Static IR Drop Prediction with Limited Data from Real Designs

Lizi Zhang, and Azadeh Davoodi
Presented by Robert Viramontes
Department of Electrical and Computer Engineering
University of Wisconsin-Madison

Outline

- ML for IR-drop prediction
- Our methodology
- Simulation results
- Conclusion

ML for IR-drop prediction: Introduction

- Static IR drop analysis of power delivery network (PDN) is a crucial task in IC design
  - Voltage drop is induced between the power pads and cells in the design
  - High IR drops can severely impact the normal functionality of chips
- Traditional techniques require solving a system of equations representing KVL and KCL and can take up to few hours using commercial tools

ML for IR-drop prediction: prior work

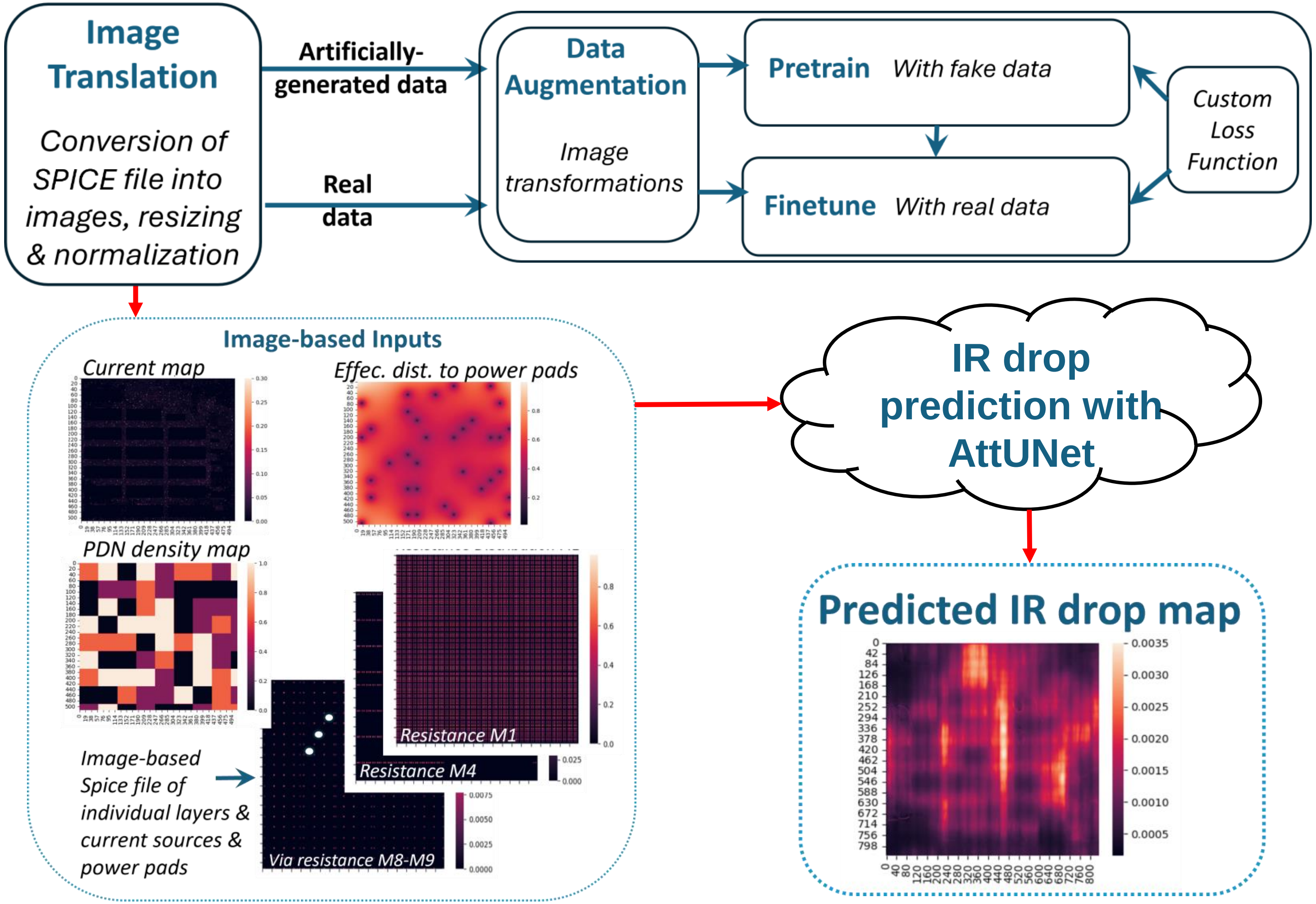
- Earlier work for PDN analysis trade off accuracy for speed by utilizing techniques like spatial locality [DAC'11], preconditioned conjugate gradient [ICCAD'11].
- Recently, machine learning (ML)-based techniques provide significantly faster and more accurate solutions
  - Limited to incremental analysis [VTS'18, VLSID'22]
  - Applicable to specific designs [ASPDAC'20]
  - Not accurate enough [ASPDAC'21]

ML for IR-drop prediction: challenges

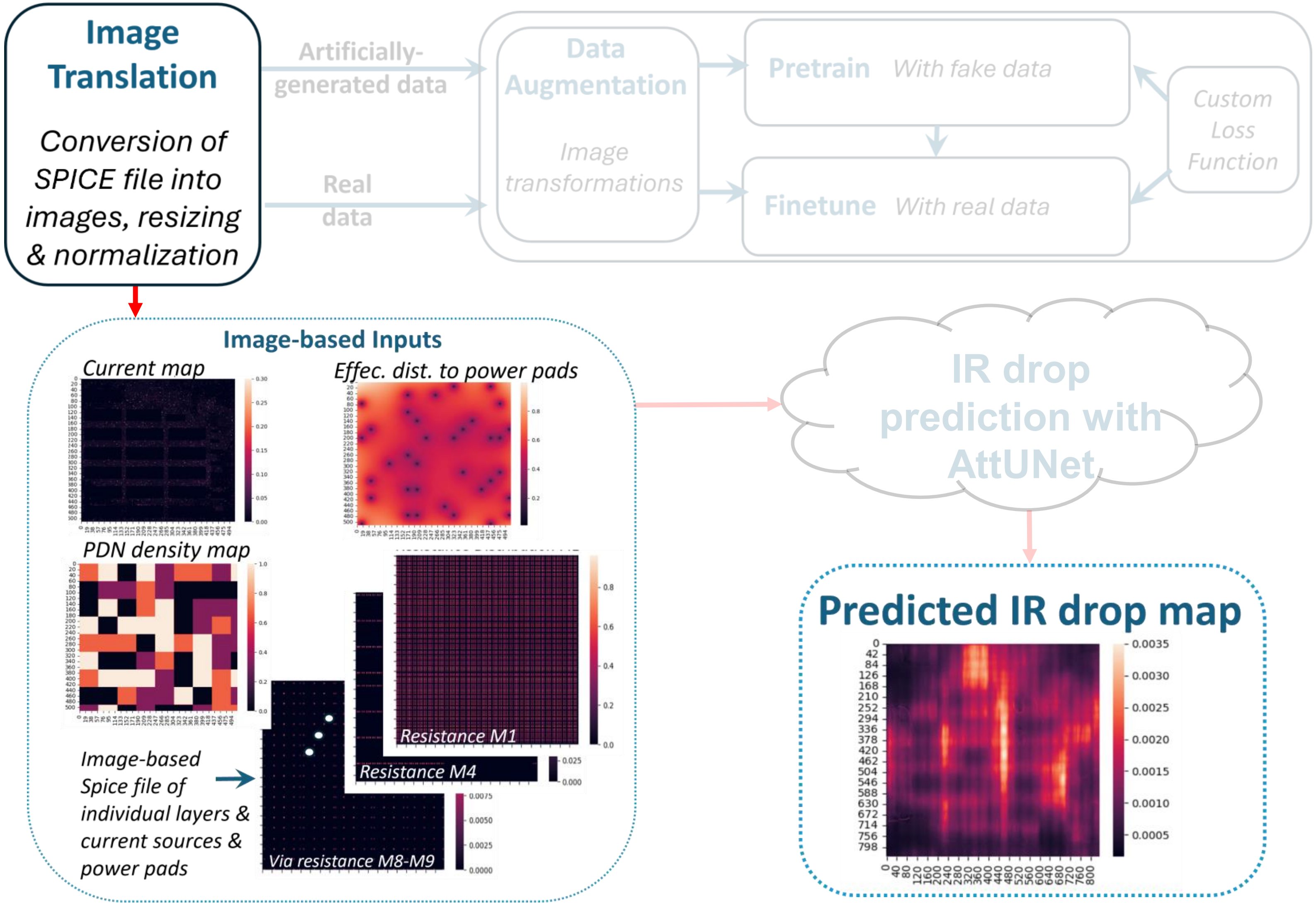
1. Complexity of PDNs
   - 3D network with up to 10 layers
   - Hard to make accurate predictions
2. Lack data from real chips for AI-based prediction
   - Large amounts of training data are often required to produce accurate predictions

Methodology: overview

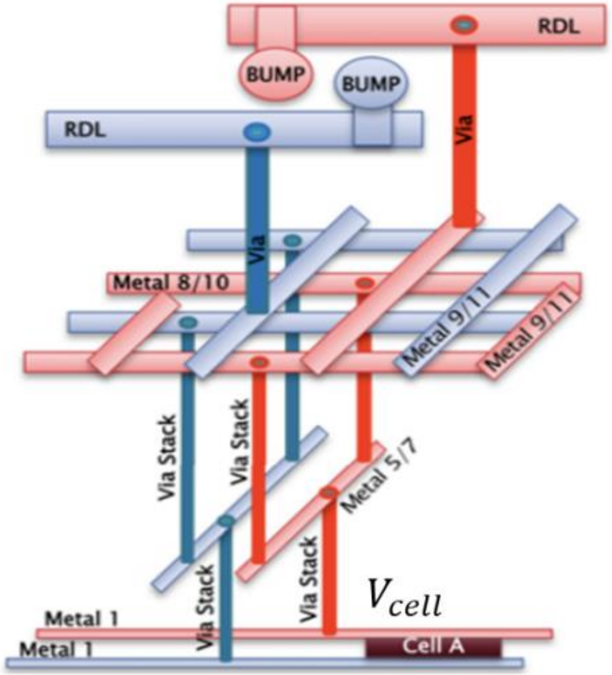
- Translate the original problem to image-to-image prediction
- Train our model using the two-step pretrain-finetune strategy
- Make prediction and evaluate

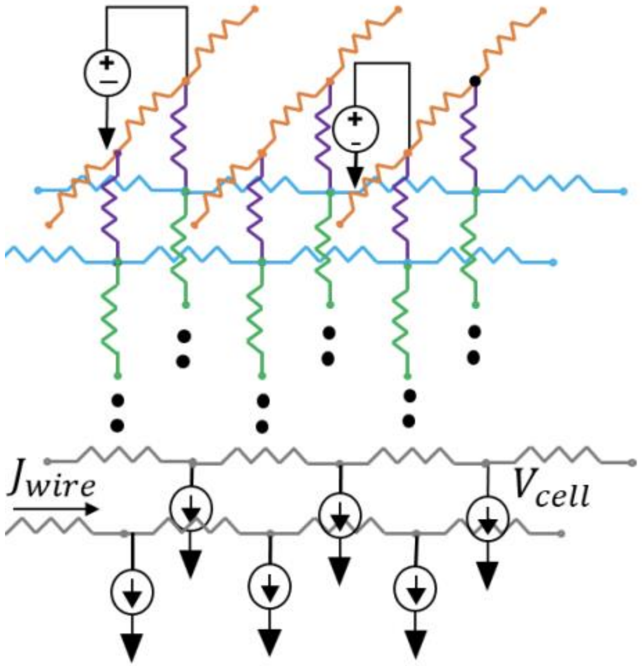


Methodology : image-based inputs & output



Methodology : image-based inputs & output



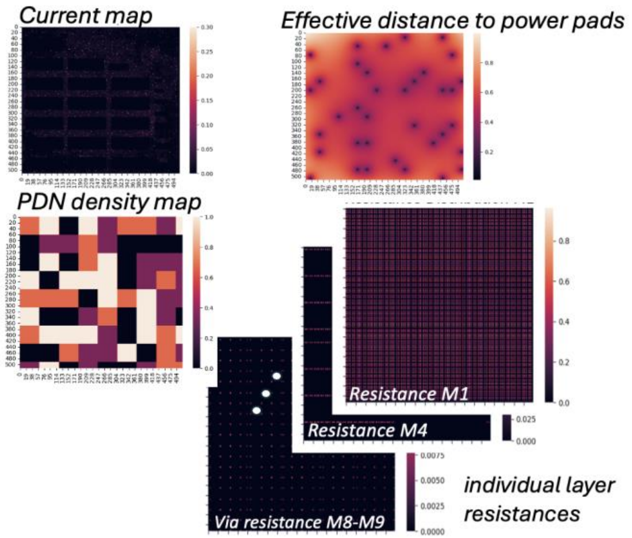


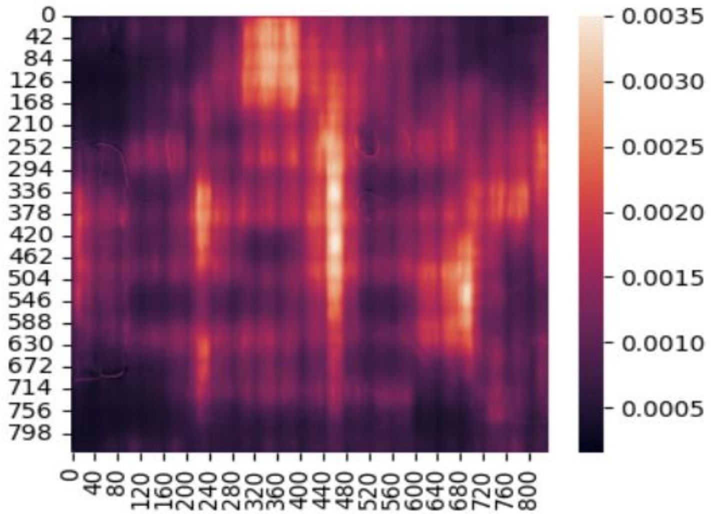
Source: CAD Contest at ICCAD. 2023.

- The Power delivery networks can be modeled as a 3D grid of voltage sources, current sources, and resistances
  - Wires are a network of resistances, the power pad (C4 bumps) are voltages sources connected to the PDN wires, and the current sources are the cells/instances

Methodology : image-based inputs & output

image-based **predicted IR drop map**



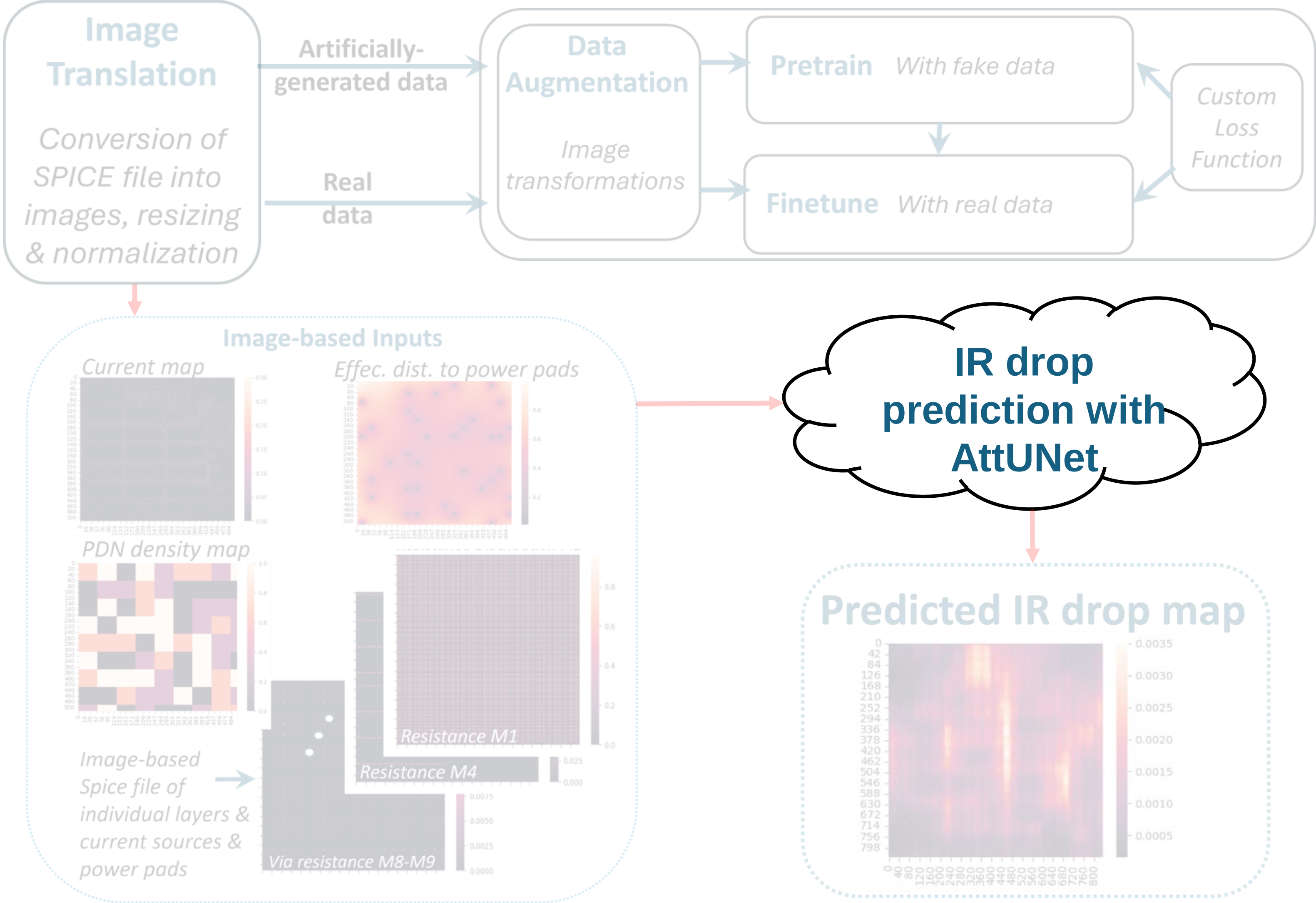


- PDN features can be represented by images
  - Current map shows locations of current sources
  - PDN density map reflects the topology of a PDN
  - Effective distance to power pads shows the location of power pads
  - Resistance maps represent resistances of all metal layers/vias
- IR drops across a chip can be represented by an IR drop map

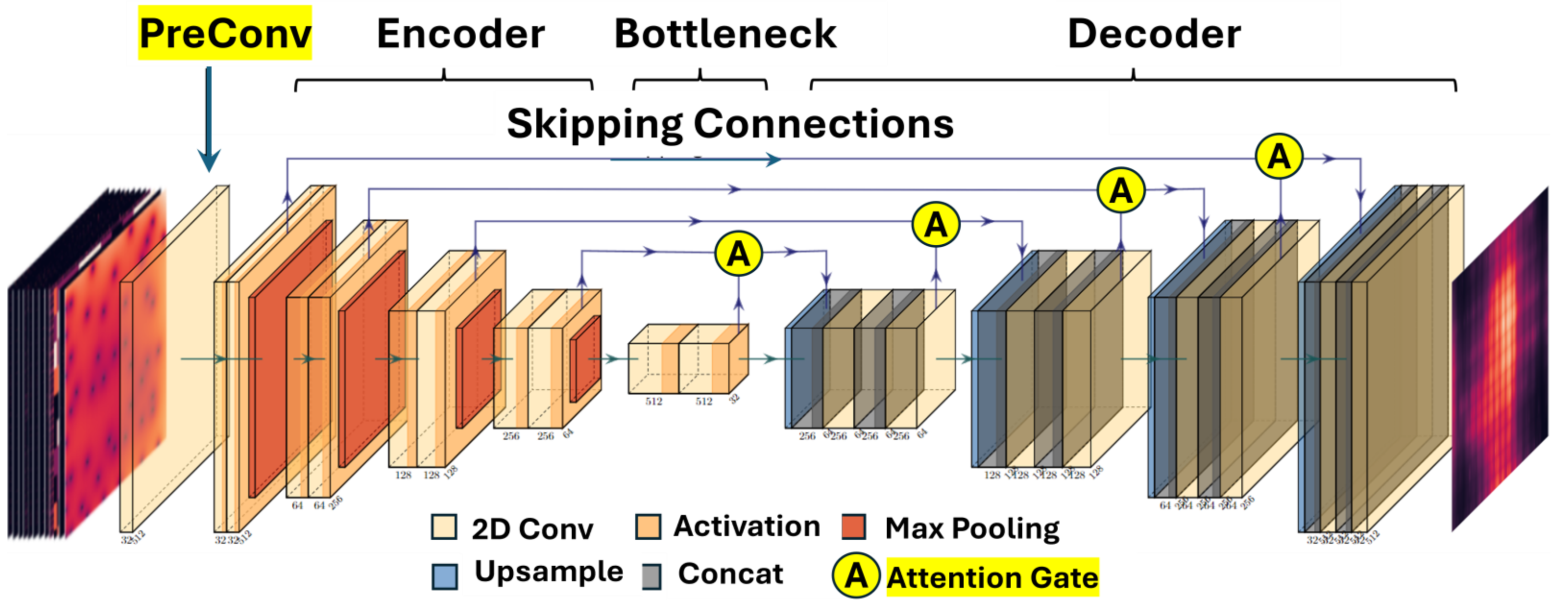
Methodology : image-based inputs & output

- Resizing
  - Since the chip dimensions may be different, we apply resizing to adjust all image-based inputs to the same dimension (512×512) to allow processing by the same NN model
- Normalization
  - For better adaptability, each input image is scaled to [0, 1] by dividing by its maximum matrix entry

Methodology : AttUNet architecture



Methodology : AttUNet architecture

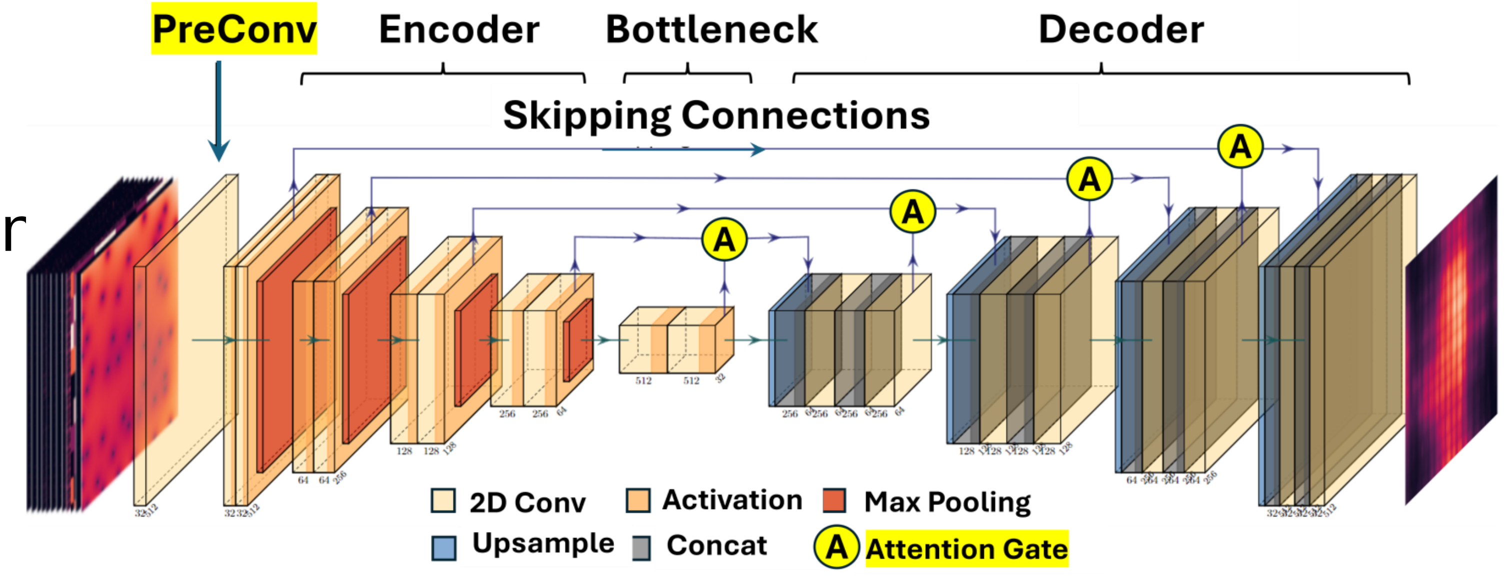


- Proposed AttUNet which is an advanced U-Net-based CNN
  - U-Net CNN: encoder-decoder structure, which is commonly used for image-to-image prediction tasks [MICCAI' 15]
  - Highlighted parts are new

Methodology : AttUNet architecture

1) PreConv Block:

- A convolutional layer inserted to preprocess the inputs which has a 2 × 2 filter and an activation function ReLU for *each* image-based input
- Works as a quick filter to highlight the salient features of each image-based input

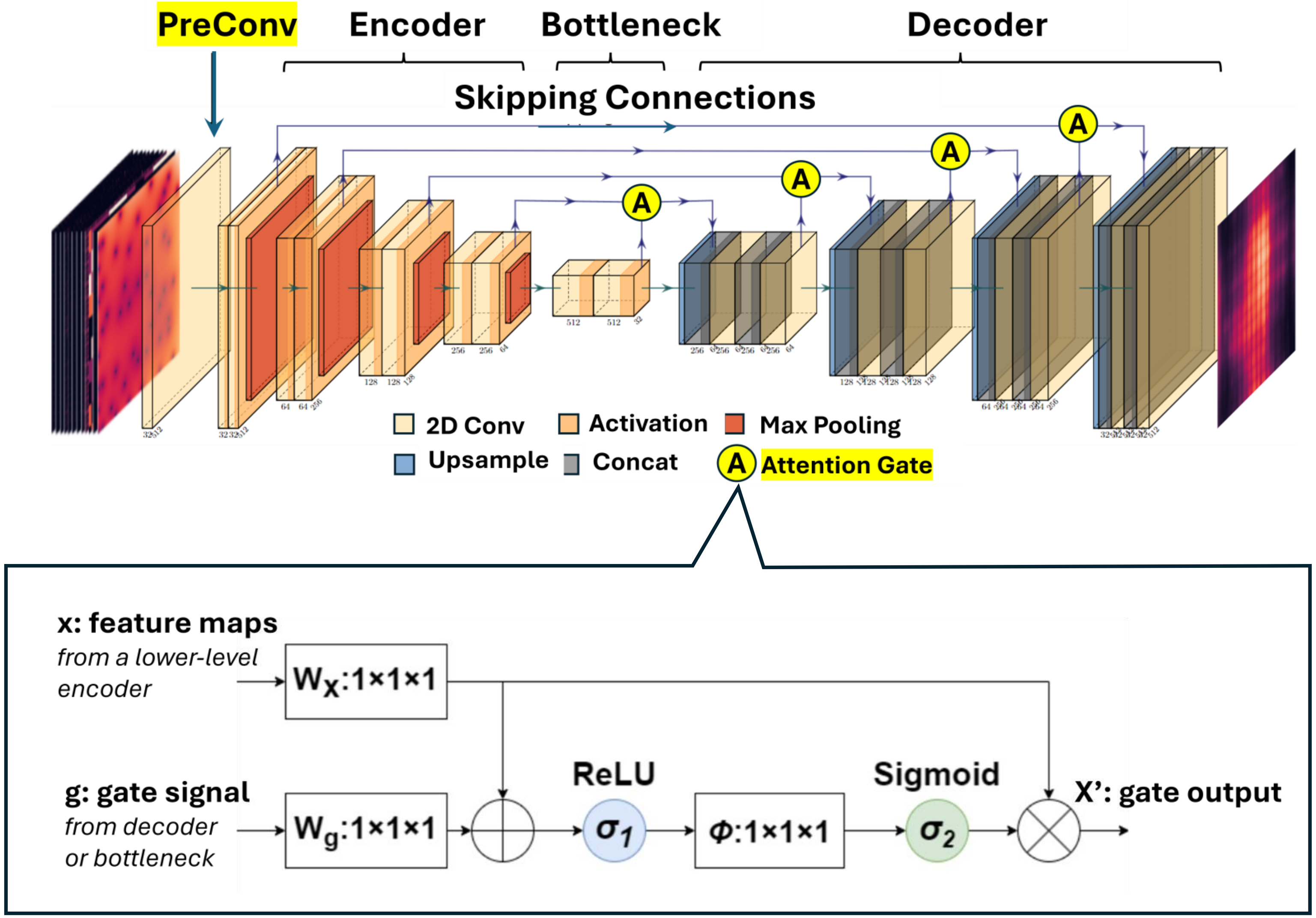


- Allows subsequent convolution operations to work with more relevant and distinguishing features, and better handle the multi-image to single-image nature of the prediction problem

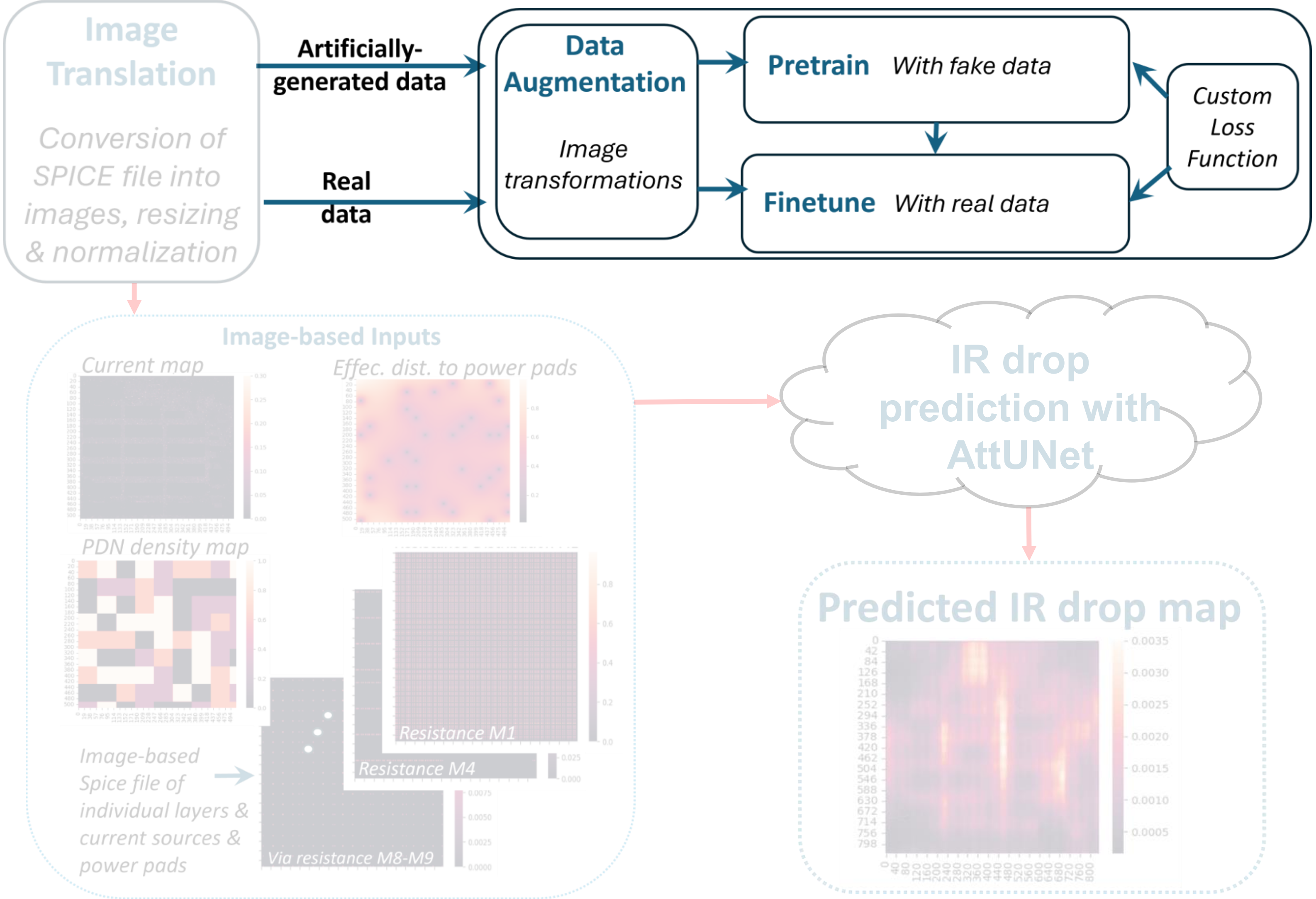
Methodology: AttUNet architecture

2) Attention gates:

- Added to the skipping connections between each pair of encoder and decoders
- Selectively emphasizes relevant features in the sparse IR drop maps
- Reduces noise and improves model accuracy



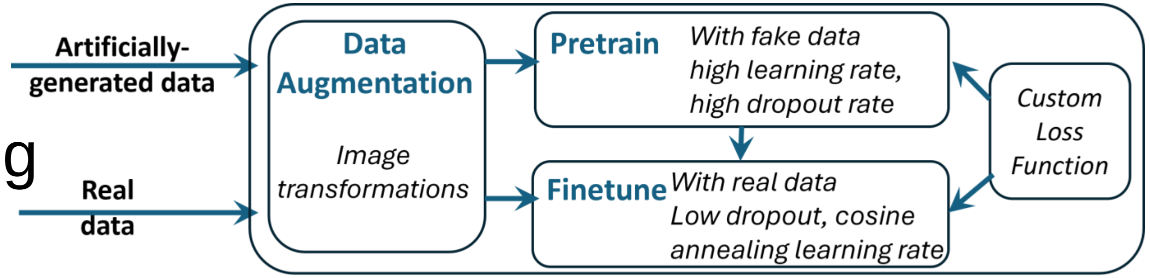
Methodology: data augment & model training

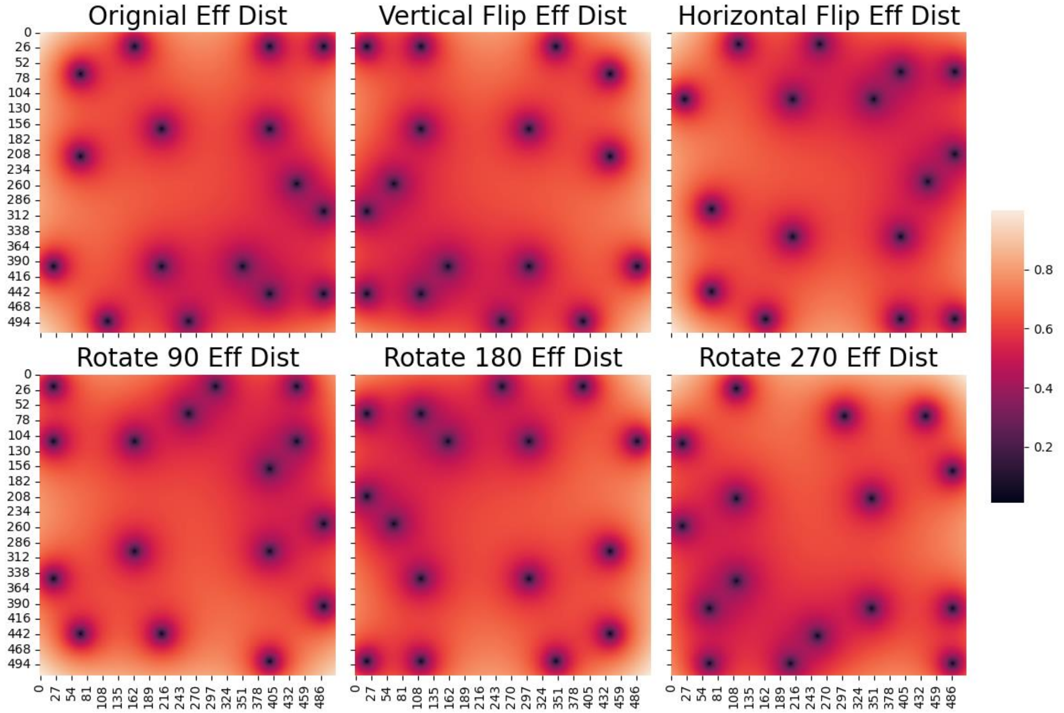


Methodology: data augment

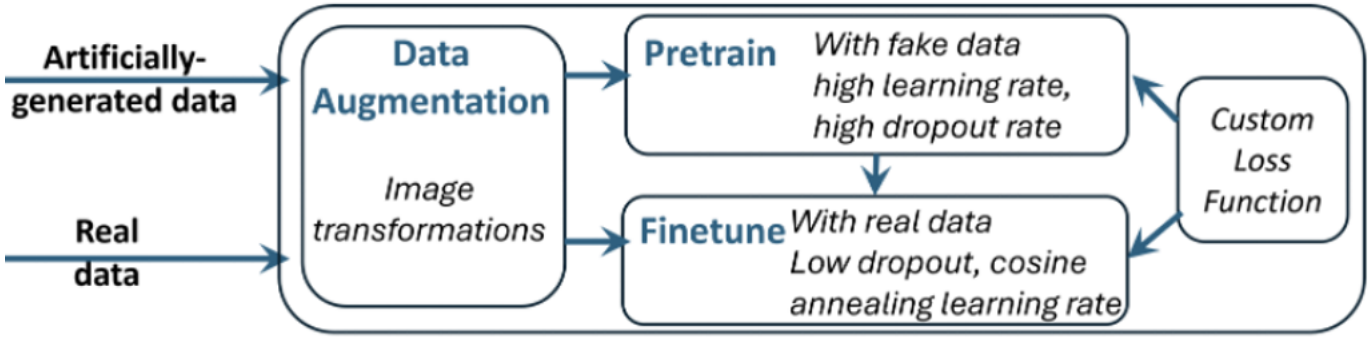
Data augmentation:

- We augment the training data by applying multiple transformations to each image-based input
  – For each input given operations are applied: vertical and horizontal flipping and three (counter-clockwise) rotations
- This process results in a sixfold increase in the number of testcases





Methodology: model training



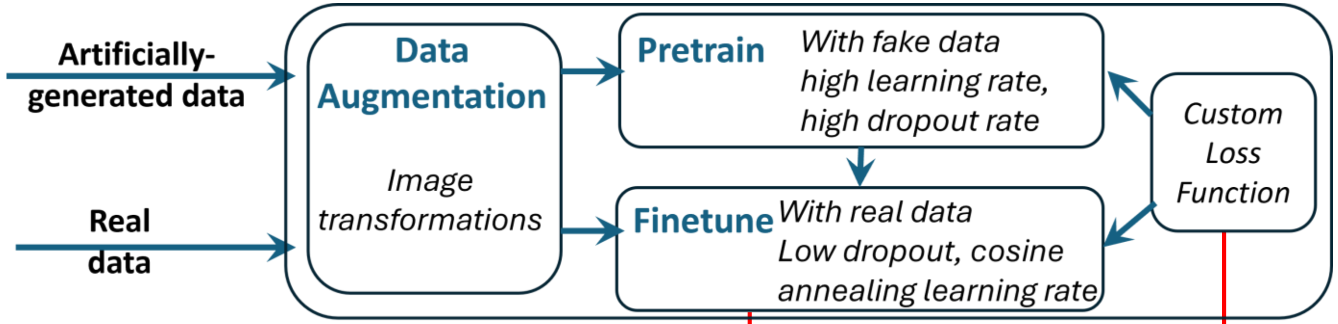
Model training:

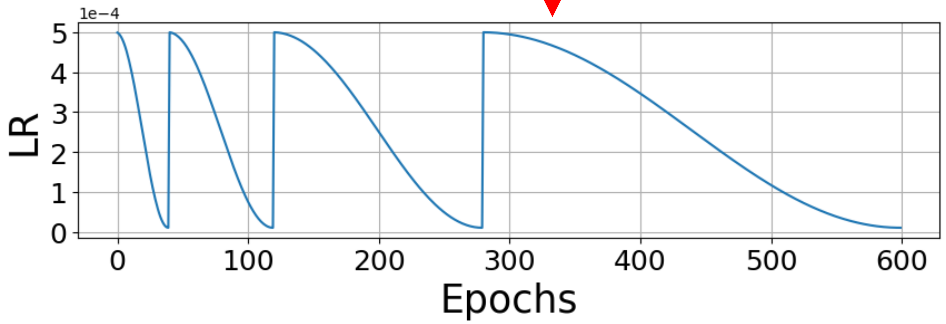
- Transfer learning strategy
  - First pretrain using large volume of artificially-generated data to prevent overfitting
  - Then finetune using limited data from real designs
- The provided dataset in the ICCAD 2023 contest contains 120 test cases in total for training, of which 100 are artificially-generated and the remaining 20 are real
- Each test case is represented as 12 image-based inputs and is also accompanied by an image-based golden output IR drop map

Methodology: model training

Model training:

- Pretrain
  - High learning rate and dropout rate to facilitate robust learning
- Finetuning
  - Cosine annealing learning rate: Balances exploration in the parameter space with precise tuning
- Custom loss function
  - Ensures conservative estimates of IR drop by penalizing underestimated values, aiming for safer design outcomes





$$Loss = \begin{cases} \frac{1}{n}\sum_{i=1}^{N} \|x_i - y_i\|, \text{if } x_i > y_i \\ \frac{\lambda}{n}\sum_{i=1}^{N} \|x_i - y_i\|, \text{if } x_i \leq y_i \end{cases}$$

Simulation results: Hyperparameters

Model hyperparameters	PreConv	filter size	2×2
		# filters	12
	C1	filter size	3×3
	U1	# filters	32
	C2	filter size	3×3
	U2	# filters	64
	C3	filter size	3×3
	U3	# filters	128
	C4	filter size	3×3
	U4	# filters	256
	Bottleneck	filter size	3×3
		# filters	512
Training parameters		Pre-train	Fine-tune
	Epochs	450	600
	Optimizer	ADAM	ADAM
	Learning rate	0.005	0.00001-0.001
	Dropout	0.3-0.5	0.15

Codes are available on https://github.com/lzzh97/Static-IR-Drop-Prediction

Simulation results: prediction quality

- The prediction quality was evaluated using the same metrics from the ICCAD 2023 contest
  - Mean Absolute Error (MAE) : reflects an *overall* prediction accuracy
    - Absolute error between predicted IR drop and the ground-truth
    - $MAE = \frac{\sum_{i=0}^{N} |\widehat{V_i} - V_i|}{N}$
  - F1 Score: reflects prediction accuracy in high drop pixels
    - The highest 10% IR drops are labeled as positive and the rest as negative
    - $F1 = \frac{2 \times precision \cdot recall}{precision + recall}$
- Besides metrics used in the contest, we also define a third metric to reflect the MAE in the very high IR drop regions
  - MAE_H: MAE in top 5% IR drop regions

Simulation results: prediction quality

- Compared AttUNet against:
  - ICCAD'23 contest winner from NTU
  - IREDGe: U-Net based model [Chhabria et al, ASPDAC'21]*
- AttUNet significantly outperforms both models
  - Improves accuracy and in predicting IR drop hotspots

	IREDGe			ConvNeXtV2 (Contest Winner)			AttUNet		
	MAE	F1	MAE_H	MAE	F1	MAE_H	MAE	F1	MAE_H
T7	0.124	0.648	0.182	0.066	**0.783**	N/A	**0.057**	0.656	**0.120**
T8	0.110	0.698	0.159	0.082	**0.816**	N/A	**0.067**	0.791	**0.113**
T9	0.205	0.120	0.307	**0.041**	**0.589**	N/A	0.074	0.562	**0.111**
T10	0.141	0.483	0.255	**0.066**	0.532	N/A	0.089	**0.610**	**0.122**
T13	**0.119**	0.417	**0.193**	0.207	0.000	N/A	0.164	**0.590**	0.220
T14	0.192	0.034	0.244	0.422	0.000	N/A	**0.089**	**0.734**	**0.230**
T15	0.157	0.000	0.286	0.097	0.088	N/A	**0.077**	0.234	**0.150**
T16	1.066	0.000	1.431	0.160	0.529	N/A	**0.096**	**0.614**	**0.150**
T19	0.131	0.037	0.250	0.091	**0.501**	N/A	0.085	0.283	**0.044**
T20	0.089	0.000	0.187	0.118	0.711	N/A	**0.035**	0.723	**0.050**
Ave.	0.233	0.244	0.349	0.135	0.455	N/A	**0.084**	**0.580**	**0.131**

** V. A. Chhabria, V. Ahuja, A. Prabhu, P. Nikhil, P. Jain, S. S. Sapatnekar. "Thermal and IR Drop Analysis Using Convolutional Encoder-Decoder Networks". ASP-DAC., pp. 690-696. 2021.*

Conclusions

- We presented AttUnet, an advanced variant of the U-Net architecture enhanced with attention mechanisms to predict static IR drop in power delivery networks
- Our findings demonstrated that AttUNet significantly surpasses the existing U-Net model and the2023 ICCAD contest winner in prediction quality.
- Our evaluation was using the setup and data provided by the ICCAD 2023 contest, and our code was released on GitHub

Thank you for
your attention!

Reference

[DAC'11] S. Köse and E. G. Friedman, "Fast algorithms for IR voltage drop analysis exploiting locality," 2011 Design Automation Conference (DAC), 2011, pp. 996-1001.

[ICCAD'11] C. -H. Chou, N. -Y. Tsai, H. Yu, C. -R. Lee, Y. Shi and S. -C. Chang, "On the preconditioner of conjugate gradient method — A power grid simulation perspective," 2011 IEEE/ACM International Conference on Computer-Aided Design (ICCAD), 2011, pp. 494-497.

[VTS'18] S. -Y. Lin et al., "IR drop prediction of ECO-revised circuits using machine learning," 2018 IEEE VLSI Test Symposium (VTS), 2018, pp. 1-6

[ASPDAC'20] Z. Xie et al., "PowerNet: Transferable Dynamic IR Drop Estimation via Maximum Convolutional Neural Network," 2020 Asia and South Pacific Design Automation Conference (ASP-DAC), 2020, pp. 13-18

[ASPDAC'21] V. A. Chhabria, V. Ahuja, A. Prabhu, N. Patil, P. Jain and S. S. Sapatnekar, "Thermal and IR Drop Analysis Using Convolutional Encoder-Decoder Networks," 2021 Asia and South Pacific Design Automation Conference (ASP-DAC), 2021, pp. 690-696

[VLSID'22] S. Kundu, M. Prasad, S. Nishad, S. Nachireddy and H. K, "MLIR: Machine Learning based IR Drop Prediction on ECO Revised Design for Faster Convergence," 2022 International Conference on VLSI Design and 2022 21st International Conference on Embedded Systems (VLSID), 2022, pp. 68-73

[MICCAI'15] O. Ronneberger, F. Philipp, T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation". In *2015 Medical Image Computing and Computer-Assisted Intervention (MICCAI), 2015,* pp. 234–241.