

PINSA: Physics-Informed Neural Spectral Imaging for Plastisphere Differentiation

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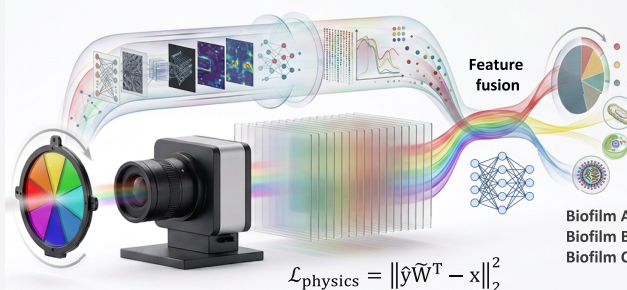
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ABSTRACT: Plastisphere, a microbial community colonizing plastic debris, poses increasing risks to ecosystems and to animal and human health by enabling the long-range transport of invasive and pathogenic species in aquatic environments. Current analytical approaches for plastisphere analysis remain confined to laboratory settings and rely on bulky, time-consuming, and costly instruments. Here, we present a physics-informed neural spectral imaging system (PINSA) for portable, low-cost, plastisphere differentiation. The system uses a customized color-film spectral encoder costing approximately USD 0.1 to optically compress hyperspectral information into a small number of snapshot measurements and reconstructs 451-channel hyperspectral image stacks using a physics-informed neural network constrained by the optical forward model. For classification, we introduce a dual-branch feature-fusion strategy that jointly exploits the spectrally detailed yet reconstruction error-prone recovered hyperspectral data and the low-dimensional yet lossless raw compressed measurements. By fusing both representations, the two branches compensate for each other's weaknesses. Multiple feature extractors are applied to both branches, and the resulting embeddings are fused before the classification. Experimental results demonstrate that the system accurately recovers 451-channel hyperspectral images and substantially improves the plastisphere classification performance, achieving 85.3% accuracy in differentiating five categories of plastisphere communities sampled from distinct aquatic environments. This work establishes a rapid and cost-effective full-field compressed spectral imaging pathway for plastisphere screening, with potential utility as a preliminary environmental monitoring tool to prioritize samples for downstream microbiological or public-health-related analyses.

KEYWORDS: spectral imaging, microplastics classification, machine learning, compressed imaging, physics-informed neural network



INTRODUCTION

Global plastic production has grown exponentially over recent decades, creating a severe environmental crisis due to the persistent nature of plastics and the fact that only approximately 9% of plastic waste is recycled.^{1,2} Among all affected compartments, plastic pollution in aquatic ecosystems is of particular concern due to the potential for long-range transport across global waterways.^{3–5} As a relatively recent anthropogenic addition to marine ecosystems, plastic debris provides a more persistent colonization substrate for microorganisms than most natural floating materials.^{6–8} Biofilm-forming microorganisms on plastic debris were first documented in marine environments as early as 1972.⁹ In 2013, Zettler et al. coined the term “plastisphere” to describe the novel artificial ecosystem that develops on the surface of microplastics (MPs).⁶ The marine plastisphere harbors diverse microbial communities, including opportunistic pathogens, and may therefore serve as a vector for the dispersal of invasive or pathogenic species, posing threats to vulnerable ecosystems.^{6,10}

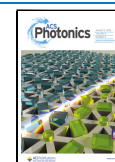
Furthermore, plastisphere-associated microorganisms can adsorb organic pollutants and heavy metals from the surrounding aquatic environment, facilitating the transfer of these contaminants into food webs.^{11–13} As a result, the plastisphere has attracted increasing attention in relation to antibiotic resistance genes (ARGs) dissemination, pollutant transport, and potential harms to both human and animal health.¹⁴ Accordingly, accurate detection and classification of plastisphere types are essential not only for assessing the transmission risks of pathogens and ARGs but also for inferring regional environmental pollution status from plastisphere composition.¹⁵

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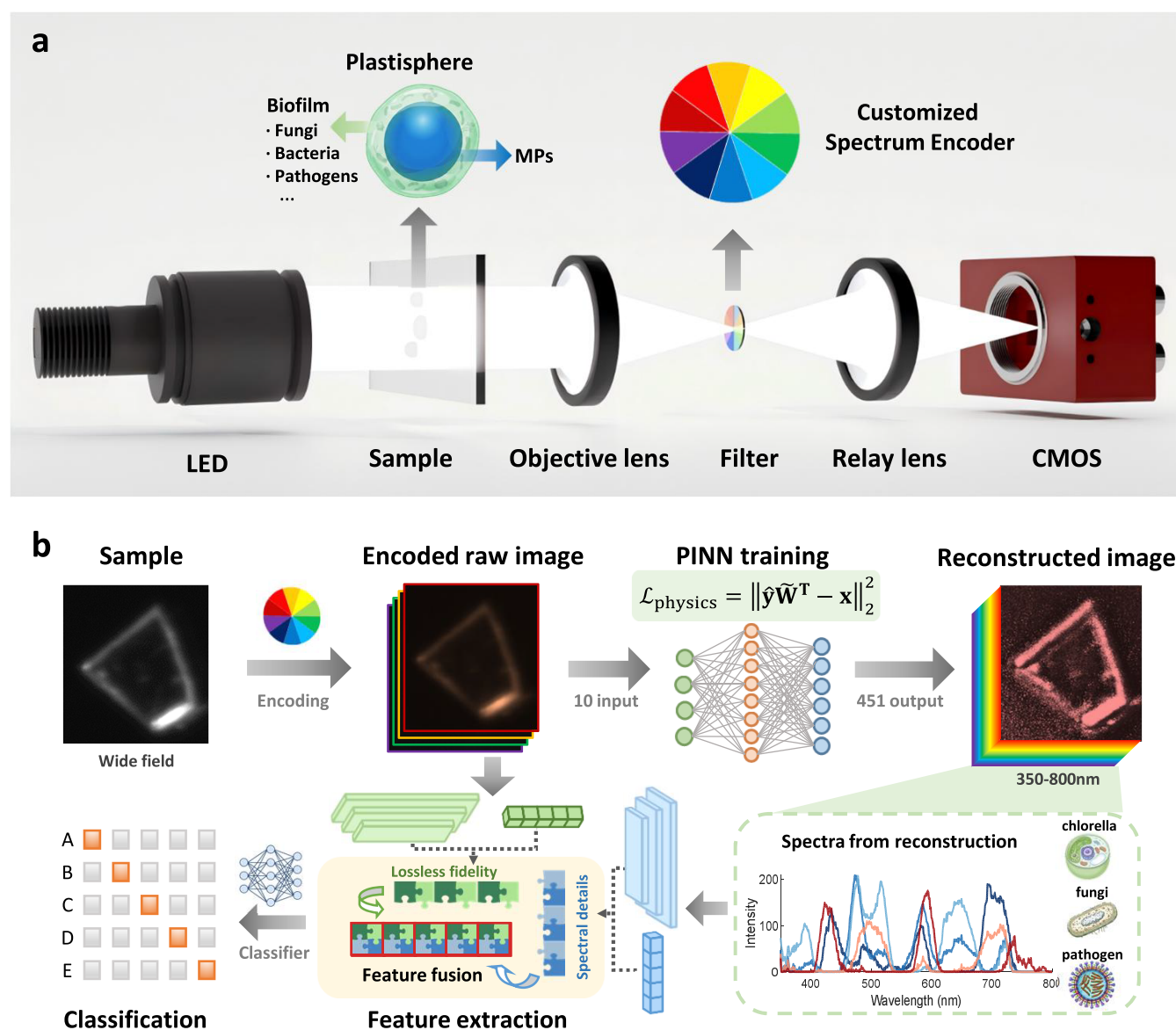


Figure 1. Overview of the PINSA for plastisphere differentiation. (a) Setup for our proposed PINSA system. Broadband illumination passes through a plastisphere sample and is spectrally encoded by a low-cost color-film filter before being captured by a monochrome CMOS sensor as coded measurements. (b) Dual-branch feature-fusion classification pipeline. PINN reconstructs 451-channel hyperspectral cubes spanning from 350 to 800 nm, while the raw compressed measurements are retained in parallel. Features from both branches are extracted and fused to combine the spectral richness of the reconstruction with the lossless fidelity of the raw data for plastisphere classification.

Numerous approaches have been explored for the *in situ* detection and classification of bacterial communities in plastispheres. Scanning electron microscopy (SEM) and Fourier-transform infrared spectroscopy (FT-IR) provide detailed morphological and compositional characterization.^{16–18} However, they are labor-intensive, costly, and poorly suited for field applications. High-throughput sequencing enables comprehensive profiling of microbial communities but requires extensive sample preparation and fails to deliver real-time spatial–spectral information.¹⁹ A major gap in current research is the lack of efficient, low-cost tools for rapid plastisphere characterization.¹⁷

Spectral imaging represents a powerful modality that enables noninvasive detection by capturing spectral signatures reflective of polymer composition and the presence of photosynthetic pigments, such as chlorophyll a, phycobiliproteins, and carotenoids.^{20,21} Nevertheless, conventional spectral

imaging systems are typically bulky and expensive, often requiring complex optical components, which severely limit their applicability in portable, in-field monitoring scenarios.^{22,23} Recent advances in deep learning have significantly accelerated the development of spectral imaging by enabling direct end-to-end mapping from measurements to reconstructions, thereby improving reconstruction speed and accuracy.^{24–28} Nevertheless, data-driven neural networks are still fundamentally constrained by their dependence on large annotated data sets.²⁹ In addition, the absence of explicit physical priors often results in poor generalization to unseen scenarios or spectral distributions, limiting their reliability in real-world deployments.³⁰ Recent polymer-based computational spectrometers have used engineered plastic elements, such as stress-induced birefringent epoxy films, for compact spectral encoding.³¹

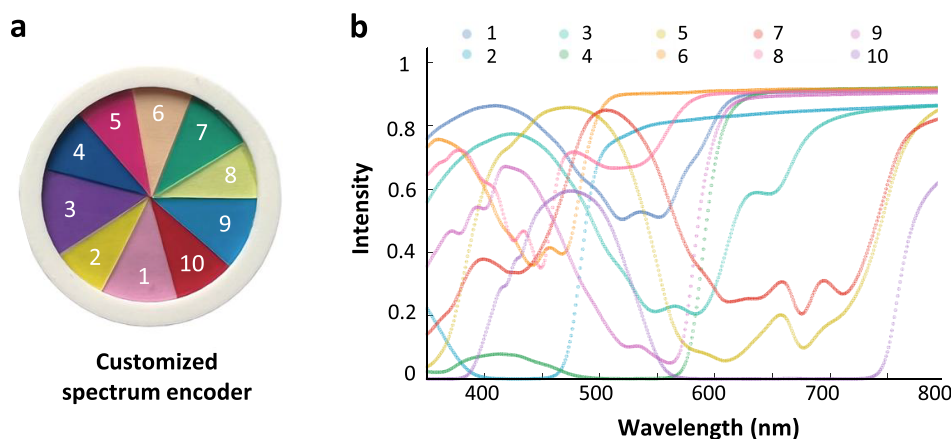


Figure 2. Customized filter wheel for spectral encoding. (a) Photo of the filter wheel used in the experiment. (b) Transmittance spectrum for filters.

Physics-informed neural networks (PINNs) provide a promising alternative for inverse problems in computational imaging by embedding physical models directly into the network architecture or objective function.³² In contrast to purely data-driven methods, PINNs incorporate known forward models to constrain solutions within physically plausible spaces while preserving the expressive capacity of deep neural networks.^{33–35} This paradigm is particularly attractive for hyperspectral imaging, where the integration of compressive sensing theory with neural network architectures and physical models enables high-fidelity reconstruction of spectral data cubes from highly undersampled compressed measurements.^{30,36} Such capability offers substantial advantages for the practical deployment of compact and portable imaging systems in environmental monitoring applications.

In this work, we developed a PINN-enhanced spectral imaging system for the classification of plastispheres in different aquatic environments. Such differentiation is relevant because wastewater conditions can shape the plastisphere community structure, biofilm composition, and pigment or extracellular polymeric substance profiles, which may in turn lead to measurable spectral differences. Therefore, rapid optical classification may serve as a preliminary screening approach for environmental monitoring and for prioritizing samples that require more detailed microbiological analysis. The framework combines a compact spectral encoding module, with a coded element cost of only USD 0.1, and a neural network architecture incorporating the physical forward model. This design enables the reconstruction of a physically constrained high-dimensional spectral data cube containing 451 spectral channels from compressed measurements. Subsequently, both the compressed signals and reconstructed spectra are jointly exploited for classification by using machine learning. To validate our method, we conducted experiments on five categories of plastisphere samples. Our system achieved a spectral reconstruction mean absolute error (MAE) of 0.0439 and a classification accuracy of 85.3%, demonstrating excellent detection capability under low-cost and miniaturized system configurations. By linking hyperspectral features with differences in plastisphere samples formed under distinct wastewater-associated environments, this study aims to establish a noninvasive, high-throughput, and portable strategy for rapid plastisphere screening, thereby enabling the integration of

multiomics data sets with optical characteristics to advance hazard assessment and environmental surveillance.

METHODS

Physics-Informed Neural Spectral Imaging System

PINSA integrates hardware-based spectral encoding, deep learning-based spectral decoding, dual-branch feature fusion, and machine-learning-based classification. Figure 1 illustrates the optical configuration and computational pipeline of the proposed PINSA (Physics-Informed Spectral Acquisition) camera system. As shown in Figure 1a, the hardware is built upon a conventional imaging architecture augmented by a spectral encoding module positioned at the intermediate image plane. The core encoding element is a rotatable filter wheel comprising ten broadband transmission filters, each fabricated from commercially available colored polyvinyl chloride (PVC) films. Despite their simplicity and extremely low cost, these filters exhibit distinct broadband transmission profiles across the visible–near-infrared range, enabling the compression of rich spectral information within the field of view into ten spectrally modulated measurements. After spectral modulation, the image is relayed by a lens pair onto a monochrome CMOS sensor (MV-CB120-10UM-C). A stack of ten encoded monochromatic images is generated for subsequent computational decoding. In our experiments, the system uses a filter wheel synchronized to the camera, which operates at 28 fps. Each filter occupies exactly one frame, so a full acquisition of one complete image stack is approximately 357 ms. The exposure time of each frame is set to 500 μ s, which is far shorter than the per-frame interval.

The computational pipeline is shown in Figure 1b. The captured ten-channel encoded image stack is fed into a PINN-enhanced transformer network that embeds the calibrated spectral transmission functions of the ten filters as a physical forward model. By constraining the reconstruction within this physics-informed framework, the network decodes the compressed measurements into a high-dimensional spectral data cube spanning 451 contiguous spectral channels (350–800 nm with 1 nm resolution). To maximize the discriminative power for plastisphere classification, the reconstructed 451-channel data cube and the original ten-channel compressed measurements are jointly fed into a machine-learning classifier. This dual-branch feature-fusion strategy leverages both the fine-grained spectral detail recovered by the PINN-enhanced reconstruction and the robust, low-dimensional spectral encoding captured directly by the hardware, thereby enhancing the classification robustness and accuracy. The PINSA system combines the hardware simplicity and low cost of broadband spectral compression with the high-dimensional representation capability of physics-informed computational imaging, providing an effective solution for compact and high-throughput plastisphere sensing.

Table 1. Quantitative Comparison of Spectral Reconstruction Methods^a

metric	ridge	LASSO	MLP	transformer	ours
RMSE ↓	0.0711	0.1110	0.1366	0.0649	0.0648
MAE ↓	0.0500	0.0817	0.0996	0.0441	0.0439
PSNR (dB) ↑	22.9576	19.0950	17.2884	23.7486	23.7633
correlation ↑	0.9646	0.8648	0.9151	0.9710	0.9711
R ² ↑	0.9380	0.8490	0.7711	0.9483	0.9485
peak MAE (nm) ↓	29.3881	38.8236	46.8350	26.0969	26.9662
SAE (rad) ↓	0.1490	0.2900	0.2405	0.1316	0.1311
SSIM ↑	0.6456	0.5620	0.5785	0.6688	0.6713

^aBold values indicate the best performance.

Physics-Informed Transformer for Spectral Reconstruction

To reconstruct dense spectra from compressed filter responses, we employed a physics-informed transformer network in the PINSA system. The model maps a low-dimensional observation vector acquired by the filter array to a continuous spectral profile over the target wavelength range.

Spectral responses of encoding filters are measured by a commercial spectrometer, as shown in Figure 2. Their slightly different responses encode the spectral information within the visible light range of every pixel into 10 values. The 10 values are used for network training and reconstruction. A synthetic data set of 8000 spectral observation pairs was generated to train and evaluate the reconstruction network. Each ground-truth spectrum was constructed as a superposition of 3–8 Gaussian peaks with randomly sampled center wavelengths, widths, and amplitudes, yielding a diverse set of spectral profiles spanning the morphological complexity expected from realistic samples. To simulate practical measurement conditions, four physically motivated noise sources, including sinusoidal baseline drift, multiplicative scattering noise, dark current offset, and additive Gaussian noise, were applied sequentially. All spectra were normalized to [0,1] after corruption. The corresponding 10-channel observation vector for each spectrum was computed by integrating the spectrum against the calibrated filter transmittance curves, following the forward model

$$x_j = \sum_{\lambda} \hat{y}(\lambda) \tilde{W}_j(\lambda), \quad j = 1, \dots, M \quad (1)$$

where $\tilde{W}_j(\lambda)$ is the normalized spectral response of the j th filter, x_j represent the encoded intensity value, and $\hat{y}(\lambda)$ denotes the reconstructed spectrum sampled at L wavelength. In this work, $M = 10$ and $L = 451$. In matrix form, the reconstructed spectrum is projected into the filter-response space as

$$\hat{\mathbf{x}} = \hat{\mathbf{y}} \tilde{\mathbf{W}}^T \quad (2)$$

This projection enables explicit enforcement of consistency between the reconstructed spectrum and the original compressed observation.

The input is first embedded by a two-layer multilayer perceptron into a latent spectral sequence of dimension 64, to which a learnable positional encoding is added. The sequence is then processed by three transformer encoder layers with four attention heads, a feedforward dimension of 128, and a dropout of 0.1. A lightweight one-dimensional convolution decoder subsequently transforms the encoded features into the final spectral output, and a sigmoid activation constrains the reconstruction to the normalized interval [0,1]. By combining global self-attention with local convolution decoding, the network captures both long-range spectral correlations and the local profile continuity.

The network is trained with a physics-informed composite loss

$$\mathcal{L} = \mathcal{L}_{\text{mse}} + 0.5\mathcal{L}_{\text{freq}} + 0.1\mathcal{L}_{\text{sam}} + \beta(t)\mathcal{L}_{\text{phys}} + \gamma(t)\mathcal{L}_{\text{smooth}} \quad (3)$$

where $\mathcal{L}_{\text{mse}}$ is the point-wise mean squared error, $\mathcal{L}_{\text{freq}}$ penalizes Fourier magnitude discrepancies, $\mathcal{L}_{\text{sam}}$ minimizes the spectral angle, $\mathcal{L}_{\text{phys}} = \|\hat{\mathbf{x}} - \mathbf{x}\|_2^2$ enforces forward-model consistency through the

calibrated filter matrix, and $\mathcal{L}_{\text{smooth}}$ regularizes the second-order finite difference. The physics coefficients $\beta(t)$ and $\gamma(t)$ increase linearly from 0 to 0.5 and 0.1 over training, allowing coarse spectral features to be learned before physical constraints are tightened. The composite design reflects the fact that, for pigment-based plastisphere discrimination, the diagnostic information resides in the shape, peak positions, and continuity of the spectral curve rather than in the per-band magnitude alone; a point-wise objective is thus necessary but not sufficient. Accordingly, each term addresses a complementary aspect of fidelity: $\mathcal{L}_{\text{mse}}$ anchors per-band accuracy; $\mathcal{L}_{\text{freq}}$ promotes recovery of the global spectral envelope and dominant frequency components rather than band-wise residual overfitting; $\mathcal{L}_{\text{sam}}$ constrains the overall spectral shape and is invariant to amplitude scaling; $\mathcal{L}_{\text{phys}}$ enforces consistency with the calibrated optical forward model by requiring the reprojected reconstruction $\hat{\mathbf{x}} = \hat{\mathbf{y}} \tilde{\mathbf{W}}^T$ to reproduce the measured compressed observation; and $\mathcal{L}_{\text{smooth}}$ suppresses spurious high-frequency oscillation in narrow diagnostic bands. The linearly increasing schedules of $\beta(t)$ and $\gamma(t)$ implement a curriculum in which the data-driven terms first establish a coarse spectral structure before the forward-model and smoothness constraints are tightened, avoiding the instability caused by strong priors dominating early optimization.

The data set was partitioned into training, validation, and test subsets (16:4:5) via stratified random splitting. The model was trained using Adam with an initial learning rate of 0.001, weight decay of 0.0001, and a batch size of 32. Gradient clipping with a maximum norm of 1.0 was applied to improve the optimization stability. A cosine annealing scheduler was used throughout training with the learning rate decayed to a minimum of 0.0001. Statistical robustness was assessed through 10-fold cross-validation, and training was performed for 500 epochs without early termination. Instead, the validation loss was monitored throughout training, and the model parameters corresponding to the minimum validation loss were restored after the optimization. This strategy ensures full training while retaining the best performing model.

To validate the effectiveness of the PINSA, we also test four conventional spectral reconstruction methods on the same data set: ridge regression,³⁷ LASSO,³⁸ MLP,³⁹ and transformer.⁴⁰ The quantitative results are summarized in Table 1. As shown in Table 1, PINSA achieves the best performance in 7 out of 8 evaluation indices. Compared with conventional linear methods (ridge and LASSO), PINSA reduces MSE by 17.6 and 65.9%, respectively. MSE is reduced by 77.5%, and R² is improved by 23.0% compared with the data-driven MLP baseline. Besides, PINSA consistently outperforms the transformer baseline across nearly all evaluation parameters. This demonstrates that the incorporation of physics-informed constraints provides effective regularization and enhances spectral fidelity. These results collectively validate that PINSA offers a robust and accurate solution to spectral reconstruction.

Feature Fusion and Joint Classification Based on Machine Learning

To assess the capability of the PINSA framework for plastisphere differentiation, a supervised machine-learning approach based on a

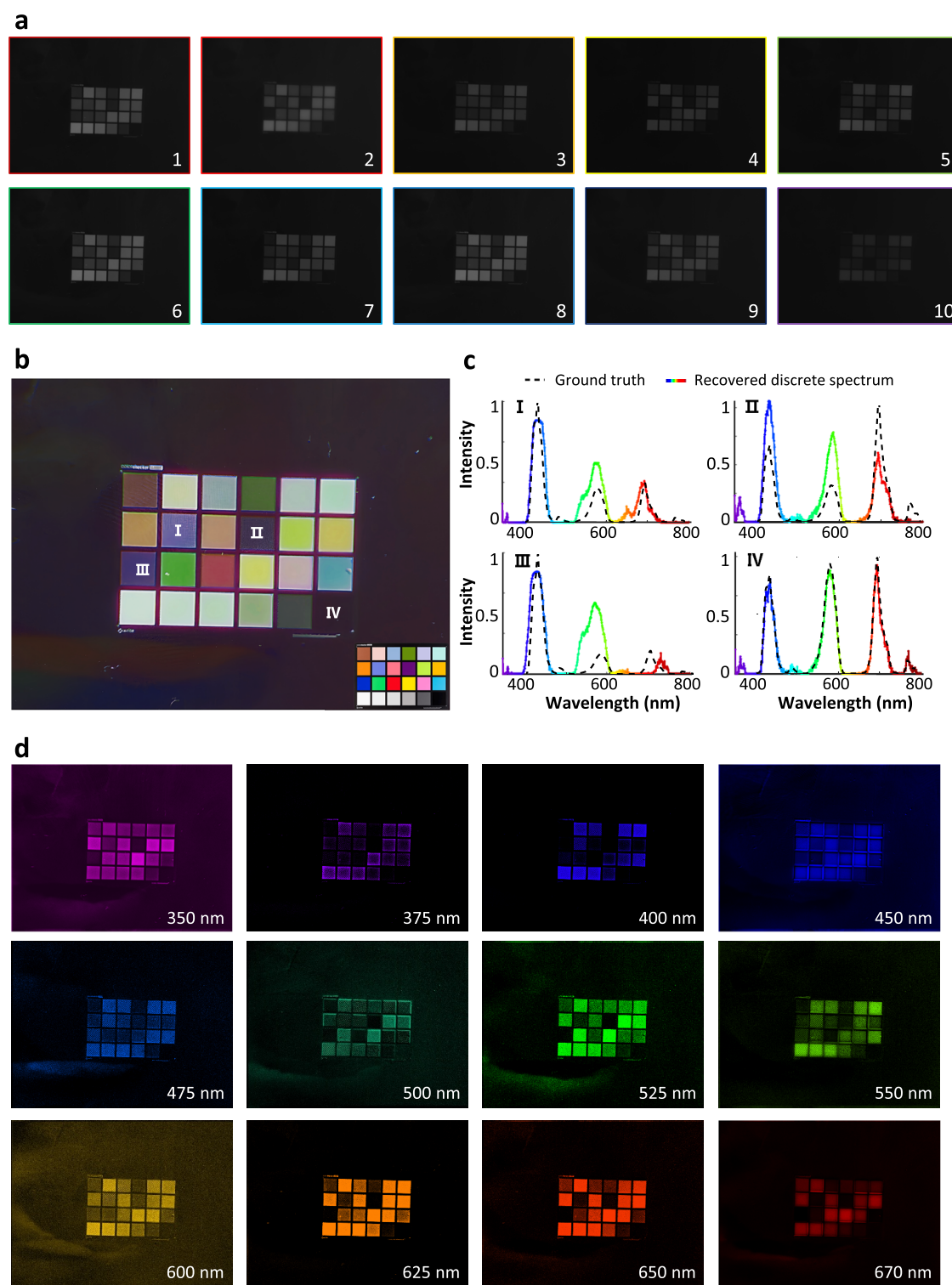


Figure 3. Experimental spectral reconstruction results of PINSA. (a) Ten raw monochromatic measurements captured for hyperspectral decoding. (b) Visualization result of the reconstructed hyperspectral image. (c) Reconstructed spectra from 4 spatial points (I, II, III, and IV) in the scene. The corresponding positions of the points are shown in panel (b). (d) Representative reconstructed spectral image slices selected from visually informative wavelength channels.

support vector machine (SVM) with a second-order polynomial kernel was employed for plastisphere classification.

For each plastisphere sample, three image data sets were collected and generated: conventional wide-field illuminated images, raw ten-channel spectrally encoded image stacks, and computationally reconstructed 451-band hyperspectral cubes. From the wide-field image, four first-order intensity statistics (mean, standard deviation,

maximum, and minimum) and two Sobel-based edge descriptors (mean and standard deviation of gradient magnitude) were extracted, yielding a six-dimensional feature vector. From the raw ten-channel encoded image stack, the same four statistics were computed per channel, producing a 40-dimensional descriptor that captures the compressed spectral distribution without reconstruction. For the reconstructed hyperspectral cube, per-band spatial means and

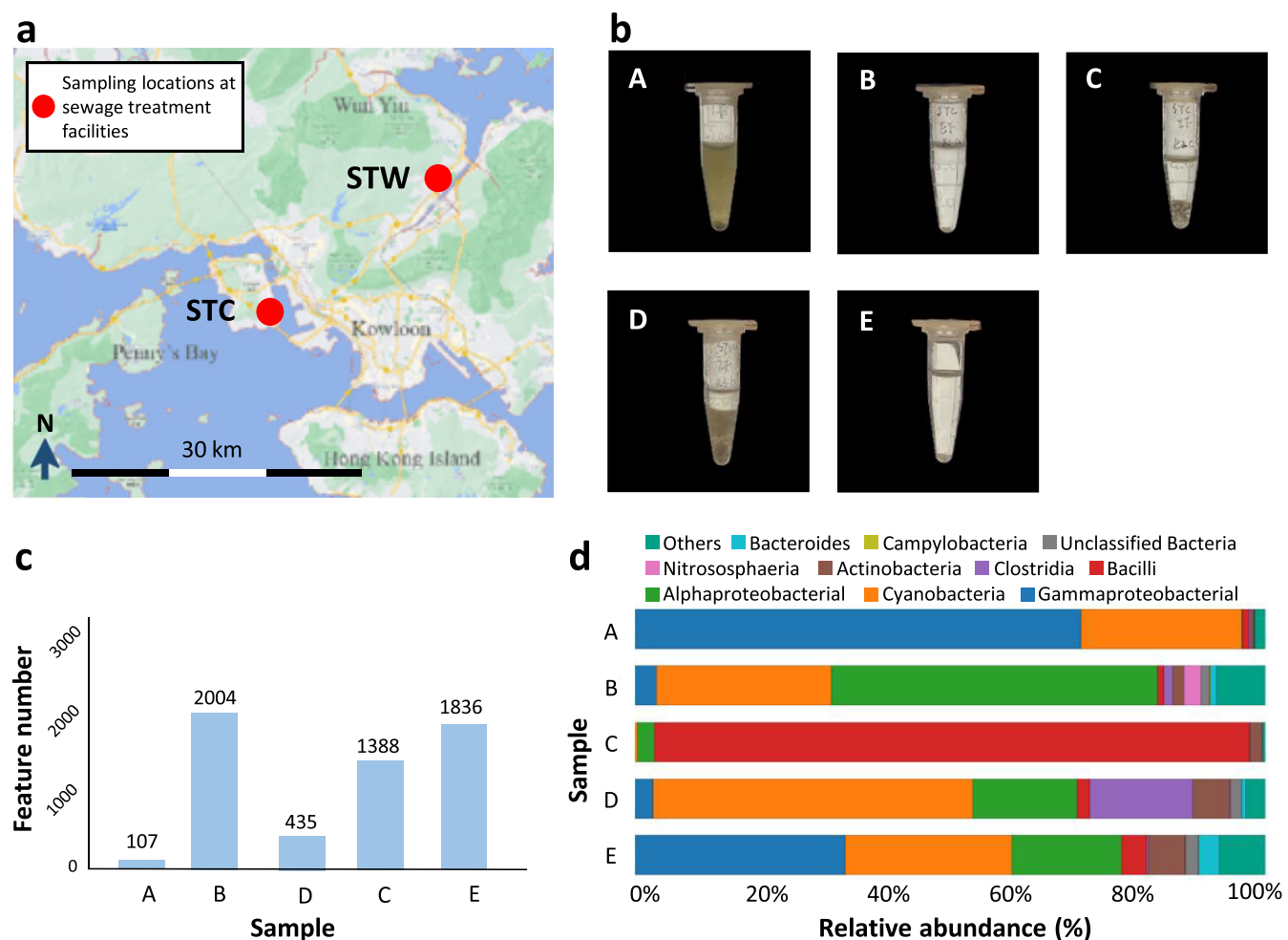


Figure 4. Sewage samples used in the experiment. (a) Map of Hong Kong showing the two sampling locations at sewage treatment facilities (STC and STW). (b) Photographs of the five water samples: (A) chlorella, (B) STC-EF-R1a, (C) STC-IF-R2c, (D) STC-IF-R3a, and (E) STW-IF-R3b. (c) Number of observed OTUs for each sample based on 16S rRNA gene amplicon sequencing. (d) Relative abundance of the top 10 bacterial classes across the five plastisphere communities.

standard deviations were calculated across all 451 wavelength bands, yielding a 902-dimensional feature vector. This vector was then reduced to 30 principal components via principal component analysis (PCA) to mitigate the curse of dimensionality.

To further exploit the nonlinear spectral structure, a fully connected autoencoder was trained on the mean spectral reflectance curves. The encoder mapped the 451-dimensional input through a hidden layer of 128 units to a 32-dimensional bottleneck, with batch normalization, ReLU activation, and 20% dropout applied at each stage; the decoder mirrored this architecture. Because only 34 original spectra were available, each spectrum was augmented 1000-fold by adding Gaussian noise scaled to 10% of its standard deviation, producing a training set of 34,000 samples. The network was optimized for 50 epochs using the Adam algorithm (learning rate 0.001, weight decay 0.0001, and batch size 256) with mean squared error as the reconstruction loss. After training, the 32-dimensional bottleneck activations of the original spectra served as the autoencoder feature vectors. The feature extracted from the autoencoder is fused with four intensity statistic features for further classification.

An SVM with a second-degree polynomial kernel and regularization parameter $C = 10$ was adopted as the classifier. Model performance was assessed under leave-one-out cross-validation (LOOCV) in which each of the 34 samples was held out exactly once for prediction.

EXPERIMENTS AND RESULTS

This section demonstrates the performance of the developed PINSA system for hyperspectral imaging and plastisphere differentiation via

Table 2. Plastisphere Samples

plastisphere type	sewage	number of samples
A	chlorella	7
B	STC-EF-R1a	8
C	STC-IF-R2c	6
D	STC-IF-R3a	7
E	STW-IF-R3b	6

joint learning. [Spectral Reconstruction Section](#) evaluates its spectral reconstruction capability in recovering 451-channel three-dimensional spectral data from 10 compressed measurements. Based on the established reconstruction network, the system is then applied to rapid and compact encoding scheme plastisphere classification with potential for portable deployment. [Joint Classification Section](#) presents the corresponding experimental results, including sample information, reconstructed spatial–spectral features, and classification performance.

Spectral Reconstruction

To validate the spectral reconstruction capability of our system, a standard color calibration board target was imaged under broadband

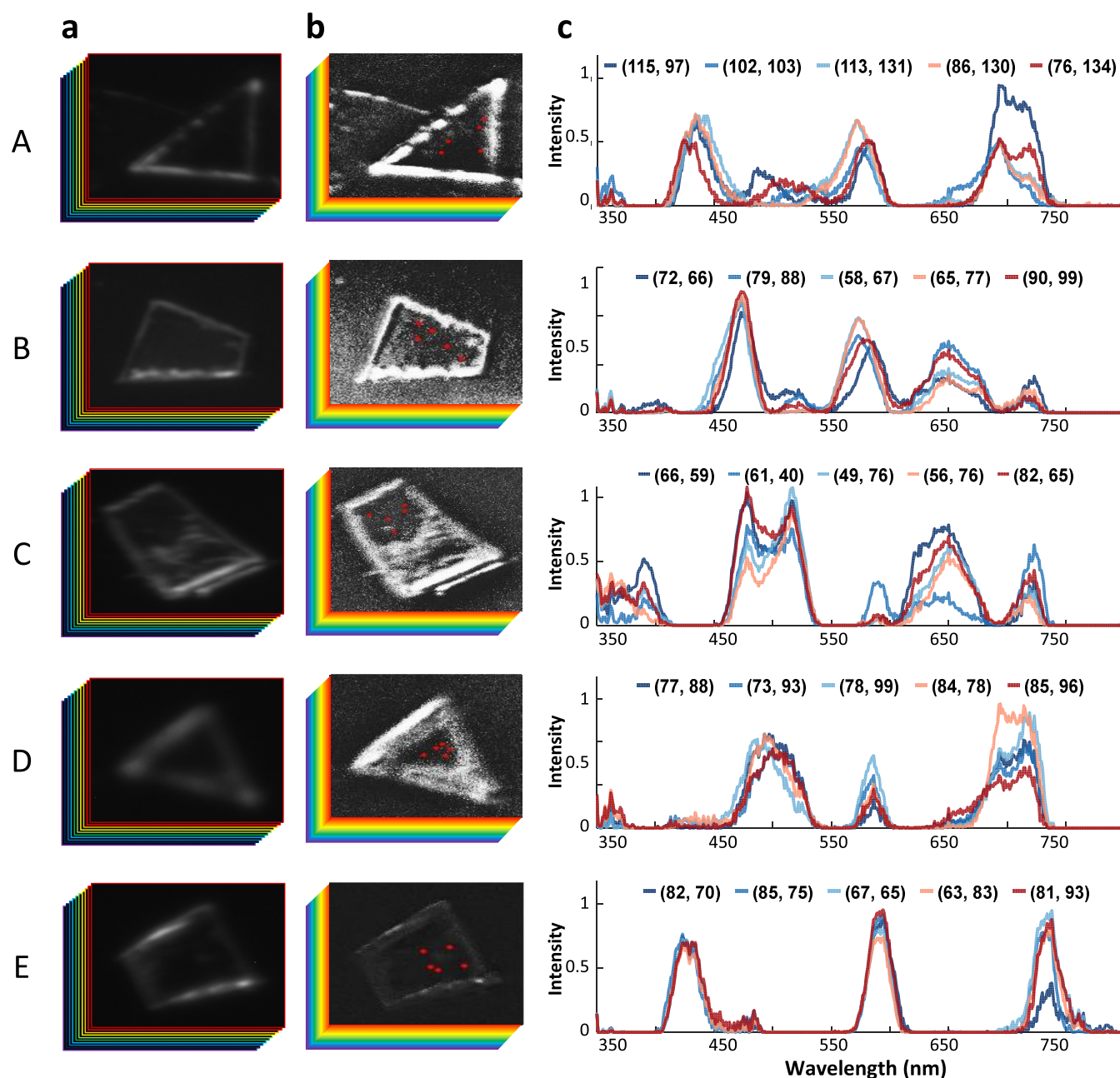


Figure 5. Examples of the data set for learning. (a) Raw encoded images of 5 sample types, and their reconstructed 451-channel hyperspectral image stacks are shown in panel (b), where the red markers overlaid on each image indicate the 5 randomly selected points whose spectra are plotted in panel (c). (c) Reconstructed spectra for 5 randomly selected points of each sample. The legend entries denote the (x, y) pixel coordinates of each point within the corresponding reconstructed image in panel (b).

illumination. Figure 3 presents the experimental results of the PINSA system. As shown in Figure 3a, 10 raw monochromatic images were captured through the broadband encoding filters as compressed inputs for the decoding process. On the basis of these limited observations, the trained reconstruction network successfully recovered a 451-channel hyperspectral data cube spanning the visible wavelength range. The reconstructed hyperspectral scene is visualized in Figure 3b, where the spatial structure and color distribution of the target are clearly preserved. A reference RGB scene is shown in the bottom right corner, demonstrating that the reconstructions spatially match the expected scene.

To further examine the spectral fidelity of the reconstruction, Figure 3c shows the reconstructed spectra extracted from four representative spatial positions, labeled I–IV in Figure 3b. In addition, representative reconstructed spectral images at 12 selected wave-

lengths are displayed in Figure 3d. The intensity variation across channels from 350 to 670 nm demonstrates that the system is able to recover wavelength-dependent image contrast with good spatial consistency. Overall, these results confirm that PINSA can reconstruct accurate hyperspectral information from cost-effective, compressed measurements.

Joint Classification

Data Set Preparation. Polyethylene terephthalate (PET) micro-particles were selected as the base material for the plastisphere formation. Five aquatic samples representing distinct water environments were collected from sewage treatment works in Hong Kong, namely, chlorella, STC-EF-R1a, STC-IF-R2c, STC-IF-R3a, and STW-IF-R3b. Here, EF and IF denote effluent and influent, respectively, while R1, R2, and R3 indicate different replicate sampling sites. The corresponding sampling locations, sample images, and relative

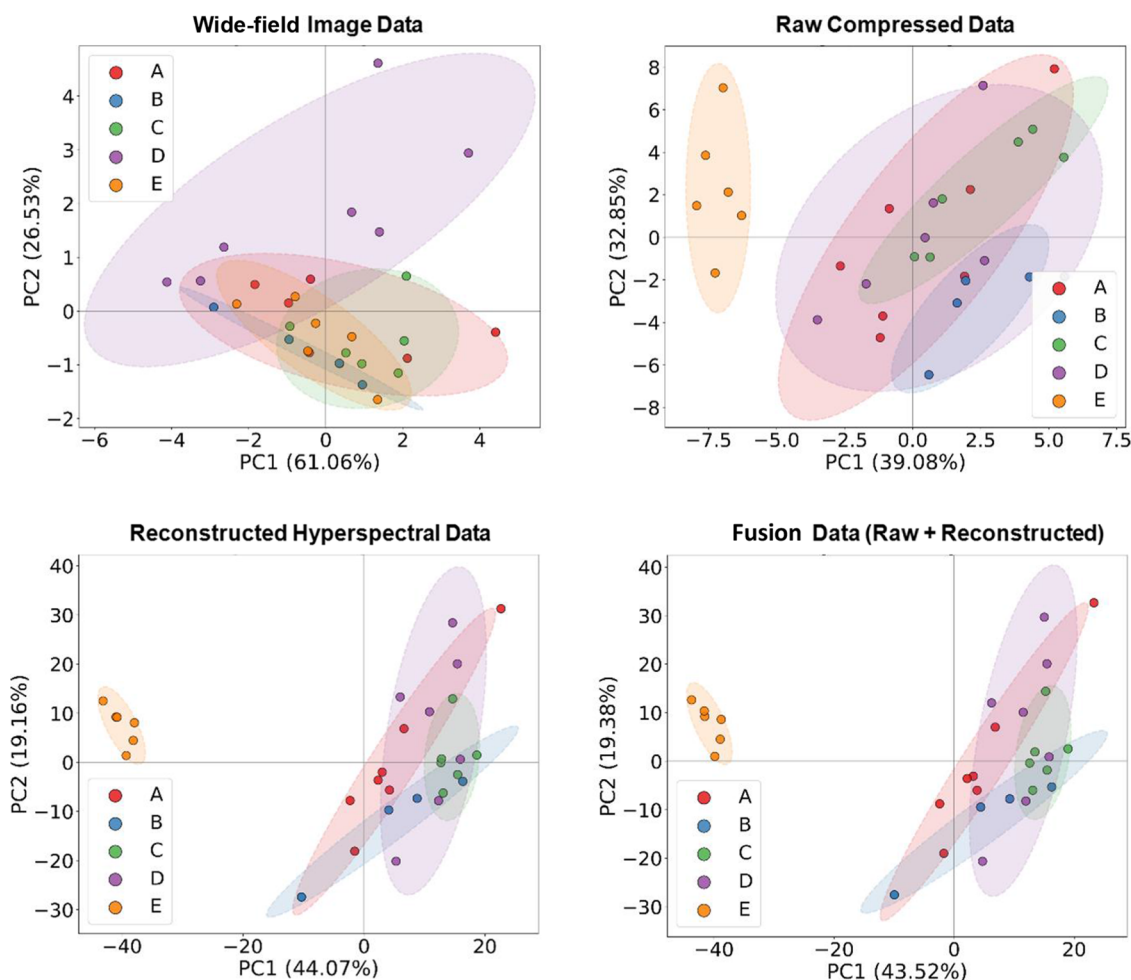


Figure 6. PCA visualization of feature distributions for image data used in the experiment.

abundances are shown in Figure 4. In the laboratory, PET microparticles were immersed separately in each collected water sample and incubated for one month to promote microbial attachment and biofilm formation on the plastic surfaces. After incubation, the biofilm-coated PET particles were defined as plastisphere samples and were used for subsequent analysis. For the classification task, the five plastisphere categories were designated as A, B, C, D, and E, as given in Table 2.

Figure 5 shows a representative example of the prepared data set. For the five plastic plastisphere categories, Figure 5a,b shows the original encoded images of each species acquired by PINSA, along with the corresponding stack of reconstructed 451-channel hyperspectral images. To more clearly illustrate the spectral differences between the categories, we randomly selected five spatial points from each sample and plotted their reconstructed spectra in Figure 5c. Within each category, the spectra from different spatial locations show consistent peak positions and overall shapes, indicating good intraclass homogeneity. The spectral features between the different categories show significant differences in peak wavelength, bandwidth, and relative intensity distribution, reflecting significant differences in the composition of microbial communities and biofilms formed in different aquatic environments.

Classification Performance. To validate the differentiation capability of the PINSA, four feature configurations of increasing spectral richness were evaluated for comparison: wide-field images, raw compressed 10-channel image stack, reconstructed hyperspectral data, and combined raw and reconstructed data. To verify that classification arises from spectrally resolved features rather than from differences in overall intensity, we normalized reconstructed spectra to [0, 1] prior to feature extraction so that absolute brightness is

removed and only the relative spectral profile across the 451 bands is retained.

To qualitatively assess the separability of the five plastisphere classes under different data sets, we performed PCA on each feature set and projected all samples onto the first two principal components (Figure 6). In the wide-field feature space, the five classes clustered tightly around the origin with heavily overlapping confidence ellipses, indicating a poor discriminative capacity. The raw compressed features provided moderate improvement, with classes B and E beginning to migrate away from the central overlap region, although classes A, C, and D remained largely entangled. A clear enhancement in interclass separation was observed when reconstructed 451-band hyperspectral features were used: class E formed a compact, isolated cluster, and the remaining classes exhibited noticeably tighter within-class grouping with reduced ellipse overlap. The fused PINSA feature (raw and reconstruction combined) space closely resembled the reconstructed case but with marginally tighter clustering, suggesting complementary information contributed by the raw measurements.

To quantitatively confirm these observations, we evaluated the LOOCV classification performance of a polynomial SVM for each feature set and constructed the corresponding confusion matrices (Figure 7). The results were consistent with PCA visualizations: wide-field features yielded the lowest accuracy of 55.9%, with class E nearly entirely misclassified at only 17% recall; raw compressed features raised the accuracy to 67.7%, notably rescuing class E to 100% recall while classes A, C, and D remained confused; reconstructed hyperspectral features further improved accuracy to 82.3%, with the principal residual errors concentrated in class D. The PINSA fusion achieved the highest accuracy of 85.3%, improving the recalls of classes C from 71 to 83% and D from 43 to 57%. Across all

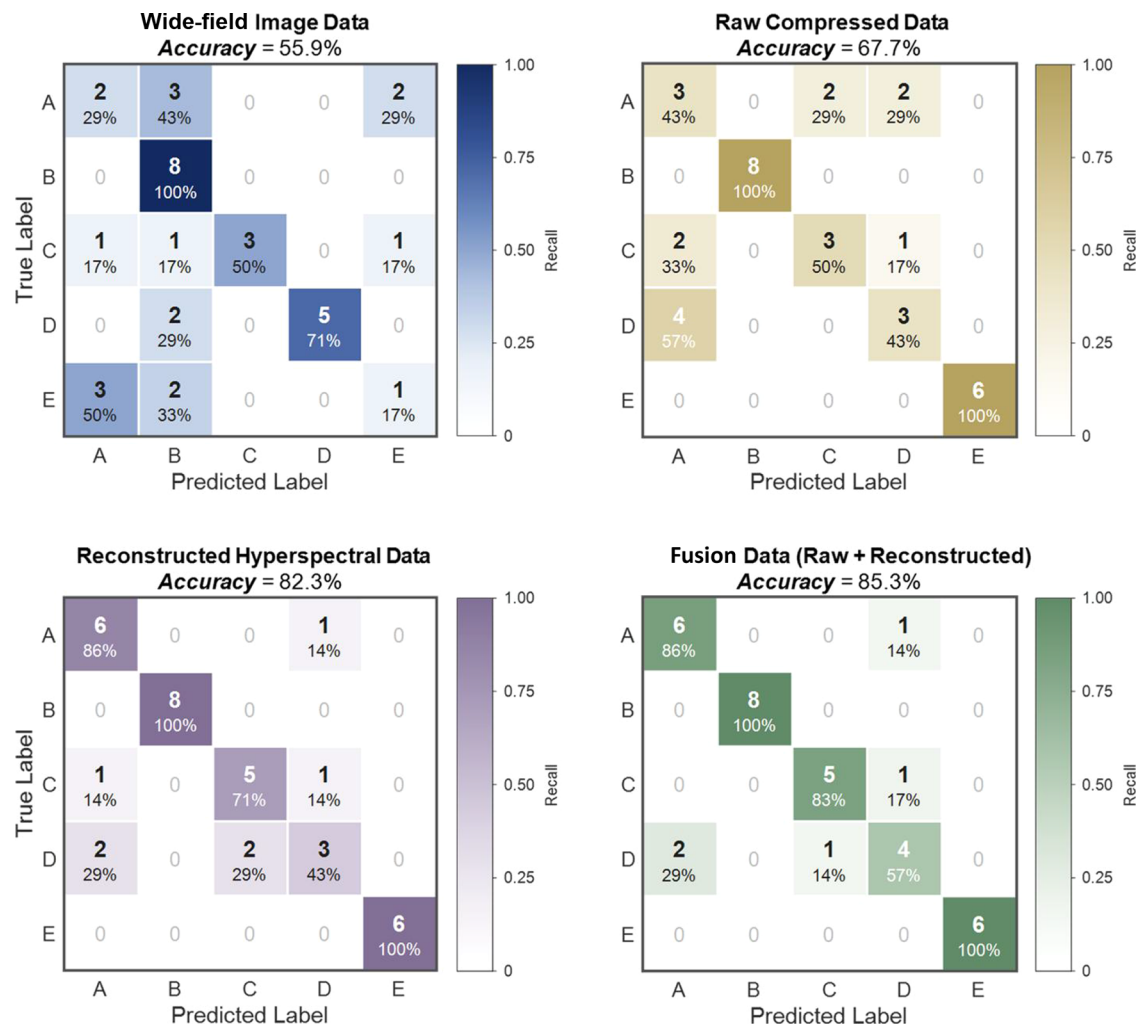


Figure 7. Confusion matrices of classification results. The PINSA fusion achieved the highest accuracy of 85.3% among all evaluated modalities.

Table 3. Per-Class F1 Score across Four Data Representations^a

class	Wide field	raw compressed	reconstructed	fusion
A	30.8	37.5	75.0	80.0
B	66.7	100.0	100.0	100.0
C	66.7	66.7	71.4	83.3
D	83.3	46.2	50.0	61.5
E	20.0	85.7	100.0	100.0
macro-F1	53.5	67.2	79.3	85.0
accuracy	55.9	67.6	82.3	85.3

^aBold values indicate the best performance.

configurations, class D consistently exhibited the lowest recall, corroborating its dispersed distribution in the PCA space and suggesting spectrally overlapping biochemical signatures with classes A and C.

Table 3 further summarizes the per-class F1 scores and macro-averaged metrics. The overall trend reinforced the hierarchy identified above: macro-F1 rose steadily from 53.5% (wide-field) through 67.2% (raw compressed) and 79.3% (reconstructed) to 85.0% (fused). Classes B and E benefited the most from spectral information, reaching perfect F1 scores at 100% once raw compressed or reconstructed features were introduced. Class A showed the largest progressive improvement, with its F1 score increasing from 30.8% to 80.0% as richer spectral representations were incorporated. One notable exception was class D, which achieved its highest F1 score of

83.3% under the wide-field configuration but dropped substantially with spectral features. This anomaly may be due to the favorable but accidental arrangement of class D in the low-dimensional wide-field space, which no longer applies when the decision boundary is redistributed by high-dimensional spectral features. Despite this, the combined PINSA representation achieved the highest F1 scores for four of the five classes. It also yielded the best macro-F1 score and overall accuracy. On a standard consumer-grade GPU (NVIDIA GeForce RTX 4090), the average classification time per image is approximately 0.93 s, enabling near-real-time monitoring capabilities in field applications. These results indicate that PINSA provides the most robust and balanced classification of plastisphere communities by fusing raw compressed and reconstructed hyperspectral features.

CONCLUSION AND DISCUSSION

In this work, we presented a physics-informed neural spectral imaging system for portable, low-cost, and rapid differentiation of plastisphere communities. PINSA employs off-the-shelf colored PVC films as broadband absorptive filters and focuses on task-oriented compressed spectral imaging for plastisphere differentiation, integrating low-cost encoding, physics-informed reconstruction, and raw–reconstructed feature fusion. The compressed measurements are subsequently recovered into 451-channel hyperspectral image cubes covering the spectral range from 350 to 800 nm using a physics-informed neural network constrained by an experimentally calibrated forward model.

Instead of using only reconstructed spectra or only raw compressed data, we combined both representations in a classification framework. The reconstructed spectra provide detailed spectral information, although some reconstruction errors are unavoidable. The raw compressed data, in contrast, preserve the original measurement response but contain a limited spectral resolution. Using both representations together helps to compensate for the weakness of each individual modality. A systematic evaluation using leave-one-out cross-validation with a polynomial SVM classifier confirmed that this fusion strategy consistently outperformed all single-representation baselines. The combined feature space achieved an overall classification accuracy of 85.3% and a macro-averaged F1 score of 85.0% across five plastisphere categories sampled from distinct aquatic environments, representing improvements of 29.4% and 31.5%, respectively, over conventional wide-field imaging. Importantly, this strategy is not restricted to the plastisphere analysis. The fusion of multiple spectral feature representations may also be useful for other material identification tasks involving subtle spectral differences such as polymer analysis, biofilm detection, food inspection, and environmental sensing.

Despite these advances, the methods have limitations. The current study was conducted on a moderately sized data set evaluated under leave-one-out cross-validation. Future work should validate the approach on larger, independently collected cohorts spanning a broader range of environmental conditions and microplastic substrates. Looking forward, we would like to integrate spatial 3D morphological features alongside spectral signatures, which may further boost the classification accuracy, particularly for spectrally ambiguous classes. Moreover, the portable imaging platform could be coupled to microfluidic sample-preparation modules. This integration may enable fully autonomous, *in situ* plastisphere surveillance in rivers, estuaries, and wastewater treatment facilities, which could help bridge the gap between laboratory analysis and actionable field-level environmental monitoring.

The feasibility of optically differentiating plastispheres rests on composition-dependent absorption within the visible range. Different biofilm constituents, including photosynthetic and accessory pigments, exhibit distinct absorption peaks and spectral profiles in the visible light window.^{41,42} The five communities differ in pigment inventory, for example, the Cyanobacteria/Alphaproteobacteria-rich community (class B) versus the largely nonphototrophic Bacilli-dominated community (class C). Therefore, their integrated visible-range signatures differ accordingly. These differences are reflected in the reconstructed spectra where the categories show distinct peak positions and band shapes. We note that, given the multispecies nature of the biofilms and the overlapping pigment absorptions, the classifier exploits the collective spectral signature rather than individual diagnostic bands. Quantitative band-to-taxon assignment via pigment unmixing is left for future work.

In summary, this study demonstrates that physics-informed compressed spectral imaging, combined with a dual-branch feature-fusion strategy, offers a viable and cost-effective pathway for plastisphere characterization. With its potential for field deployment, the approach could support environmental screening and help prioritize plastisphere samples for subsequent ecological- or public-health-related microbiological assessment.

■ ASSOCIATED CONTENT

Data Availability Statement

The data that support the findings of this study are openly available at <https://github.com/jingyan0110/plastisphere-classification>

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Notes

The authors declare no conflicts of interest.
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