Antenna modelling based convolutional neural network

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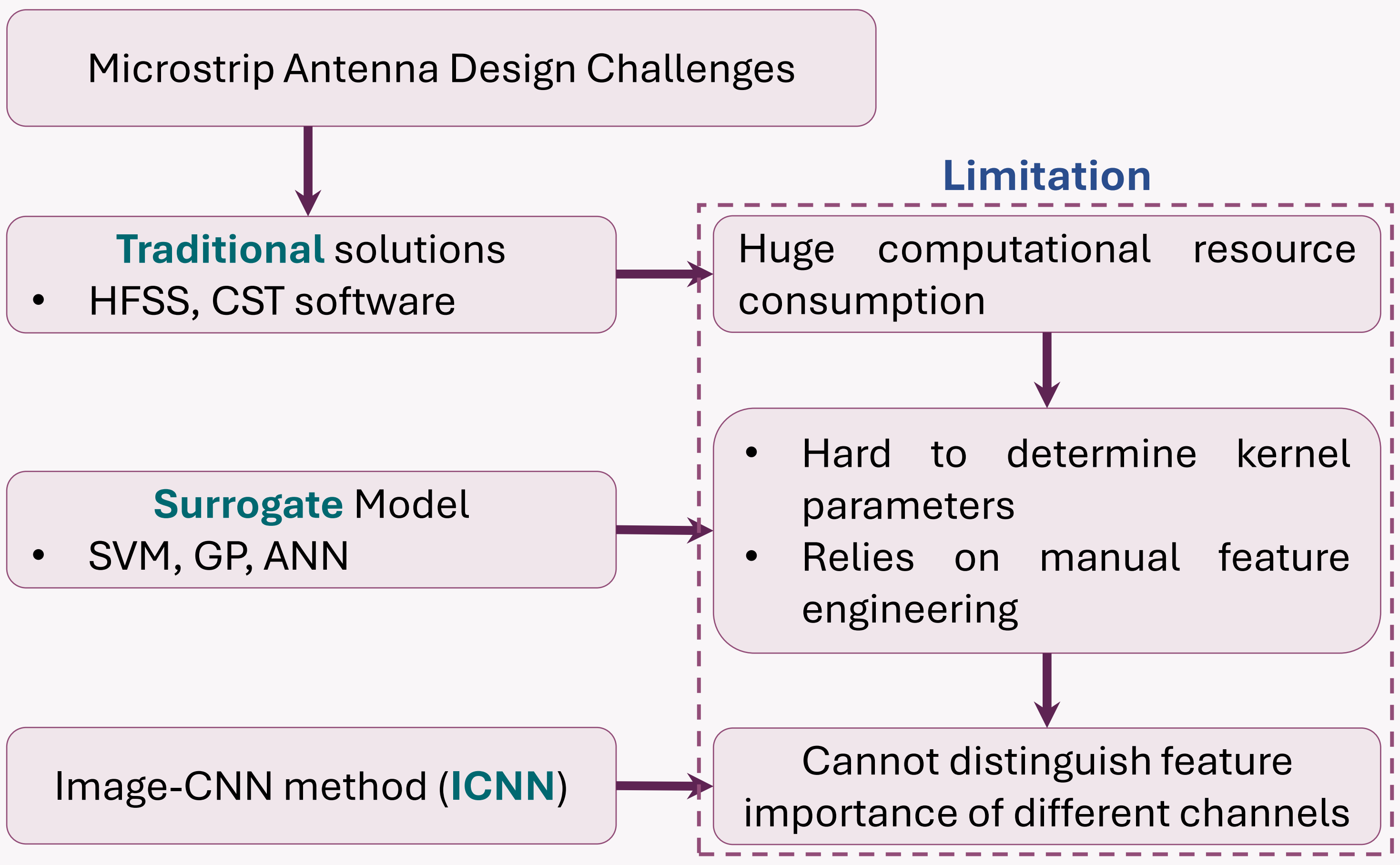
Abstract

This thesis addresses a limitation in antenna design where traditional electromagnetic simulation software requires excessive computational resources. The proposed **ICNN-ECA** methodology combines convolutional neural networks with an efficient channel attention mechanism to predict **microstrip antenna resonant frequencies**. Unlike conventional models, ICNN-ECA adaptively enhances relevant electromagnetic features through a lightweight attention mechanism. Experimental results show a **48.8%** improvement in prediction accuracy compared to traditional CNN approaches.

Introduction



Methodology

Image model construction

- **Input Parameters**: Acquire four physical parameters of the antenna, $X = [L, W, h, \varepsilon_r]$, as the original.
- **Parameter Normalization**: Map all parameters to a unified interval to eliminate dimensional differences.
- **Binary Encoding**: Apply **10-bit** binary encoding to provide **1024** discrete values for each parameter.
- **Matrix Arrangement**: Arrange the four sets of binary numbers into a 4×10 image matrix.

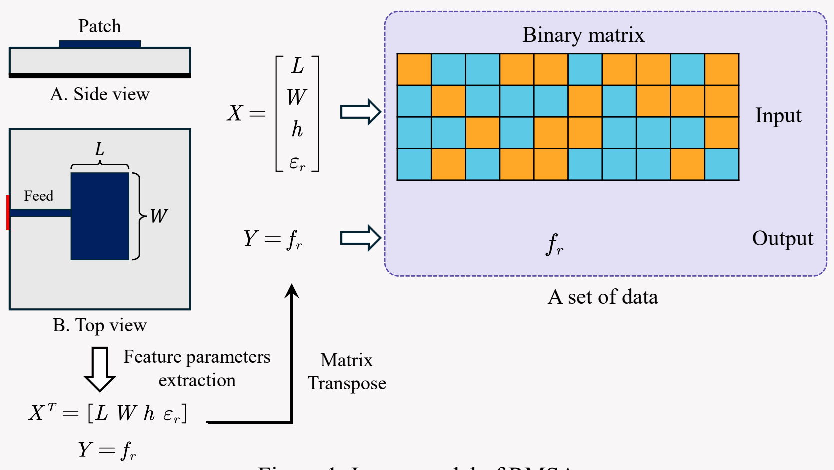


Figure 1: Image model of RMSA

Parameter encoding normalization

$$B = \left\lfloor \frac{X_i - (X_i)_{min}}{(X_i)_{max} - (X_i)_{min}} \cdot (2^n - 1) \right\rfloor$$

ICNN-ECA network architecture

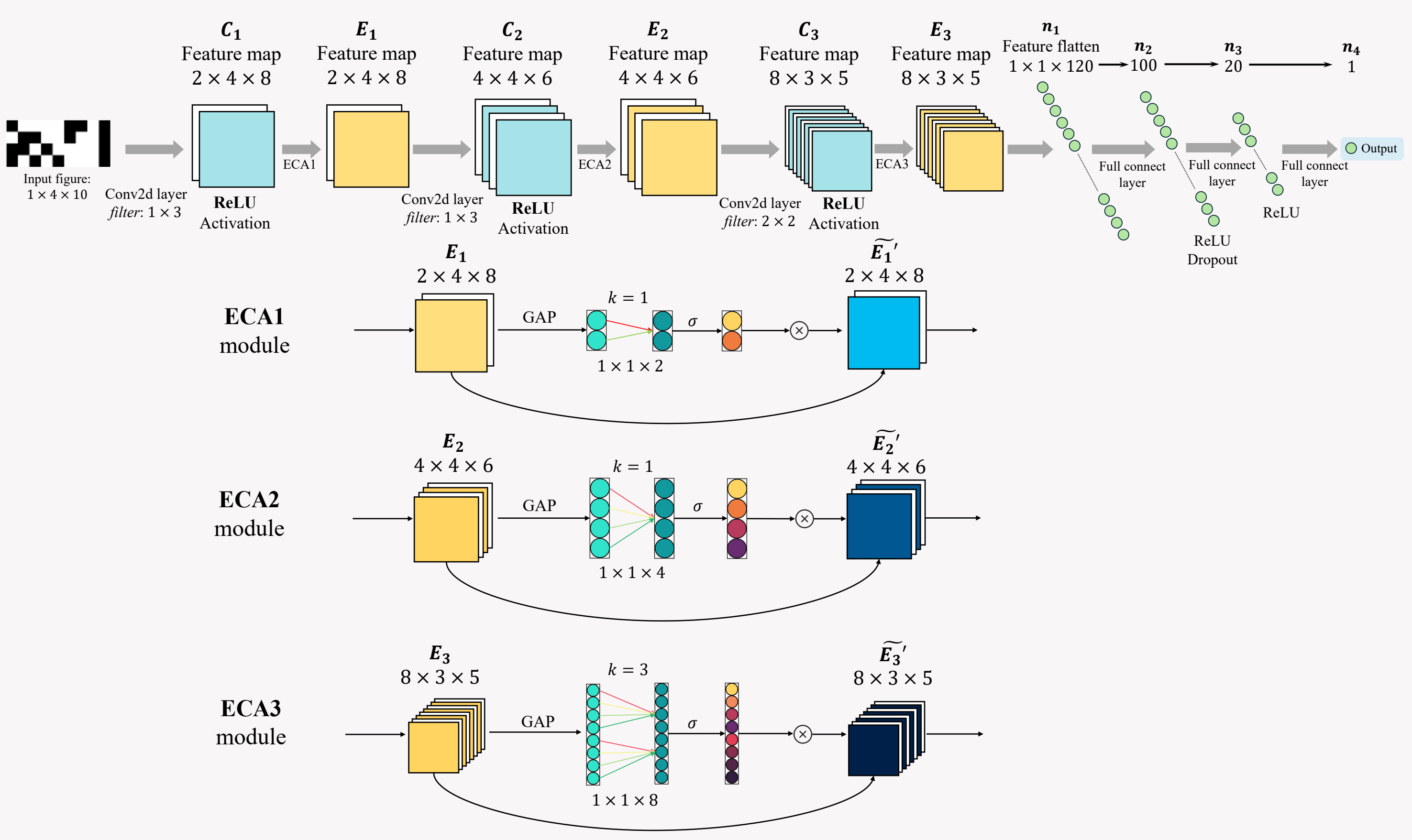
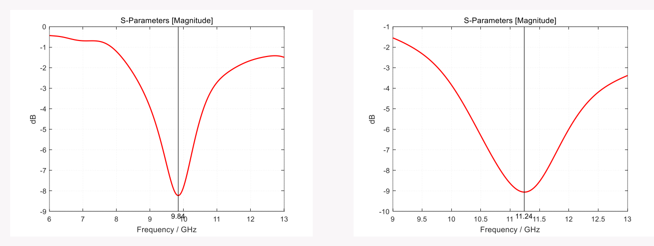


Figure 2: ICNN-ECA network structure

Simulation and Optimization

Dataset construction

- Software tools: CST Microwave Studio 2021 + MATLAB R2023b, as shown in Figure 3.
- Dataset sample size: **500 sets** (400 training/100 validation) + **20 test sets**
- Dataset parameters range: As shown in Table 1.



(a) $f_r = 9.84\ GHz$ (b) $f_r = 11.24\ GHz$

Figure 3: S11 Resonance Curves

Table 1: Parameters range

Parameter	$L(mm)$		$W(mm)$		$h(mm)$		ε_r	
	min	*max*	*min*	*max*	*min*	*max*	*min*	*max*
Range	1.24	68.66	2.7	87.51	0.5	2	2.21	6.12

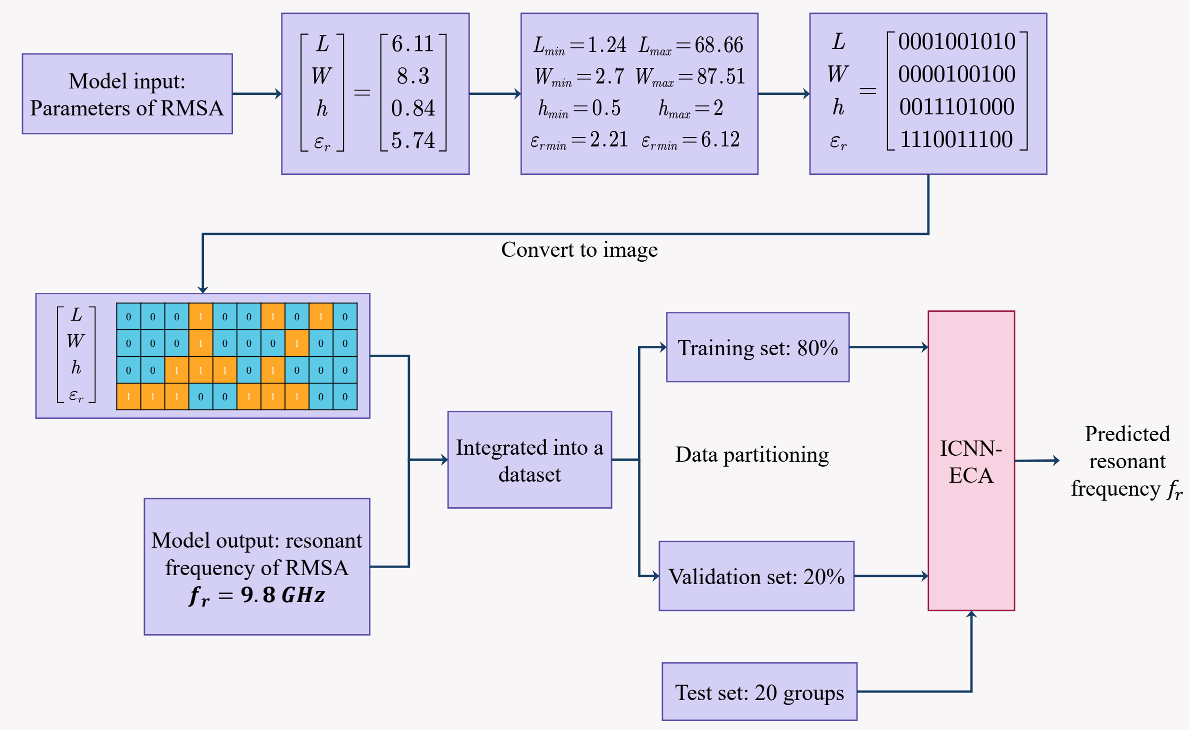


Figure 4:Flowchart of the proposed ICNN-ECA model

Network parameters

Table 2: Hyperparameter setting

Hyperparameter name	Value
batch_size	3
learning_rate	0.001
num_epochs	200
train_val_split	0.8
dropout_rate	0.1
normalization_mean	[0.5]
normalization_std	[0.5]
Optimizer	SGD

Table 3: ICNN-ECA Model Architecture Parameters

Layer Name	Input Size	Output Size	Kernel Size/ Number of Nodes	Activation Function
Convolution Layer 1	$4 \times 10 \times 1$	$4 \times 8 \times 2$	$(1,3) \times 2$	ReLU
ECA Module 1	$4 \times 8 \times 2$	$4 \times 8 \times 2$	Adaptive	Sigmoid
Convolution Layer 2	$4 \times 8 \times 2$	$4 \times 6 \times 4$	$(1,3) \times 4$	ReLU
ECA Module 2	$4 \times 6 \times 4$	$4 \times 6 \times 4$	Adaptive	Sigmoid
Convolution Layer 3	$4 \times 6 \times 4$	$3 \times 5 \times 8$	$(2,2) \times 8$	ReLU
ECA Module 3	$3 \times 5 \times 8$	$3 \times 5 \times 8$	Adaptive	Sigmoid
Flatten Layer	$3 \times 5 \times 8$	120	—	ReLU
Full Connected Layer 1	120	100	100	ReLU
Full Connected Layer 2	100	20	20	ReLU
Full Connected Layer 3	20	1	1	—

Results and Evaluation

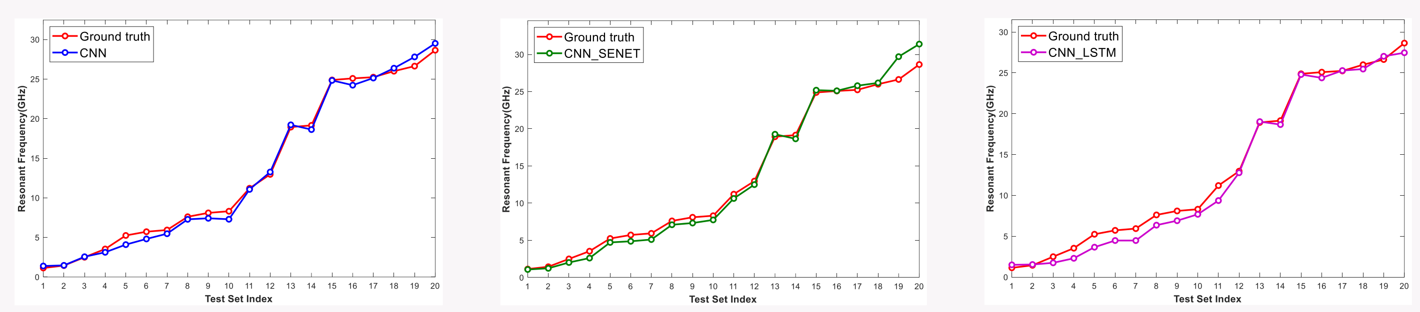
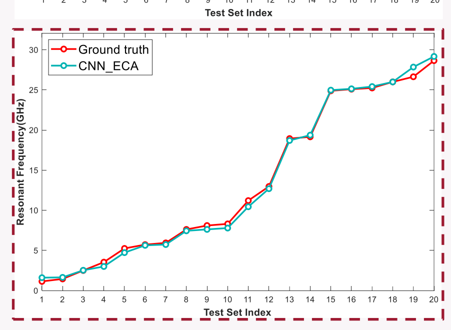


Figure 5: Resonant Frequency Prediction Comparison



Conclusions:

- **48.8% reduction** in MSE compared to baseline CNN
- Highest R^2 value of 0.9978 demonstrating **excellent fit**
- ECA mechanism enables **selective feature enhancement** for higher accuracy

Table 4: ICNN-ECA network structure

Model	MSE	MAE	RMSE	MAPE(%)	SMAPE(%)	R^2
CNN [1]	0.3848	0.4994	0.6203	4.4769	6.6819	0.9958
CNN_SENET	1.1159	0.7252	1.0564	8.3061	8.8150	0.9877
CNN_LSTM [2]	0.8901	0.7674	0.9434	12.5327	13.7422	0.9902
CNN_ECA (Ours)	**0.1971**	**0.3374**	**0.4440**	**5.9613**	**5.6914**	**0.9978**

REFERENCE

[1] H. Fu, Y. Tian, F. Meng, Q. Li, and X. Ren, "Microstrip antenna modelling based on image-based convolutional neural network," Electronics Letters, vol. 59, no. 16, p. e12910, Aug. 2023. https://doi.org/10.1049/ell2.12910

[2] Z. Zhu, Y. Tian and J. Sun, "Antenna Modeling Based on Image-CNN-LSTM," in IEEE Antennas and Wireless Propagation Letters, vol. 23, no. 9, pp. 2738-2742, Sept. 2024, doi: 10.1109/LAWP.2024.3405996.

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