MAUnet: Multiscale Attention U-Net for Effective IR Drop Prediction

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INTRODUCTION

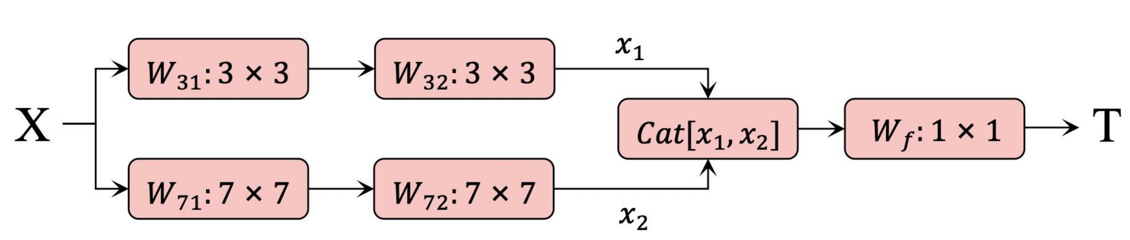
Estimating power supply noise in contemporary semiconductor chips, particularly with respect to IR drop, presents a formidable computational challenge. Modified Nodal Analysis (MNA) leverages Kirchhoff's Current Law to address this but often results in systems with millions of voltage nodes and interconnect segments.

To expedite IR drop analysis, we introduce MAUnet, an innovative machine-learning model for full-chip static IR drop prediction. MAUnet integrates multi-scale convolutional blocks, attention mechanisms, and U-Net architecture to optimize accuracy. It also effectively transfers learned knowledge across different real circuit data.

METHODOLOGY

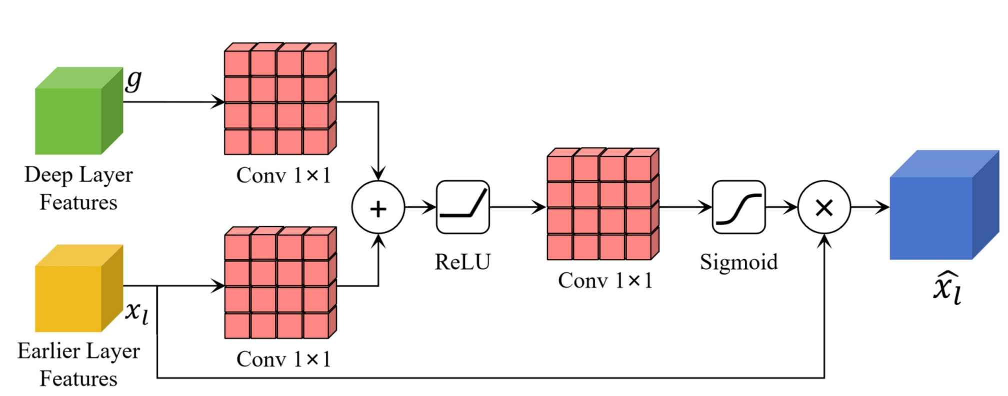
M For Multi-Scale

We introduces multi-scale convolutional blocks in the downsampling to enhance the feature extracting, each block consists of two convolution kernels with different receptive fields achieved by employing multiple kernel sizes.



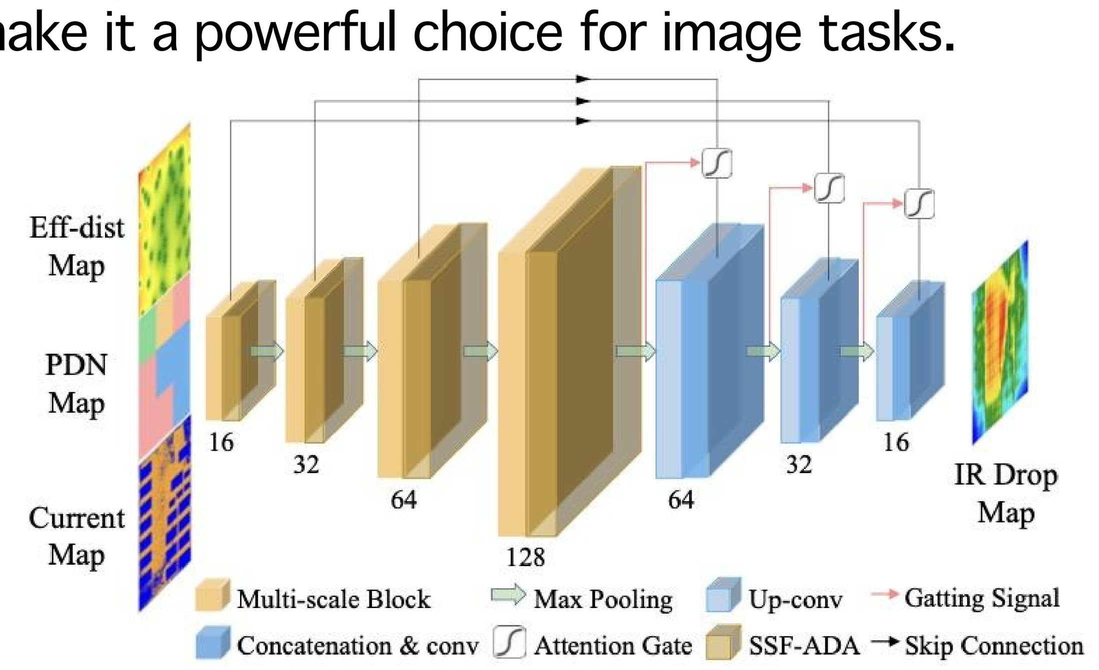
A For Attention

The incorporation of attention mechanism can help suppress the activation of irrelevant regions within downsampling features. By employing it, relevant portions of features are assigned higher weights, while less relevant portions receive lower weights.



U For U-Net

U-Net is inherently a fully convolutional network, which means it can accept input images of varying sizes, its U shape and skip connection make it a powerful choice for image tasks.



FURTHER EXPLORATION

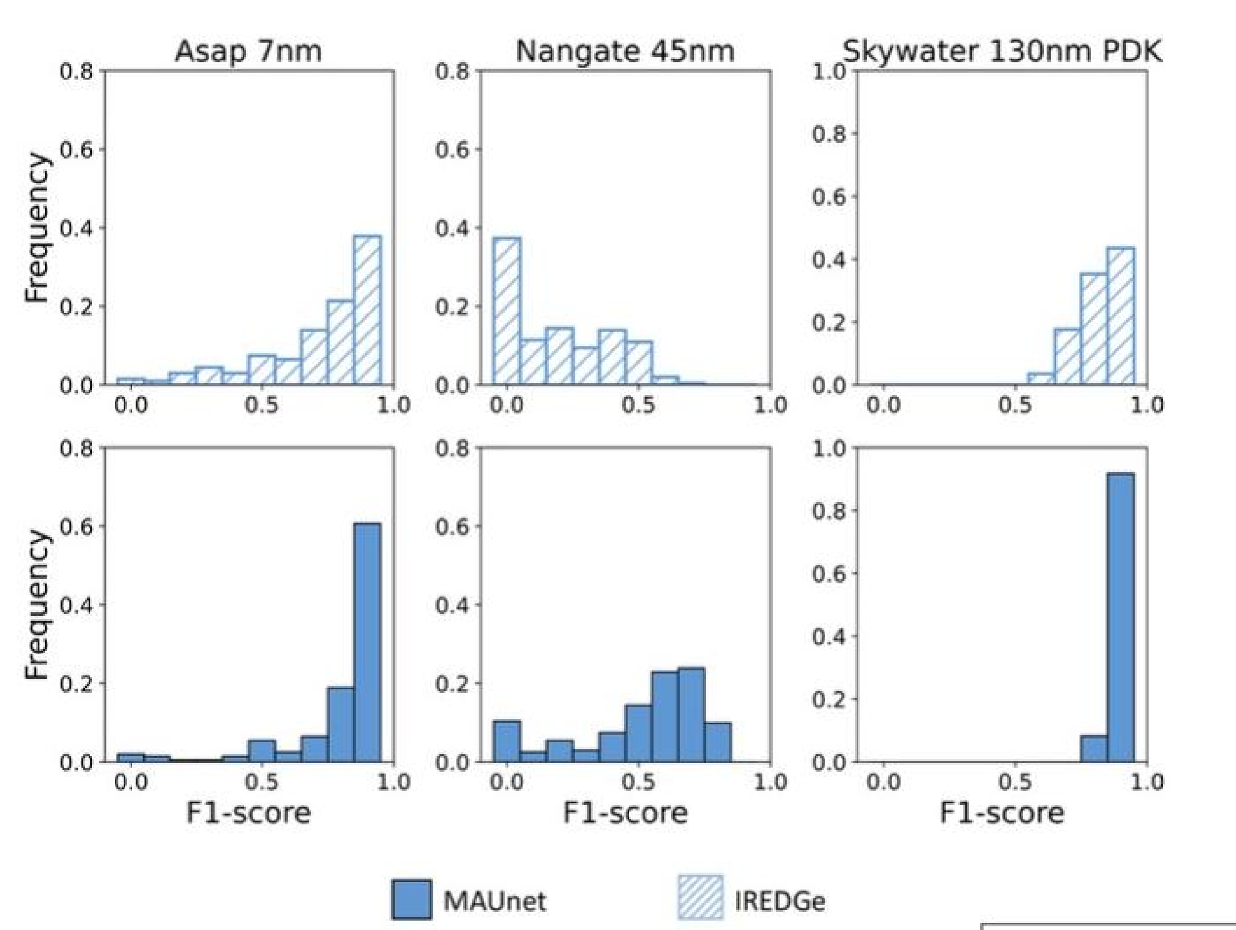
Deep Features Extraction for PDN

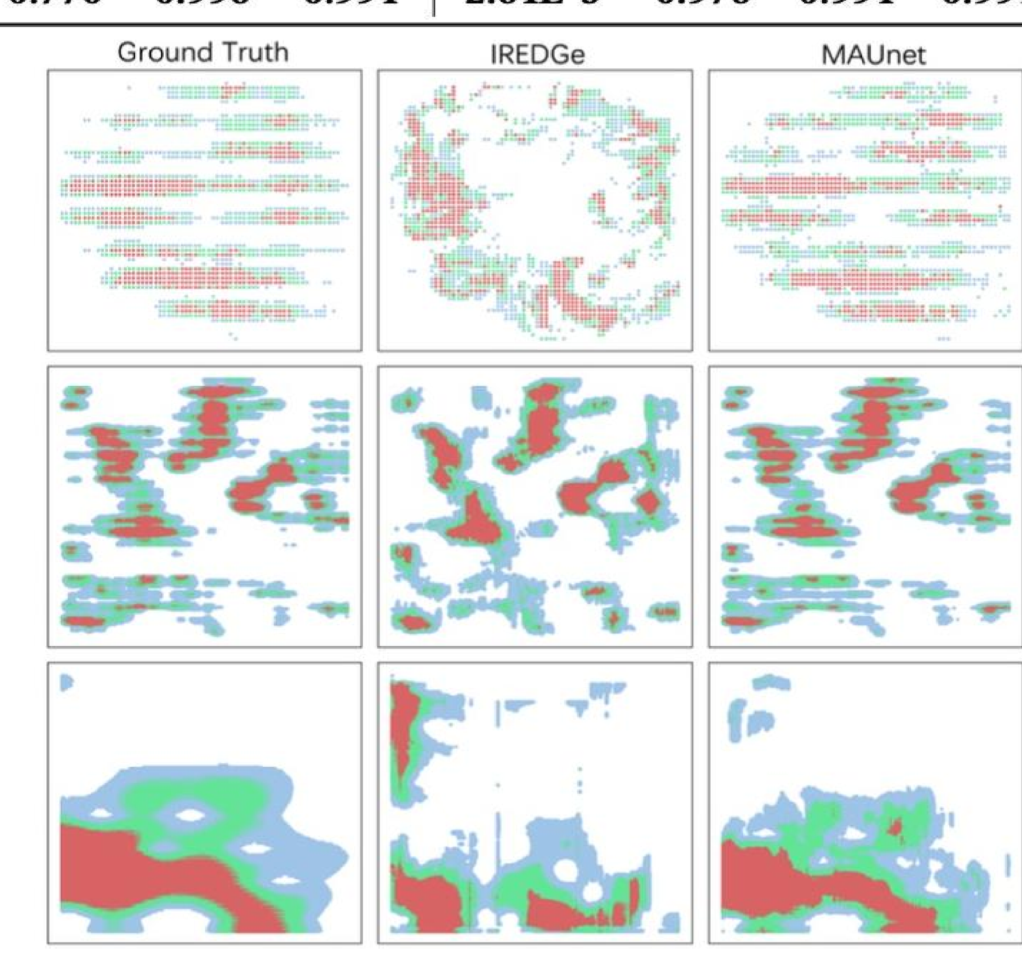
To streamline the extraction process for vias, resistances, and pitches, we propose:

- Vias: Components characterized as resistors with connections spanning multiple layers undergo a coordinate transformation.After transformation, vias are precisely mapped to pixels on feature maps.
- Resistance(R): For resistors connected within the same layer, a coordinate transformation maps them onto the feature maps. The pixel value is then set equal to the corresponding resistance.
- Pitch: Utilizing the connection of resistors, we ascertain coordinates of these connecting points. Points sharing the same x/y are deemed into same pitch, enabling us to derive pitch data layer-by-layer.

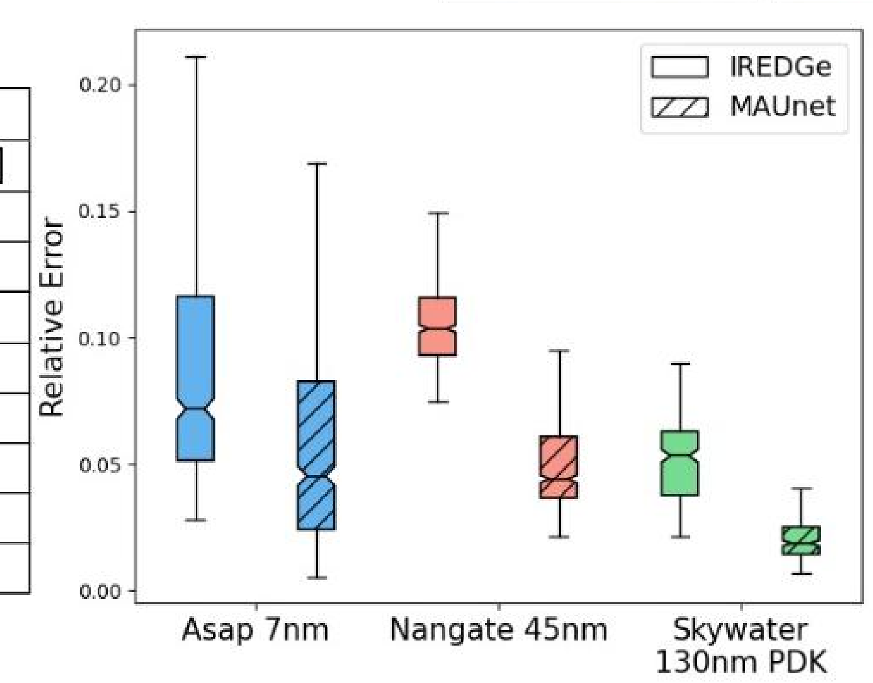
EXPERIMENTAL RESULTS

	Asap 7nm				Nangate 45nm				Skywater 130nm PDK			
Method	MAE (V)	F1	CC	SSIM	MAE (V)	F1	CC	SSIM	MAE (V)	F1	CC	SSIM
IREDGe	1.87E-3	0.786	0.708	0.602	1.25E-4	0.256	0.881	0.891	8.22E-5	0.877	0.809	0.896
IREDGe with DF	1.64E-3	0.809	0.789	0.639	1.15E-4	0.318	0.8937	0.8716	5.95E-5	0.933	0.908	0.948
MAUnet	**1.23E-3**	**0.843**	0.948	0.841	6.35E-5	0.580	0.980	0.982	3.43E-5	0.959	0.982	0.967
MAUnet with DF	1.33E-3	0.833	**0.9721**	**0.941**	**4.33E-5**	**0.770**	**0.996**	**0.994**	**2.61E-5**	**0.976**	**0.994**	**0.991**





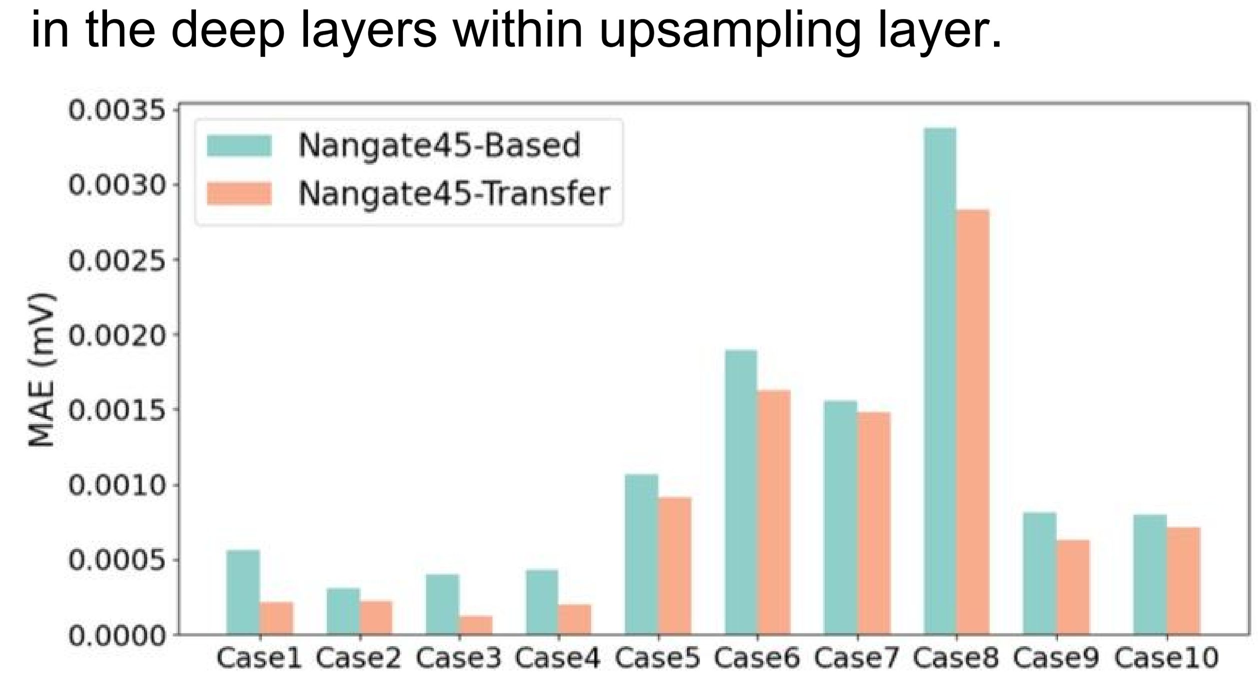
Parameters		Settings
Model parameters	Filters	[64,32,12,64]
	Maxpooling filter size	2x2
	Multi-scale block filters	[3,7]
Training parameters	Epoch	400
	Optimizer	ADAM
	Loss function	MAE
	Learning rate	1e-3
	Decay rate	0.6
	Decay step	50

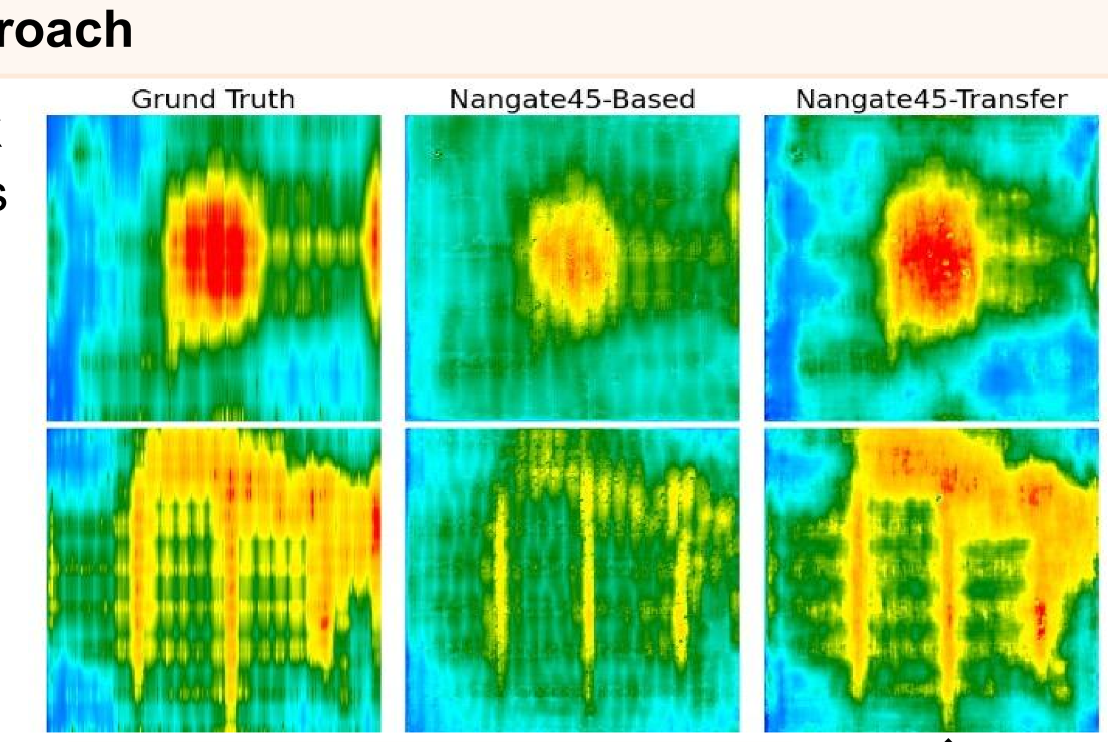


Achieve average error of less than 6% outperform SOTA method by 29%, 65%, 68% in three benchmarks!

Transfer Learning Approach

We introduce a SSF-ADA following each convolution block in upsampling. When transferring, we unfreeze parameters associated with SSF-ADA within the downsampling path. Simultaneously, we maintain the trainability of parameters in the deep layers within upsampling layer.





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