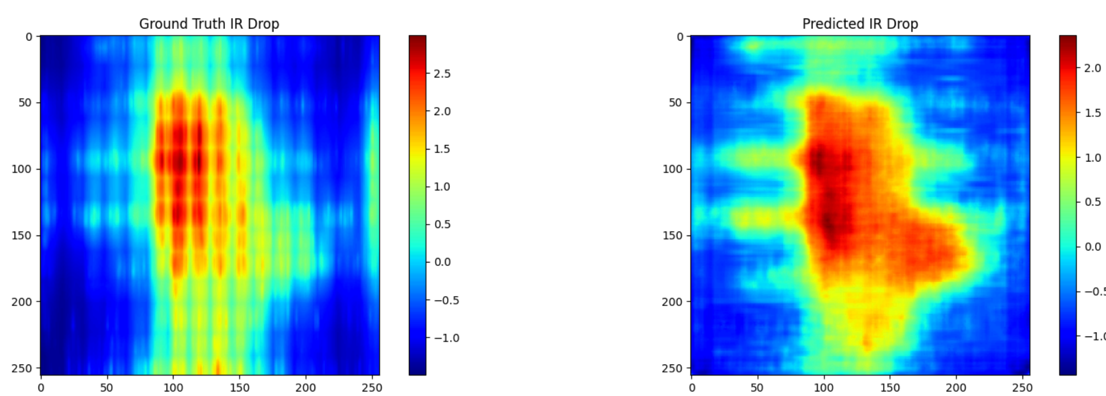

Fig.10. Actual vs Predicted IR drop for testcase6

testcase11.sp

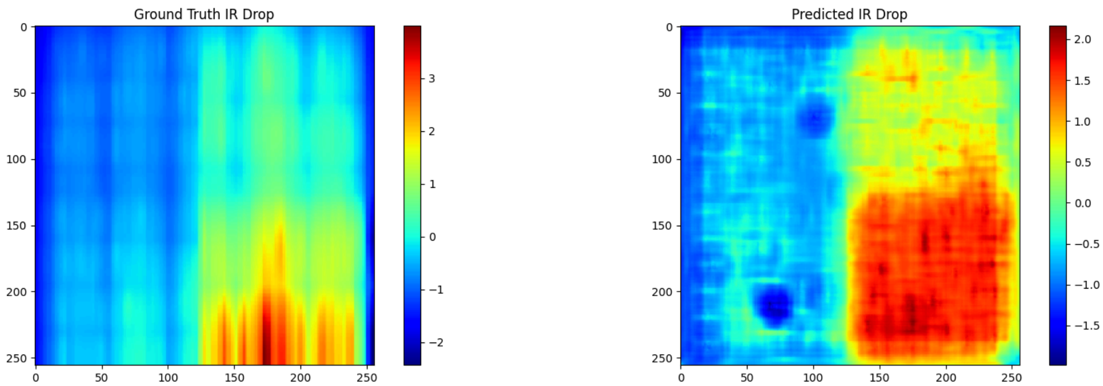

Fig.11. Actual vs Predicted IR drop for testcase11

testcase12.sp

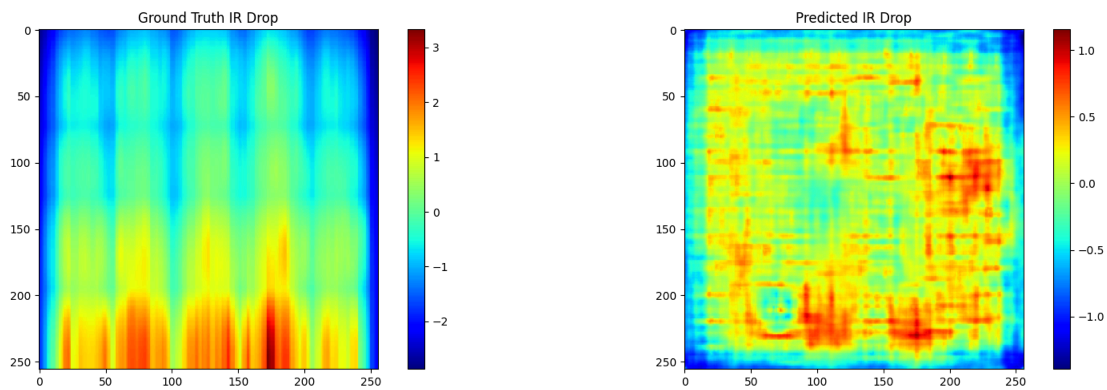

Fig.12. Actual vs Predicted IR drop for testcase12

testcase17.sp

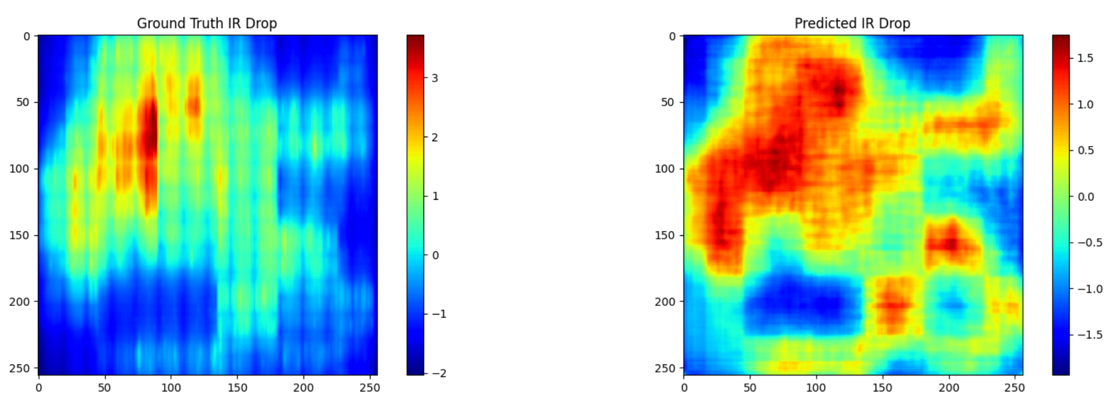

Fig.13. Actual vs Predicted IR drop for testcase17

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testcase18.sp

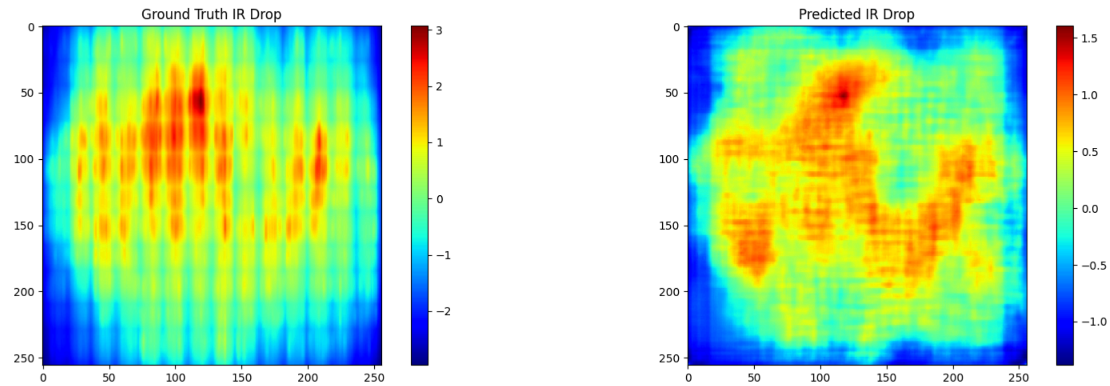

Fig.14. Actual vs Predicted IR drop for testcase18

References:

[1] Zhang, L., & Davoodi, A. (2024). Static IR Drop Prediction with Attention U-Net and Saliency-Based Explainability. https://arxiv.org/pdf/2408.03292v1

[2] ChatGPT. (n.d.). Retrieved April 27, 2025, from https://chatgpt.com/