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Supplementary Note S1 Principle and Simulation of SSPP transmission line

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The design of the SSPP transmission line begins with the determination of unit cell dimensions, which critically govern both the stopband frequency and the dispersion characteristics. In periodic electromagnetic structures, the dispersion relation defines the relationship between the propagation constant and the operating frequency, thereby characterizing the phase variation accumulated within each unit cell. This frequency-dependent phase behavior is the fundamental mechanism of the sensing capability of the proposed transmission line.

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To identify the optimal transmission line topology for frequency-diverse sensing, we compared the dispersion characteristics of three commonly employed planar waveguide structures. As shown in Fig. S1, these three structures exhibit different dispersion curves. The microstrip line and CPW exhibit relatively flat dispersion characteristics with limited frequency-dependent phase variation, which restricts their sensitivity in broadband sensing applications. In contrast, the SSPP transmission line offering enhanced phase sensitivity across the frequency band.

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A key advantage of the SSPP transmission line lies in the tunability of its dispersion properties through geometric parameter adjustments. Specifically, the dispersion curve can be tailored by varying either the stub length ($L7$) or the structural periodicity. As illustrated in Fig. S2, increasing $L7$ lowers the stopband frequency while simultaneously increasing the rate of phase variation within the passband. However, a flat dispersion slope is undesirable, as it compresses the usable bandwidth by shifting the stopband to lower frequencies, which would limit the operational frequency range available for sensing. Therefore, the selection of $L7$ requires a careful balance: the dispersion slope must be sufficiently flat to provide adequate phase sensitivity for sensing, yet moderate enough to preserve a practical stopband margin. Based on this consideration, a stub length of $L7 = 4$ mm was determined as the optimal value.

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The detailed geometric parameters of the SSPP unit cell and the overall transmission line layout are annotated in Extended Data Fig. 1 and Fig. S3, and the complete dimensions of both the small and large transmission line configurations are summarized in Table S1. To validate the design, we fabricated and characterized both transmission line variants. The measured S -parameter responses, including the insertion loss (S_{21}) and return loss (S_{11}), are presented in Fig. S4 and Fig. S5 for the small and large transmission lines, respectively. The experimental results confirm that both designs exhibit the expected passband behavior and stopband characteristics consistent with the full-wave simulation predictions, thereby verifying the accuracy of the design methodology.

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Table S1. Geometric parameters of the small and large device configurations.

Parameter	Small	Large
$L1$	120 mm	260 mm
$L2$	55 mm	
$L3$	30 mm	
$L4$	3 mm	
$L5$	0.2 mm	
$L6$	2 mm	
$L7$	4 mm	5 mm
D	14 mm	50 mm

Supplementary Note S2 Derivation of the two-dimensional sensing kernel

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The main text introduces the one-dimensional (1D)-to-two-dimensional (2D) sensing model in a compact matrix form. Here we provide the intermediate steps and clarify the assumptions underlying the derivation. The model is based on a weak-scattering approximation, in which reflections induced at different positions add coherently at the input port and multiple reflections between perturbations are neglected. We also assume that the background transmission line is impedance matched, so that terminal reflections are either negligible or removed by background calibration. For clarity, propagation loss is omitted in the phase factor below; for a lossy line, $\exp[-2j\beta(\omega)s]$ can be replaced by $\exp[-2\gamma(\omega)s]$, where $\gamma(\omega) = \alpha_{\text{line}}(\omega) + j\beta(\omega)$.

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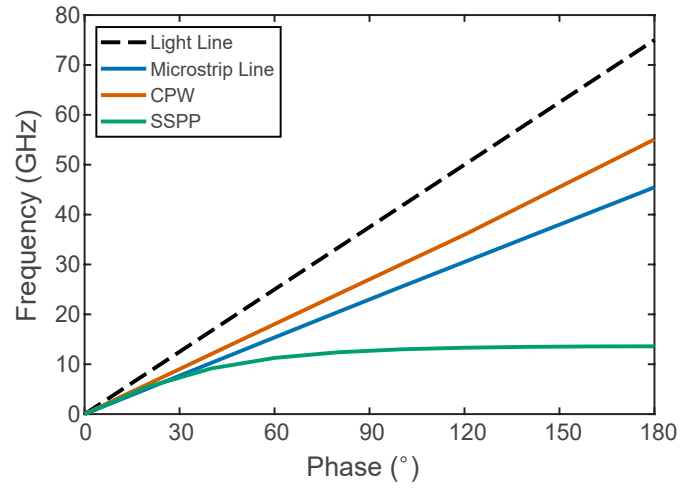


Figure S1. Comparison of dispersion curve when using different structure in same unit period.

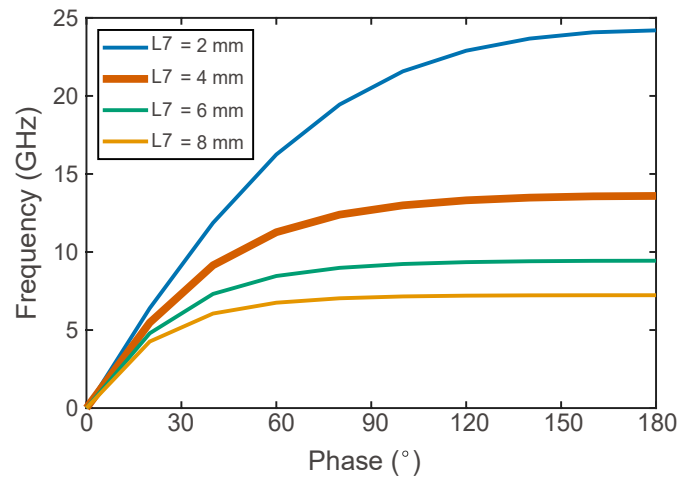


Figure S2. Simulated results of dispersion curve when SSPP have different L_{spp} .

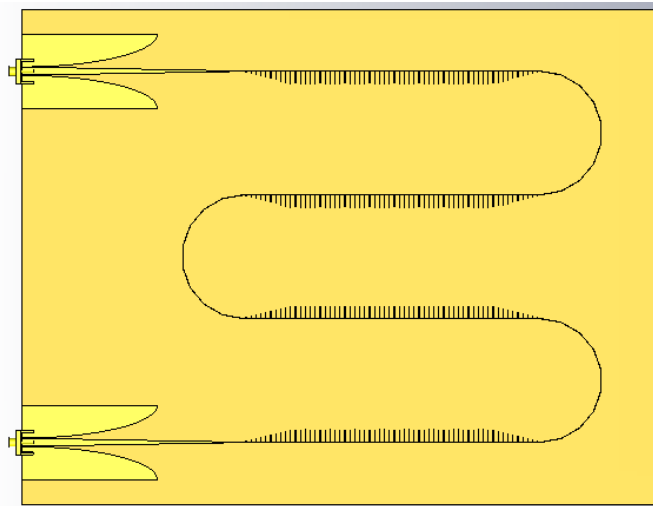


Figure S3. Design of large SSPP transmission line.

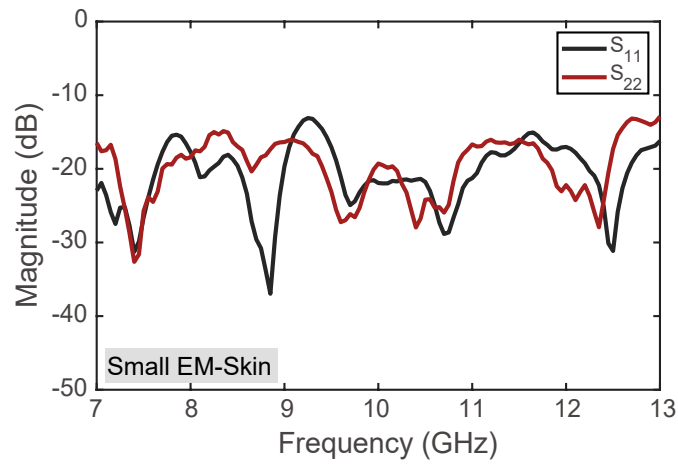


Figure S4. Measured S-parameter results of small transmission line.

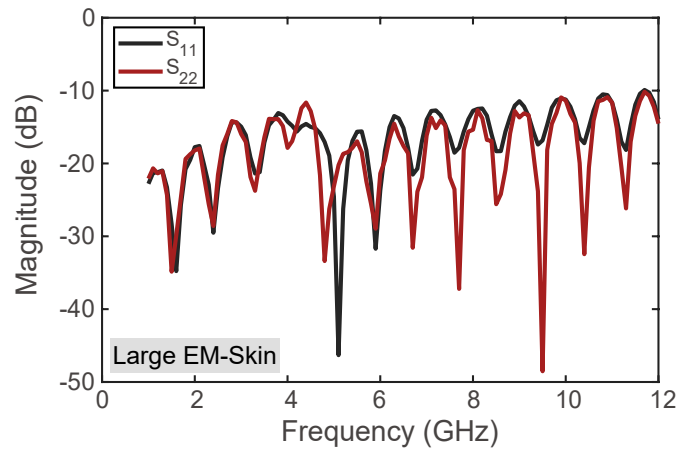


Figure S5. Measured S-parameter results of large transmission line.

We first consider a 1D propagation coordinate s , measured along the routed transmission path from the input port. Under the weak-scattering approximation, the input reflection coefficient can be written as

$$\Gamma_{\text{in}}(\omega) \simeq \int_0^L r(s) \exp[-2j\beta(\omega)s] ds, \quad (\text{S1})$$

where $r(s)$ is the spatial reflection density induced along the line. The exponential term represents the round-trip phase accumulated by a wave that propagates from the input port to position s and then returns to the input port.

Discretizing the routed line into M segments gives

$$\Gamma_{\text{in}}(\omega) \simeq \sum_{m=1}^M r_m \exp[-2j\beta(\omega)s_m] \Delta s_m, \quad (\text{S2})$$

where $r_m = r(s_m)$, s_m is the cumulative propagation coordinate of the m th segment, and Δs_m is the segment length. If the reflection spectrum is sampled at frequencies ω_ℓ , Eq. S2 can be written in matrix form as

$$\Gamma \simeq \mathbf{A} \mathbf{r}, \quad (\text{S3})$$

with

$$A_{\ell m} = \exp[-2j\beta(\omega_\ell)s_m] \Delta s_m. \quad (\text{S4})$$

This 1D model relates the measured reflection spectrum to the reflection density along the propagation path.

To extend this model to 2D sensing, we express the effective reflection density on each line segment as the perturbation induced by objects distributed over the sensing plane. The plane is discretized into N candidate points with coordinates (x_p, y_p) , local object-induced response density q_p , and associated area element ΔA_p . The m th routed line segment is located at (X_m, Y_m) in the sensing plane. The in-plane distance between surface point p and line segment m is

$$d_{mp} = \sqrt{(x_p - X_m)^2 + (y_p - Y_m)^2}. \quad (\text{S5})$$

For a fixed object height above the sensing plane, the vertical offset is constant and can be absorbed into the calibration of the coupling strength. More generally, d_{mp} can be replaced by the corresponding three-dimensional distance.

We describe the near-field coupling between surface point p and line segment m using a phenomenological distance-decay weight,

$$W_{mp} = \exp(-\alpha d_{mp}), \quad (\text{S6})$$

where $\alpha > 0$ is an effective decay constant. This exponential form provides a compact description of evanescent near-field attenuation. In practice, W_{mp} can also be replaced by a simulated or experimentally calibrated coupling function without changing the linear structure of the model.

The effective reflection density induced at line segment m is then written as the superposition of contributions from all surface points:

$$r_m^{\text{eff}} = \sum_{p=1}^N q_p W_{mp} \Delta A_p. \quad (\text{S7})$$

Here, $q_p \Delta A_p$ represents the area-integrated perturbation associated with point p , and proportionality factors associated with the object polarizability and local field normalization are absorbed into q_p or the calibrated coupling weight.

Substituting Eq. S7 into the discretized 1D propagation model in Eq. S2 yields

$$\Gamma_{\text{in}}(\omega) \simeq \sum_{m=1}^M \left(\sum_{p=1}^N q_p W_{mp} \Delta A_p \right) \exp[-2j\beta(\omega)s_m] \Delta s_m. \quad (\text{S8})$$

Because the sums are finite, their order can be interchanged:

$$\Gamma_{\text{in}}(\omega) \simeq \sum_{p=1}^N q_p \left[\Delta A_p \sum_{m=1}^M W_{mp} \exp[-2j\beta(\omega)s_m] \Delta s_m \right]. \quad (\text{S9})$$

We therefore define the geometry-dependent sensing kernel for surface point p as

$$K_p(\omega) = \Delta A_p \sum_{m=1}^M W_{mp} \exp[-2j\beta(\omega)s_m] \Delta s_m. \quad (\text{S10})$$

Using the explicit distance-decay form of W_{mp} gives

$$K_p(\omega) = \Delta A_p \sum_{m=1}^M \exp\left[-\alpha\sqrt{(x_p - X_m)^2 + (y_p - Y_m)^2}\right] \exp[-2j\beta(\omega)s_m] \Delta s_m. \quad (\text{S11})$$

The measured reflection coefficient can then be expressed as a linear superposition over the 2D sensing plane:

$$\Gamma_{\text{in}}(\omega) \simeq \sum_{p=1}^N K_p(\omega) q_p. \quad (\text{S12})$$

After sampling the reflection spectrum at frequencies ω_ℓ , Eq. S12 becomes

$$\Gamma_\ell \simeq \sum_{p=1}^N K_{\ell p} q_p, \quad (\text{S13})$$

where

$$K_{\ell p} = \Delta A_p \sum_{m=1}^M \exp\left[-\alpha\sqrt{(x_p - X_m)^2 + (y_p - Y_m)^2}\right] \exp[-2j\beta(\omega_\ell)s_m] \Delta s_m. \quad (\text{S14})$$

In matrix form, this relation is

$$\Gamma \simeq \mathbf{K}q, \quad (\text{S15})$$

where Γ contains the measured reflection coefficients at different frequencies, q is the discretized 2D object-induced response distribution, and $\mathbf{K}$ is the sensing matrix determined by the routed-line geometry, the near-field coupling weights and the propagation phase.

For dual-port measurements, the same derivation applies to each port. If $s_m^{(1)}$ and $s_m^{(2)}$ denote the propagation coordinates of segment m measured from port 1 and port 2, respectively, then the corresponding kernels are

$$K_{\ell p}^{(a)} = \Delta A_p \sum_{m=1}^M W_{mp} \exp[-2j\beta(\omega_\ell)s_m^{(a)}] \Delta s_m, \quad a \in \{1, 2\}. \quad (\text{S16})$$

For a reciprocal line with total path length L , one may take $s_m^{(1)} = s_m$ and $s_m^{(2)} = L - s_m$. The background-subtracted dual-port measurements can then be stacked as

$$\begin{bmatrix} \Delta S_{11} \\ \Delta S_{22} \end{bmatrix} \simeq \begin{bmatrix} \mathbf{K}^{(1)} \\ \mathbf{K}^{(2)} \end{bmatrix} q. \quad (\text{S17})$$

This stacked formulation combines perturbation information collected from opposite propagation directions, which helps compensate for attenuation and improves spatial coverage across the sensing plane.

The kernel $\mathbf{K}$ therefore provides a physical forward model for understanding how a perturbation on the sensing plane is encoded into the measured reflection spectrum. The distance-dependent weight W_{mp} describes how a perturbation at a 2D surface point is projected onto nearby line segments through near-field coupling, whereas the phase factor $\exp[-2j\beta(\omega_\ell)s_m]$ describes the round-trip phase accumulated along the routed 1D propagation path. Frequency diversity changes this phase term and produces complementary spectral encodings of the same spatial perturbation distribution.

In the experiments, however, we do not explicitly invert the analytical matrix $\mathbf{K}$ for localization. The simplified kernel omits practical non-idealities, including fabrication tolerances, frequency-dependent loss, port mismatch, finite object size and deviations of the near-field coupling from a simple exponential decay. Instead, $\mathbf{K}$ serves as a physical interpretation of the sensing mechanism, while the actual localization is performed by a neural network trained on calibrated differential spectra. This data-driven inverse model learns the effective mapping from the measured dual-port response,

$$\begin{bmatrix} \Delta S_{11} \\ \Delta S_{22} \end{bmatrix}, \quad (\text{S18})$$

to the object coordinates. For a localized object, the trained network identifies the position whose calibrated spectral signature best matches the measured response.

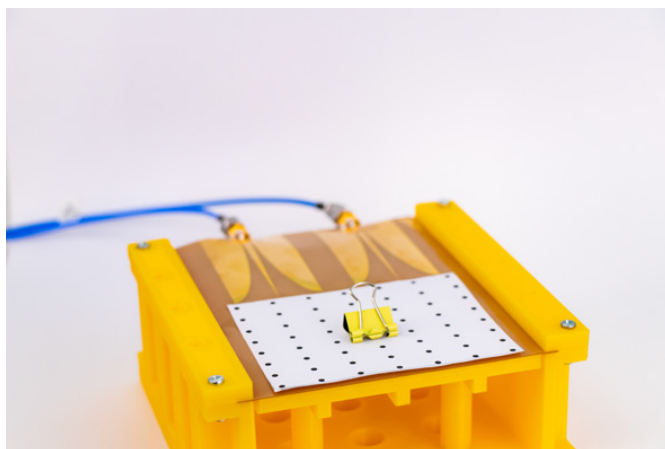


Figure S6. Object classification demonstration.

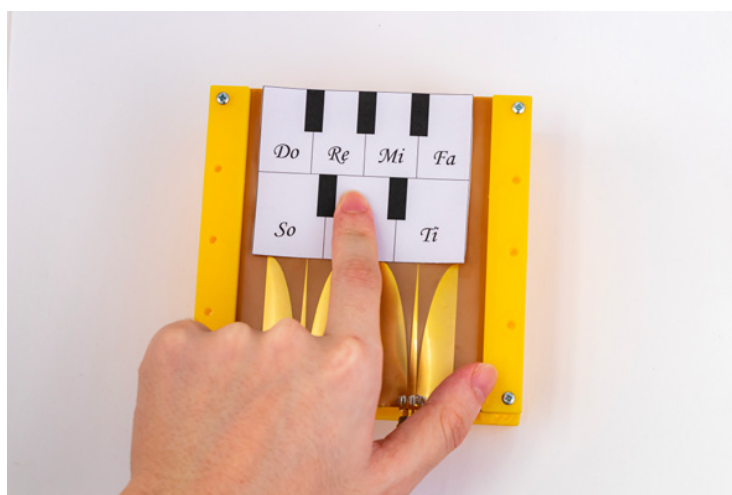


Figure S7. Piano application demonstration.

Supplementary Note S3 Neural network architecture search strategy.

To identify the optimal width and depth of each branch MLP and the fusion MLP, we employed a constrained neural architecture search strategy based on validation-set performance. Specifically, the architecture search was implemented using the Optuna framework, with a Tree-structured Parzen Estimator sampler used to generate candidate network architectures. For the branch MLPs, the search variables included the branch depth, branch output dimension, and the widths of intermediate hidden layers determined by scaling factors. A monotonically non-increasing width constraint was imposed to ensure the structural stability of the branch networks. For the fusion MLP, the width of the first layer was determined by scaling the concatenated feature dimension from the four branches, while the widths of subsequent layers were progressively reduced through consecutive scaling factors. A minimum tail width was further constrained to prevent excessive compression of the feature representation.

Each candidate architecture was trained under identical training settings, with the two-dimensional RMSE on the validation set used as the optimization objective. During training, the validation error was periodically reported to the architecture search algorithm, and poorly performing candidates were terminated early using a median-pruning strategy, thereby reducing the computational cost of unpromising trials. Compared with manual tuning or exhaustive search, this strategy adaptively explores more promising architectural regions based on the validation performance of previous trials, thereby improving search efficiency. Finally, by imposing constraints on network depth, width variation, and tail dimensionality, the proposed search strategy effectively avoids impractically large or overly narrow architectures, enhancing model expressiveness while maintaining training stability and generalization performance.

Supplementary Note S4 Simulation of the localization capability of EM-skin systems with different sizes

In the experiment for evaluating the scalability of our 2D sensing system, we established the dataset by simulating the S-parameters at the same spatial location under different SSPP-line lengths and interline gaps D . This simulation was performed using CST Studio Suite. Because these simulations are highly time-consuming, only 25 sample points could be simulated for each design. These sample points correspond to a $5\text{ mm} \times 5\text{ mm}$ region at the center of the transmission line. Since the simulated data represent ideal, noise-free measurement results, we measured the noise level in the VNA-acquired experimental data and added it to our dataset to emulate the localization capability of the sensing system under realistic conditions and different designs. For this small-sample regression task, we adopted a ridge-regression-based algorithm. Owing to the highly limited number of samples, we used a leave-one-out strategy for dataset splitting and trained the model with 100 different random seeds. Finally, the mean prediction error of each point was used to represent the localization capability under the corresponding dataset.

Supplementary Note S5 Object Classification Error Analysis.

During object classification, we observed an interesting phenomenon. Whether XGBoost was trained only on non-metallic objects or jointly on all objects, the largest classification error consistently occurred between the ceramic cat and the tennis ball. Specifically, the tennis ball was misclassified as the ceramic cat with a probability of 27%, as shown in Fig. 5b. This observation was initially puzzling, as these two objects are not intuitively similar. However, by observing Supplementary Fig. S14, we found that they have similar contact areas with the transmission line, and both contact regions are approximately circular. In addition, both objects are made of non-metallic materials. Therefore, from the perspective of transmission-line-based sensing, their measured responses can indeed exhibit similarity, even though their three-dimensional shapes are different.

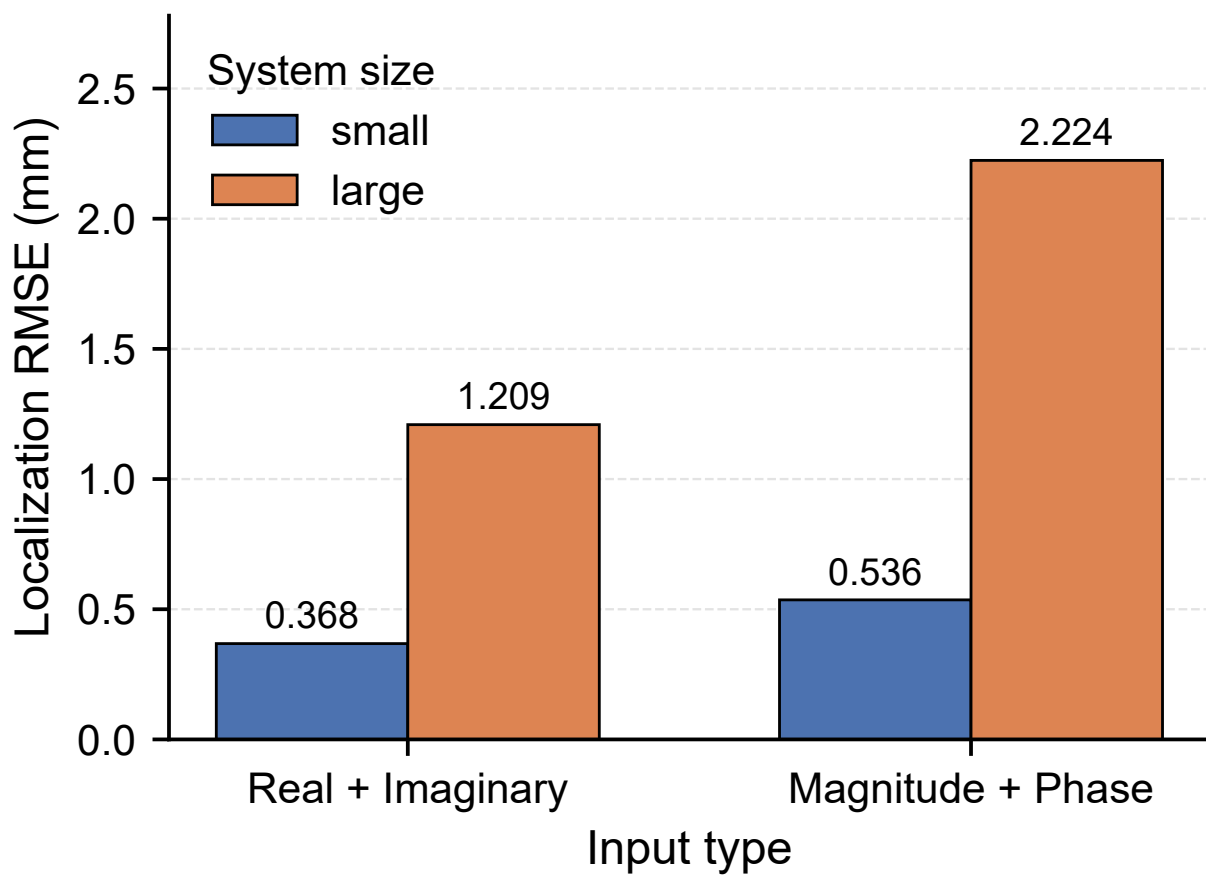


Figure S8. Localization errors exhibited by neural networks trained with different input types.

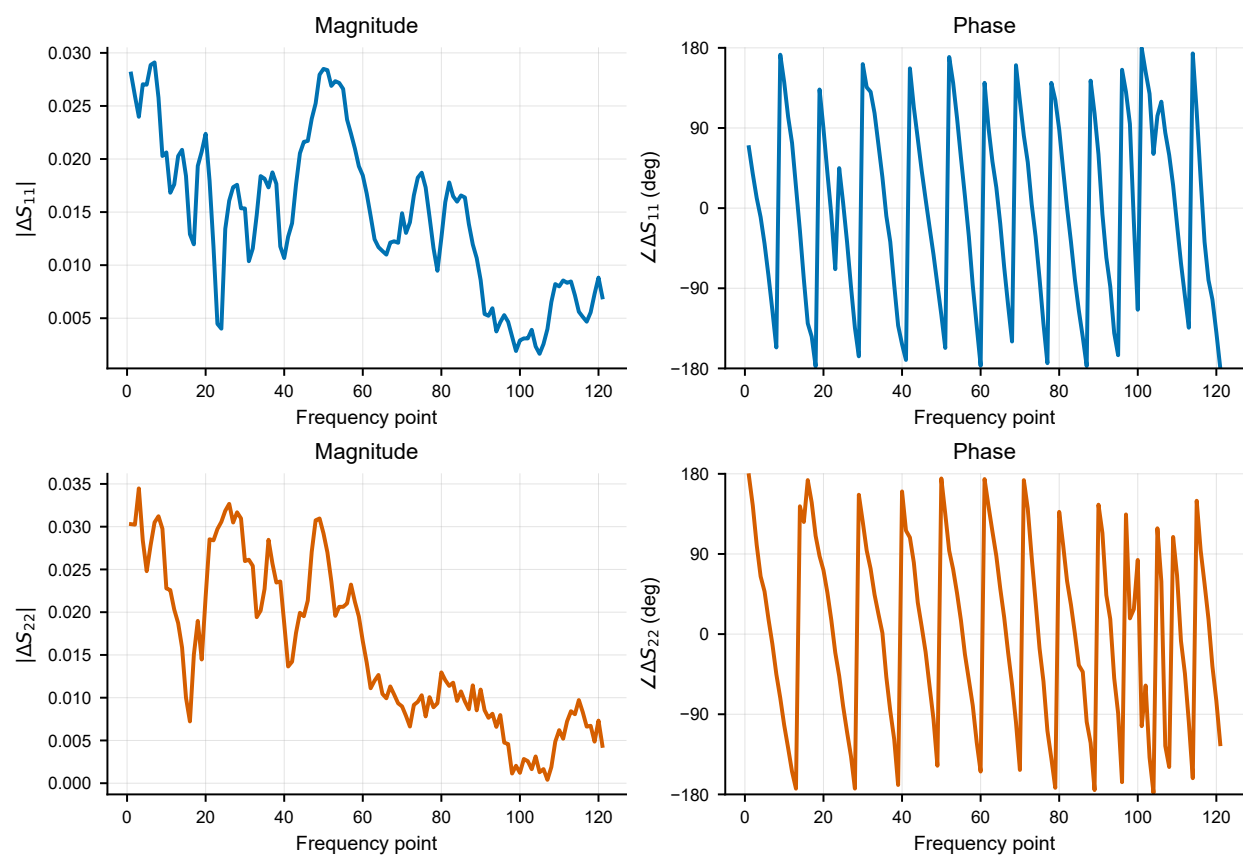


Figure S9. Visualization of ΔS_{11} and ΔS_{22} in terms of magnitude and phase.

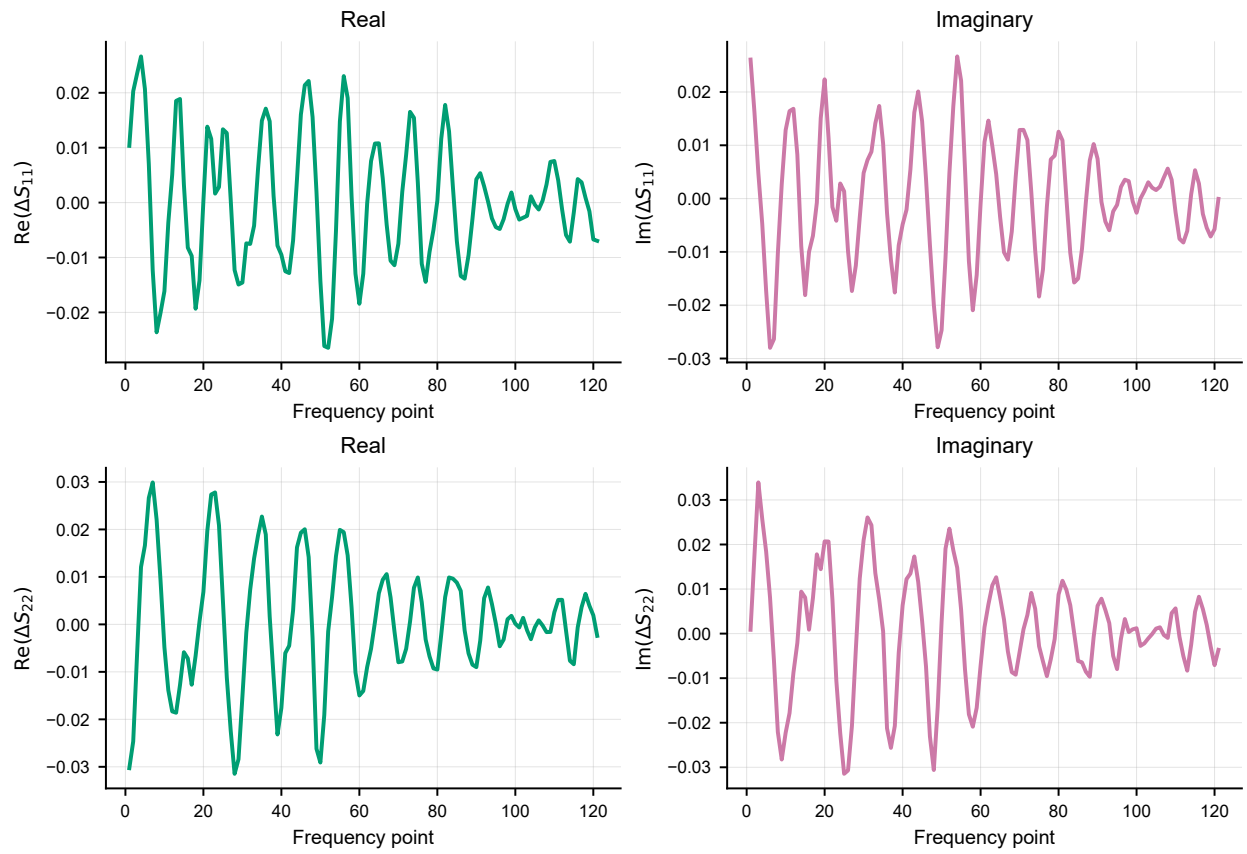


Figure S10. Visualization of ΔS_{11} and ΔS_{22} in terms of real component and imaginary component.

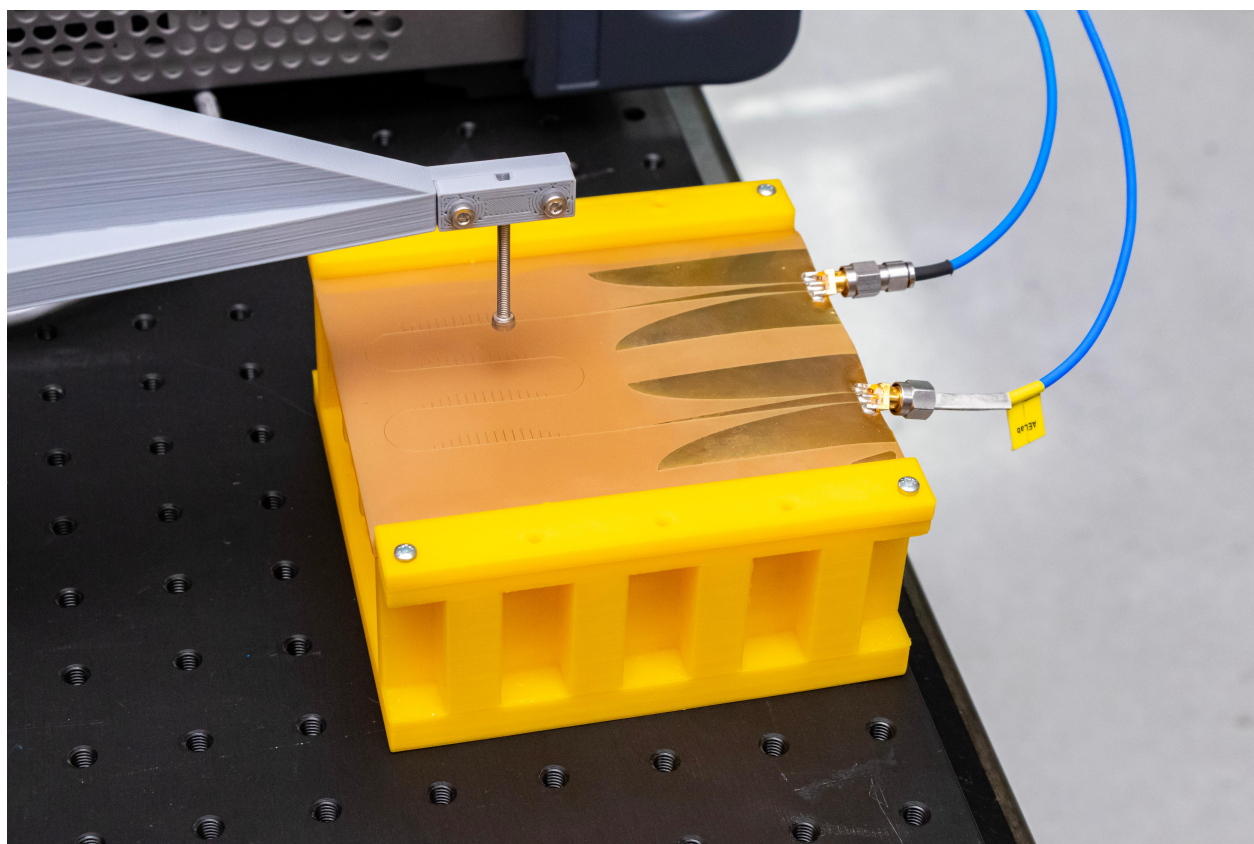


Figure S11. Experimental photos taken during dataset creation.

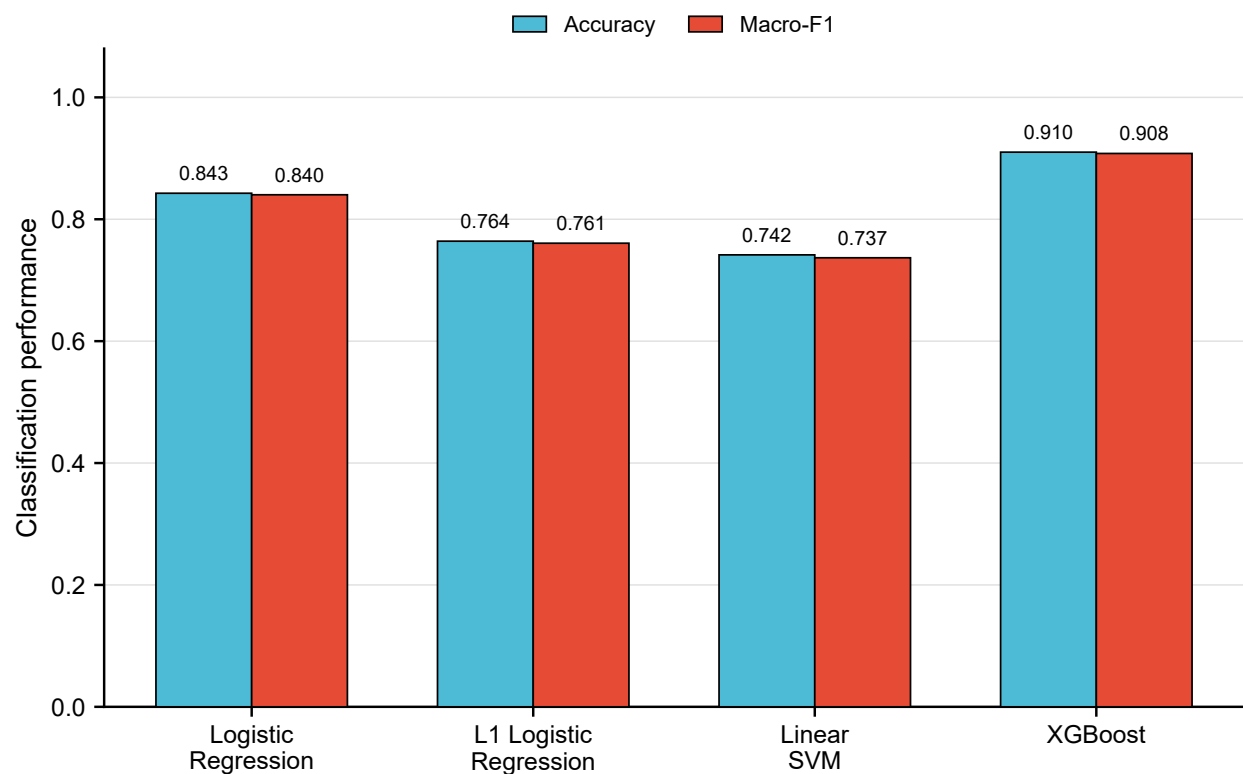


Figure S12. Comparison of classification performance among different algorithms for daily-life object categories.

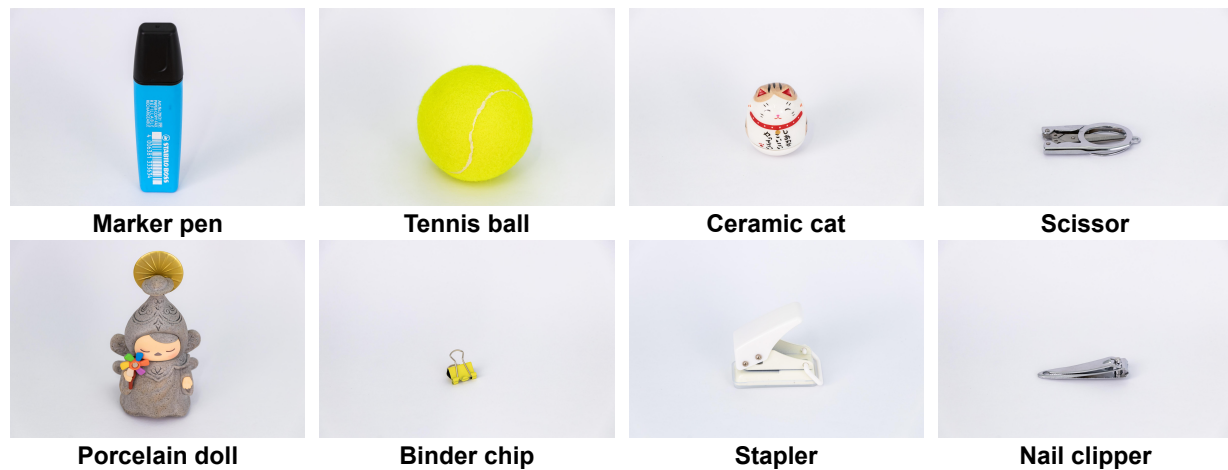


Figure S13. List of daily objects

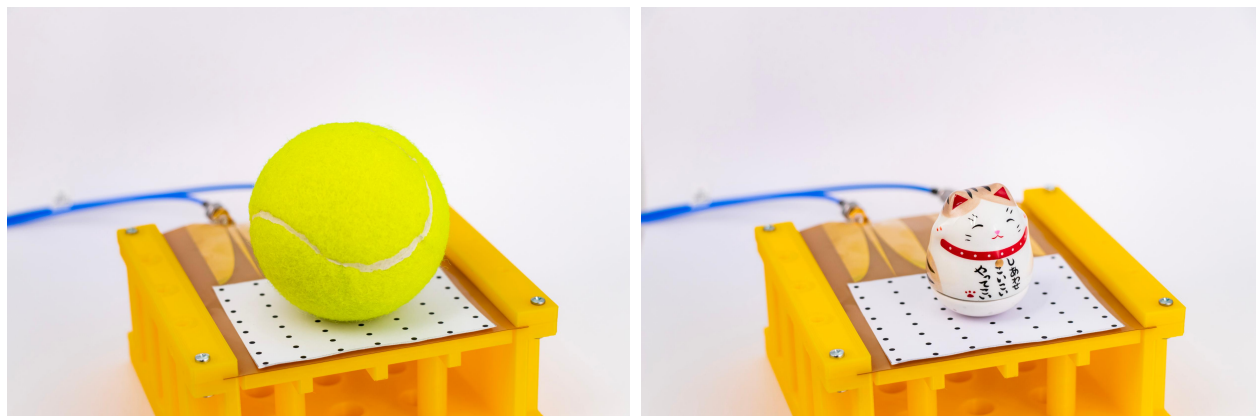


Figure S14. Photos for ceramic cat and tennis ball during experiment

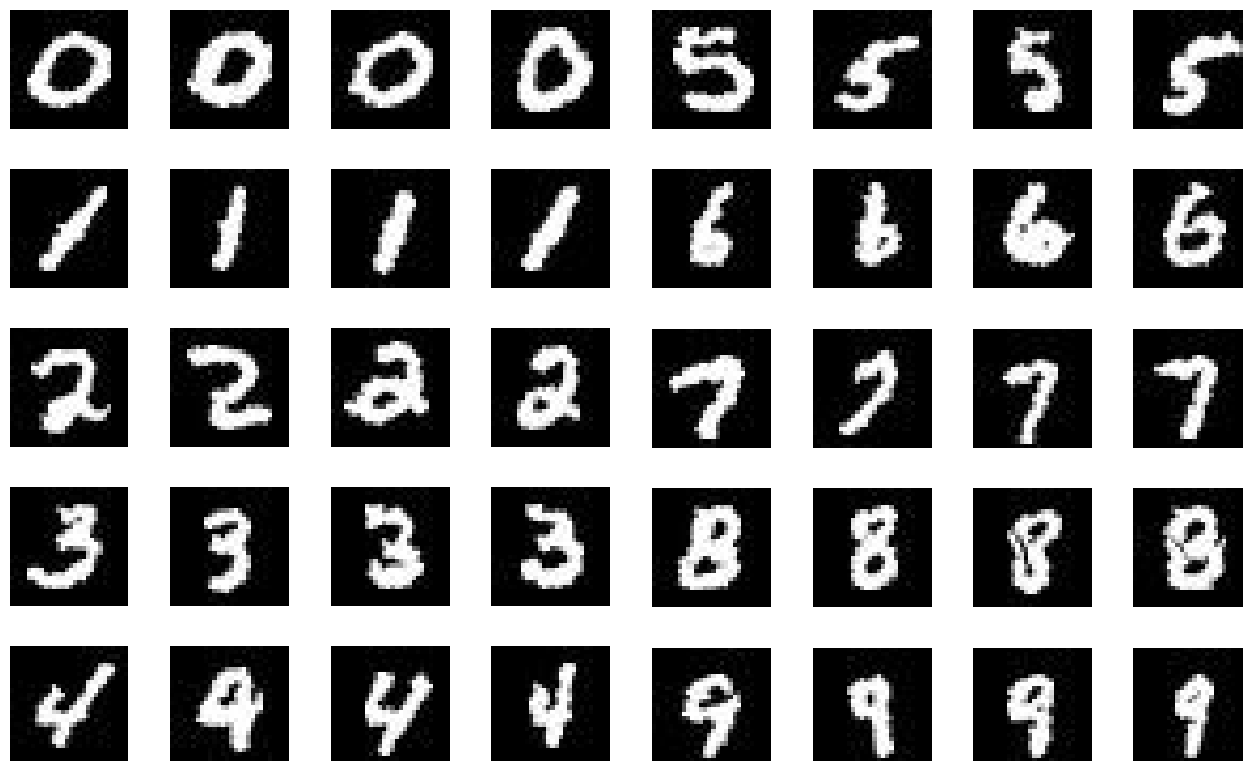


Figure S15. Detailed results for the reproduced MNIST-like digits

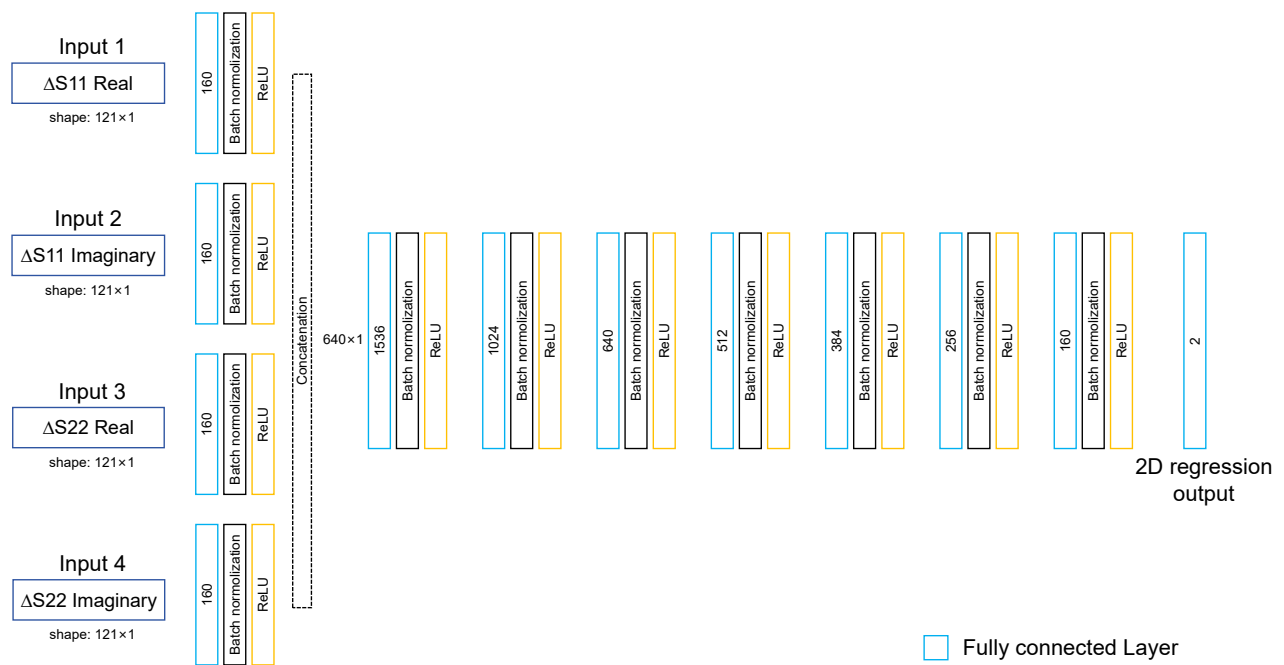


Figure S16. The optimal localization regression model for small EM-skin system obtained through the proposed neural network architecture search strategy.

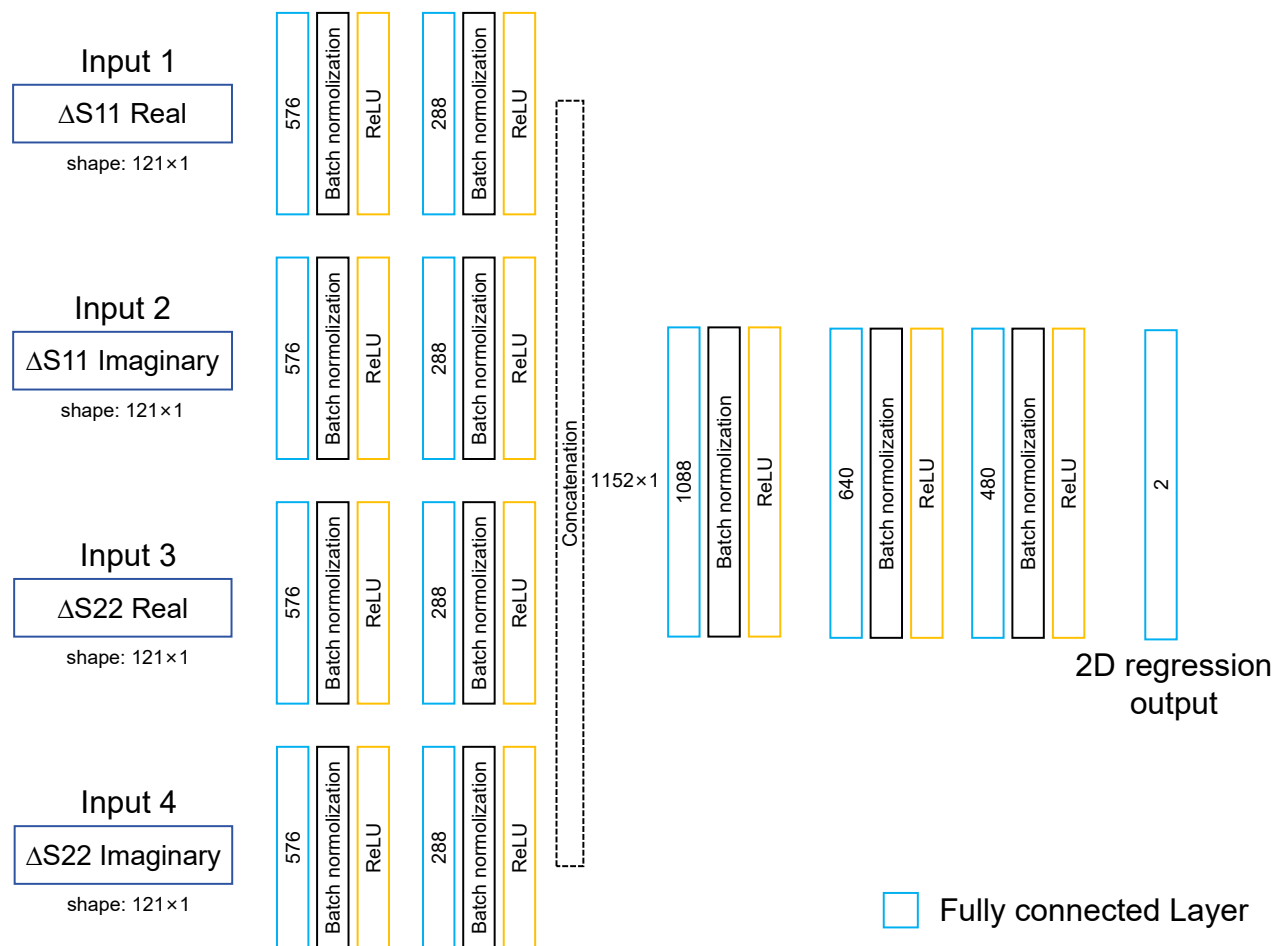


Figure S17. The optimal localization regression model for large EM-skin system obtained through the proposed neural network architecture search strategy.

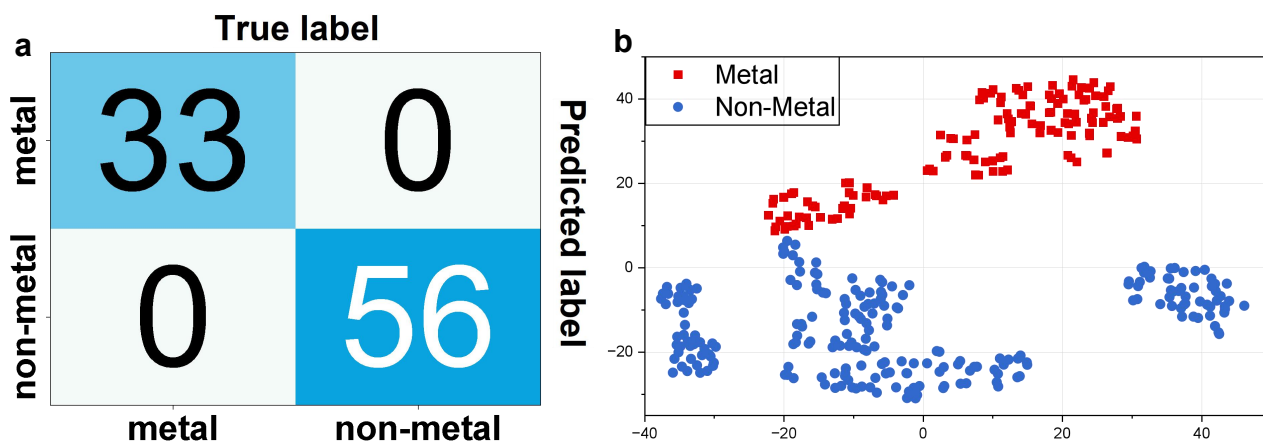


Figure S18. **a** Confusion matrix for binary classification between metal and non-metal. **b** T-SNE visualization of XGBoost leaf-index for binary classification task.