

Application of Cascaded Convolutional Neural Network in Electromagnetic Imaging [†]

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[†] Presented at the 6th International Conference on Electronic Communications, Internet of Things and Big Data (ICEIB 2026), New Taipei, Taiwan, 24–26 April 2026.

Abstract

A cascaded neural network framework is developed to solve the two-dimensional inverse scattering problem under transverse magnetic wave illumination. The framework employs a multi-stage deep learning architecture in which each sub-network iteratively refines the reconstruction from the previous stage. The framework enhances image resolution and structural accuracy. The cascaded design is adopted to address the inherent nonlinearity and ill-posedness of the problem, particularly when reconstructing high-contrast and geometrically complex dielectric objects. Numerical simulation results showed the effectiveness and superior performance of the framework in terms of structural similarity index and root-mean-square error when compared with a convolutional neural network. The framework's cascaded architecture enables robust and high-fidelity reconstructions even under significant measurement noise.

Keywords: electromagnetic imaging; cascaded convolutional neural network; multi-stage deep learning; inverse scattering problem

1. Introduction

Electromagnetic inverse scattering is a fundamental but challenging problem in imaging technology for non-destructive evaluation. It is used to reconstruct the spatial distribution of dielectric properties from scattered field measurements under limited and noisy observation conditions. Traditional iterative methods have been applied to solve this problem. While these physics-based schemes maintain interpretability, they suffer from high computational cost. Slow convergence and degraded performance also hinder their application in high-contrast or strongly nonlinear regimes. In addressing these problems, data-driven approaches using deep learning show promising capabilities in accelerating inverse scattering and improving reconstruction accuracy.

Therefore, a cascaded convolutional neural network (CNN) has been introduced for electromagnetic inverse scattering (EMIS), in which each stage progressively refines the output of the previous one to enhance image resolution. The cascaded CNN shows a superior reconstruction accuracy and robustness to noise compared to traditional iterative methods and single-pass networks, while significantly reducing computational time [1]. A learning-assisted inversion method is also used to employ physics-informed inputs and a



Academic Editors: Teen-Hang Meen, Shu-Han Liao and Cheng-Fu Yang

Published: 9 October 2026

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self-attention-enhanced pix2pix generative adversarial network (GAN) to reconstruct complex scatterers. This method improves accuracy, robustness, and generalization compared with those of conventional iterative techniques and purely data-driven models [2]. A deep learning framework with a conditional deep convolutional generative adversarial network for EMIS (CDCGAN-EMIS) is employed to address EMIS problems with high-contrast targets. Numerical results show that CDCGAN-EMIS can reconstruct high-contrast dielectric profiles with good accuracy, demonstrating its potential for nonlinear inverse scattering [3]. Du et al. proposed a physics-assisted deep learning scheme for EMIS with a module that integrates a global self-attention layer with conventional convolutional layers to better capture global and local features in multiple scattering. The deep latent sparse Gaussian process used in the study shows a high reconstruction accuracy and strong generalization across synthetic, noisy, and experimental datasets, confirming the effectiveness of the globally perceptive module in capturing multiple scattering effects [4].

2. Cascaded CNN

To address the nonlinearity and ill-posedness of EMIS problems, we developed a cascaded CNN architecture that progressively refines an initial reconstruction through multiple learning stages. Its framework is shown in Figure 1. In each refinement stage in the cascaded network of an encoder–decoder architecture, convolutional layers conduct batch normalization and rectified linear unit activations. Downsampling is performed using max-pooling in the encoder, whereas upsampling in the decoder is achieved using transposed convolutions. Skip connections between corresponding encoder and decoder layers are used to preserve spatial detail, and a residual connection adds the input of each stage to its output, allowing the network to focus on learning residual corrections.

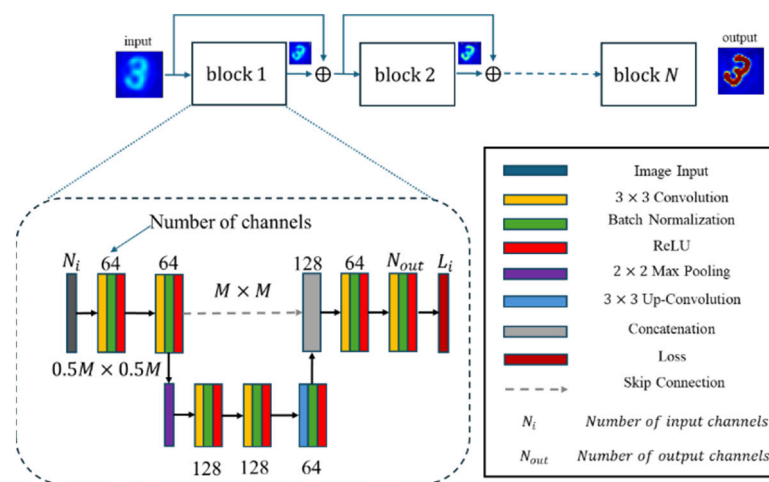


Figure 1. Cascaded CNN framework.

By cascading multiple refinement stages, the developed framework progressively improves the reconstruction result rather than directly generating the final image in a single step. This multi-stage design is well-suited for EMIS, where the reconstruction process is sensitive to measurement noise, limited observation data, and modeling uncertainty. In such cases, a single-stage network might have difficulty in recovering global structures and fine local details simultaneously. In contrast, the cascaded framework enables the network to perform correction step-by-step, so that reconstruction artifacts can be gradually suppressed and the target profile can be iteratively refined.

In each stage, the encoder is responsible for extracting hierarchical feature representations from the current reconstruction. Through repeated convolution and pooling operations, the network in each stage captures low-level spatial features and high-level

semantic information. The decoder restores the spatial resolution and reconstructs the refined image based on the learned feature maps. The skip connections compensate for the information loss caused by downsampling, since they enable the transfer of shallow-layer features to the decoding path. This helps preserve boundary information and improves the recovery of fine-scale structures in the reconstructed image.

The residual connection in each stage improves learning efficiency by encouraging the subnet to estimate only the discrepancy between the current reconstruction and the desired output. Instead of relearning the entire image content, in each stage, the remaining errors are corrected from the previous stage. Such a residual refinement mechanism conducts network optimization and enhances reconstruction stability and accuracy. Therefore, the Cascaded-CNN is an effective and practical framework for progressively improving the quality of EMIS reconstructions. In this study, the k -th refinement module is established for supervision by embedding the physics of transverse magnetic (TM)-polarized scattering into the label construction. The corresponding target permittivity distribution is given as follows:

$$\varepsilon_z^{r,k} = F_{TM}^H \cdot \left[M_z^s \circ \left(F_{TM} \cdot \left(\bar{\varepsilon}_z - \tau_z^b \right) \right) \right] + \tau_z^b \quad (1)$$

where F_{TM} denotes the discretized forward scattering operator under TM polarization, and F_{TM}^H denotes its Hermitian transpose, namely, the adjoint operator. In this equation, F_{TM} is used to map the permittivity contrast with respect to the background τ_z^b into the corresponding scattered-field representation, whereas F_{TM}^H transfers the modulated field response back to the reconstruction domain. M_z^s denotes the stage-dependent modulation term and $\circ$ represents the Hadamard product. Hence, the operator pair F_{TM} and F_{TM}^H lead to the establishment of a physics-consistent transformation between the image domain and the scattering domain so that the supervisory label for each refinement stage is not imposed as a purely image-level target. Instead, it is derived under the physical mechanism of TM-wave interaction. This equation is used to ensure that the target label at each refinement stage preserves physical consistency with the underlying scattering process.

In contrast to enforcing all subnetworks to regress toward the final dielectric profile, the developed framework enables intermediate supervision that is explicitly constrained by the forward-adjoint scattering model. As a result, each refinement module learns a physically meaningful correction with respect to the current estimate to improve the stability of the cascaded optimization and enhance the interpretability of the refinement process. The loss function for the k -th refinement module is defined as:

$$L_k = \sum_{i=1}^N \left(\varepsilon_i^{r,k'} - \varepsilon_i^{r,k} \right)^2 \quad (2)$$

The overall training objective is formulated as:

$$L_{CaseNN} = \sum_{k=1}^{N_B} (\lambda_k \cdot L_k)^2 \quad (3)$$

where N_B denotes the number of refinement blocks and λ_k is the weighting factor for the k -th stage. This physics-guided multi-stage supervision enables each block to learn a progressively refined correction, improving the robustness and accuracy of the cascaded reconstruction framework.

3. Results

In this study, the relative permittivity values are set in a range of 1.0 to 1.5. To construct a dense electromagnetic imaging system and ensure sufficient scattering data acquisition, 32 transmitters and 32 receivers are uniformly distributed around the region of interest. To enhance simulation realism and evaluate the model's robustness under

varying noise conditions, additive Gaussian noise at a level of 5% is introduced into the measurement environment to assess noise resilience. Regarding the scatterer configuration, ten distinct permittivity distributions are considered. Each distribution is randomly applied at 50 different positions within the imaging domain, resulting in a total of 500 simulation cases (10 distributions $\times$ 50 positions). The generated dataset is split into training (80%), validation (10%), and testing (10%) subsets to ensure the generalization and stability of the learning process.

To enhance model convergence and reduce learning difficulty, an initial permittivity is computed from the measured scattered fields using the backpropagation scheme. This reconstruction serves as the input to the cascaded neural network. Then, the framework is reconstructed in various cascade depths to assess the effect of network depth on imaging accuracy. Figure 2 shows the reconstruction results for an inhomogeneous L-shaped dielectric object under 5% Gaussian noise. Table 1 presents the quantitative reconstruction results for inhomogeneous dielectric objects under 5% Gaussian noise.

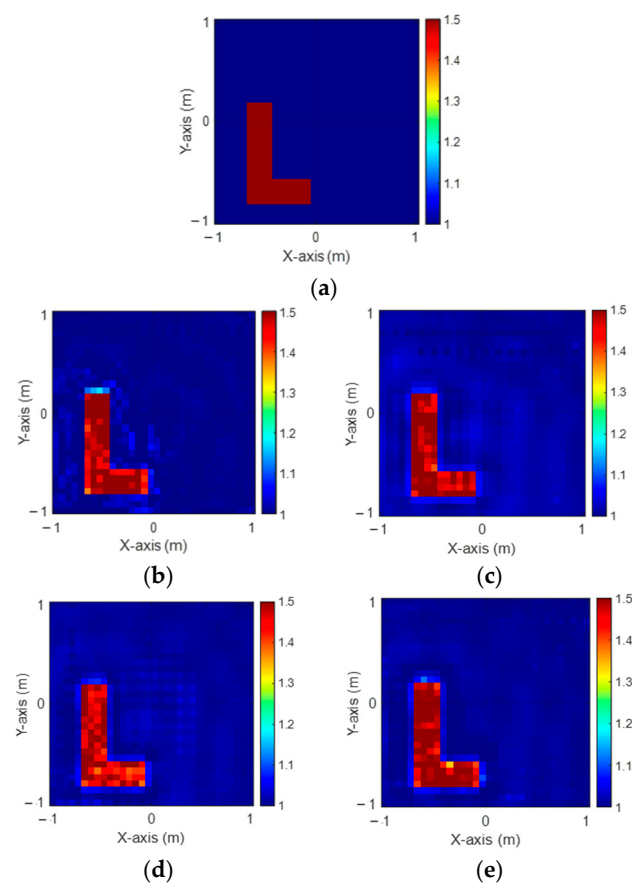


Figure 2. Reconstruction. results for inhomogeneous dielectric objects under 5% Gaussian noise: (a) Ground truth; (b) CNN; (c) 2 layers; (d) 3 layers; (e) 4 layers.

Table 1. Comparison of structural similarity index measure (SSIM) and root mean square error (RMSE) for inhomogeneous dielectric object reconstruction under 5% Gaussian noise using different methods.

Performance		CNN	2 Layers	3 Layers	4 Layers
ϵ_z	RMSE	4.169%	3.7766%	3.5781%	5.6897%
	SSIM	92.7456%	94.2629%	95.3766%	89.8461%

4. Conclusions

A cascaded convolutional neural network framework is developed in this study to solve the EMIS problem and enhance robustness and reconstruction accuracy. By taking the initial permittivity estimate generated from the backpropagation scheme as input, the framework refines the solution through multiple cascaded CNNs. Its coarse-to-fine architecture enables hierarchical feature enhancement to mitigate the ill-posedness of the inversion problem. Experimental results on homogeneous dielectric objects showed that the framework significantly improved reconstruction quality under moderate noise levels. By increasing the number of cascaded stages, high structural fidelity and reduced errors were achieved, showing the effectiveness of the refinement strategy of the framework. It also shows strong resilience against measurement noise by generalizing to different object distributions. The framework can be expanded to 3D problems by integrating physics-informed constraints explicitly and validating the approach under experimental measurement scenarios.

The enhanced effectiveness of the framework is attributed to its progressive refinement mechanism, in which each cascaded stage improves the intermediate reconstruction obtained from the previous stage. The design enables the network to gradually reduce residual errors and suppress reconstruction artifacts, not relying on a single direct mapping from the initial estimate to the final result. As a result, the framework is well-suited to handle the nonlinearity and instability that commonly arise in EMIS problems.

Another important feature of the developed framework is the backpropagation scheme used for the initialization of the cascaded network. Since the initial estimate already contains coarse information about the target profile, the CNN does not need to learn the entire inversion process from scratch. Instead, it refines structural details to compensate for missing information and maintain the consistency between the reconstructed permittivity distribution and the ground truth. This hybrid design with a physics-based initialization and data-driven refinement serves as a practical and effective framework for electromagnetic imaging.

The cascaded architecture offers an advantage in reconstruction performance as the number of refinement stages increases. Multi-stage learning is beneficial for recovering more accurate object profiles, especially in cases where the initial reconstruction suffers from blurred boundaries or incomplete dielectric contrast information. Therefore, the framework improves reconstruction accuracy and is flexible to be extended to other challenging inverse scattering scenarios. By introducing complicated dielectric distributions and uncertainties, the applicability of the framework can be expanded in realistic imaging problems.

Author Contributions: Methodology, T.-H.K.; software, J.-Y.L.; validation, T.-Y.L.; formal analysis, T.-H.K.; investigation, J.-Y.L.; resources, T.-Y.L.; data curation, T.-Y.L.; writing—original draft preparation, P.-H.C.; writing—review and editing, C.-C.C.; visualization, J.-Y.L.; supervision, T.-H.K.; project administration, C.-C.C.; funding acquisition, P.-H.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Science and Technology Council Taiwan, grant number 115-2222-E-032-001-MY2.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding authors.

Conflicts of Interest: The authors declare no conflict of interest.

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