

Regression-derived probabilistic feature generation for hyperspectral image classification using a lightweight framework

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Abstract

Accurate and computationally efficient classification of hyperspectral images (HSI) remains a challenging task due to spectral redundancy, limited labeled samples, and high data dimensionality. This study presents a regression-derived probabilistic feature generation framework for lightweight HSI classification. Unlike conventional methods that directly predict class labels, the proposed approach adopts a two-stage process. In the first stage, class-wise regression models are trained to map spectral responses to continuous estimates of class probability. The resulting probability maps are then concatenated into a compact, low-dimensional probabilistic feature space, which serves as input to standard classifiers in the second stage. Experiments on three benchmark datasets—Indian Pines, Pavia University, and Salinas—using three representative classifiers (SVM, RF, and MLP) under multiple train/test ratios (70/30, 60/40, and 50/50) demonstrate consistent performance gains across all metrics. The proposed framework improved Overall Accuracy by approximately 4%, Average Accuracy by 6%, F1-score by 5%, and Kappa coefficient by 4% compared with direct classification. Statistical analyses using paired t-tests and Wilcoxon signed-rank tests confirmed that these improvements are highly significant ($p < 0.002$). Moreover, the regression-based framework outperformed the lightweight 3D-CNN model across all three datasets (by approximately 0.3–2.0% points) and surpassed the 2D-CNN baseline in two datasets, trailing by only $\sim 1.1\%$ points on the third. Overall, this study demonstrates that regression-derived probabilistic representations can substantially enhance class separability, generalization, and efficiency, providing an interpretable and resource-aware alternative for hyperspectral image classification.

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Keywords: Classification; Machine learning; Regression model; SVM; Random Forest; MLP

1. Introduction

Remote sensing technologies play a vital role across diverse domains, including agriculture, urban management, environmental monitoring, and geological exploration (Khanal et al., 2020; Li et al., 2020; Wellmann

et al., 2020). In agricultural applications, they support crop yield prediction and resource management, while in environmental studies, they enhance the monitoring of oceanic phenomena such as eddies and other ecological indicators (Nejad et al., 2024; Safari et al., 2024). Among these technologies, hyperspectral imaging has attracted significant attention due to its ability to capture hundreds of narrow spectral bands, enabling fine-grained material identification and detailed surface analysis (Li et al., 2019). This capability makes hyperspectral data indispensable for precision agriculture, crop monitoring, land resource assessment,

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gas detection, oil spill identification, water quality analysis, and vegetation mapping.

Despite these advantages, accurate pixel-level hyperspectral image classification remains a challenging task. High spectral dimensionality, spectral redundancy, sensor noise, class imbalance, and complex spectral–spatial variability often degrades classification performance, even when advanced machine learning and deep learning approaches are employed (Borsoi et al., 2021; Feng et al., 2023, Sharma and Gosain, 2025). Furthermore, the limited availability of labeled samples frequently leads to overfitting, while redundant or overlapping spectral information increases computational cost and reduces model robustness (Farmonov et al., 2024; Kumar et al., 2024).

To mitigate these limitations, numerous dimensionality-reduction and band-selection strategies have been developed to enhance discriminative feature representation while reducing redundancy. Among them, two-stage frameworks are widely adopted, where the first stage performs structured band partitioning and the second stage applies a convolutional neural network (CNN)-based classification. Parallel optimization approaches further aim to maximize information content and minimize spectral redundancy, thereby improving efficiency and robustness (Phaneendra Kumar et al., 2024; Sawant et al., 2022).

While semi-supervised and self-supervised learning frameworks have shown promise in addressing labeled data scarcity, recent advancements have shifted towards more efficient and lightweight paradigms that further improve hyperspectral image classification. Semi-supervised methods leverage both labeled and unlabeled samples to enhance generalization, often employing pseudo-label refinement and graph-based spectral–spatial modeling to extract discriminative representations (Li et al., 2024; Wu et al., 2024; Zhao et al., 2024). Additionally, zero-shot models and generative architectures, such as WGAN-based and ConvLSTM models, have proven effective in addressing data scarcity and cross-domain adaptation challenges (Ranjan and Girdhar, 2022). Lightweight CNN hybrids inspired by architectures like Xception and DenseNet have achieved competitive accuracy with reduced computational cost, reflecting a broader shift toward scalable and efficient hyperspectral classification systems (Ranjan and Girdhar, 2022; Ranjan et al., 2024; Ranjan and Gupta, 2023; Ranjan et al., 2025; Ranjan et al., 2023).

Recent frameworks, such as ResMorCNN and HypsLiDNet, have further advanced hyperspectral classification by integrating 3D CNN architectures with spatial–spectral morphology and attention mechanisms. These innovations enable the extraction of highly discriminative spectral–spatial features, improving model robustness across benchmark datasets (Esmaeili et al., 2023; Farmonov et al., 2024).

Beyond deep architectures, lightweight and metaheuristic frameworks have emerged as computationally efficient alternatives for hyperspectral image classification

(Manoharan and Boggavarapu, 2021; Phaneendra Kumar and Manoharan, 2021; Vaddi and Manoharan, 2020). Unsupervised band-selection methods based on spectral reconstruction error, information entropy, and noise suppression have demonstrated strong compatibility with CNN classifiers and improved classification efficiency (BLN et al., 2025; Manoharan and Boggavarapu, 2021). Optimization-driven algorithms, including the Whale Optimization Algorithm (WOA) and its variants, preserve spectral–spatial integrity while enabling accurate classification with fewer bands (BLN et al., 2025; Manoharan and Boggavarapu, 2021; Phaneendra Kumar and Manoharan, 2021; Vaddi and Manoharan, 2020).

Furthermore, hybrid learning strategies integrating spectral, spatial, and contextual information have shown effectiveness in balancing accuracy and computational efficiency (Camps-Valls and Bruzzone, 2005). Transfer learning and domain adaptation further reduce reliance on large labeled datasets (Tuia et al., 2016), while tensor-based hybrid models such as TDRLR combine spectral–spatial feature extraction with robust regression to enhance classification performance under limited training conditions (Deng et al., 2025).

Despite these extensive advances, a persistent research gap remains—the need for a lightweight yet discriminative model capable of achieving strong generalization while minimizing computational cost. To bridge this gap, we propose a regression-based two-stage framework that integrates class-specific regression outputs into a unified probabilistic feature space, thereby enhancing inter-class discrimination and generalization.

The core contribution of this study lies in utilizing regression as an intermediate representation rather than a direct predictor. In the first stage, an independent regression model is trained for each class using its spectral features to produce probability maps that represent pixel-wise class-probability estimates. These maps are concatenated into a comprehensive probabilistic feature space, which serves as input to the second stage. In this classification stage, the combined probabilistic representations are processed to produce the final classification map. Unlike existing pseudo-labeling or feature-fusion approaches, the proposed framework embeds regression outputs as probabilistic layers, explicitly encoding inter-class relationships while remaining computationally efficient and model-agnostic.

To validate the robustness and adaptability of the proposed design, the framework was evaluated on three benchmark hyperspectral datasets—Indian Pines, Pavia University, and Salinas—across multiple training ratios (70–30, 60–40, 50–50). Three classifiers—Support Vector Machine (SVM) with Support Vector Regression (SVR), Random Forest (RF) with Random Forest Regression (RFR), and Multilayer Perceptron (MLP) with Multilayer Perceptron Regression (MLPR)—were employed for comparative analysis. Across all configurations, the regression-

based framework consistently outperformed direct classification, demonstrating notable gains in accuracy, stability, and generalization.

2. Image datasets

In this study, three datasets—Salinas, Pavia, and Indian Pine—along with their ground truth maps, were used to evaluate the proposed method. The RGB color representation, along with the ground truth map for each dataset, is shown in Fig. 1.

2.1. Dataset descriptions

Indian Pines: This dataset was captured by the AVIRIS sensor over the Indian Pines test site in northwestern Indiana. It consists of a 145×145 pixel image with 224 spectral bands in the wavelength range of 0.4 to $2.5 \mu\text{m}$. This scene represents a portion of a larger dataset and features a mix of agricultural and natural land cover, with two-thirds of the area being agricultural fields and the remaining one-third consisting of forests and perennial vegetation. The ground truth for this dataset is divided into 16 classes. Additionally, 200 bands were retained after removing those affected by water absorption (bands: [104–108], [150–163], 220).

Pavia: University: This scene was acquired by the ROSIS sensor during a flight campaign over Pavia, northern Italy. The number of spectral bands is 103, and the image has a resolution of 610×610 pixels. Some of the samples in this image contain no useful information and were discarded prior to the analysis. The geometric resolution is 1.3 m. The ground truth for this dataset includes 9 distinct classes.

Salinas: The Salinas dataset was collected using the 224-band AVIRIS sensor over the Salinas Valley in California, offering a high spatial resolution of 3.7 m per pixel. It covers an area of 512×217 pixels and is labeled with 16 classes of land cover. The dataset was processed by removing 20 spectral bands associated with water absorption, specifically bands [108–112], [154–167], and 224.

2.2. Data preparation

Each hyperspectral dataset was reshaped into a two-dimensional matrix in which rows represent individual pixels and columns correspond to spectral bands. All spectral features were standardized using z-score normalization computed from the training samples (mean and standard deviation). The same normalization parameters were subsequently applied to the test data to ensure comparability between sets and to prevent data leakage.

No dimensionality reduction techniques (e.g., Principal Component Analysis, PCA) or band selection methods were applied before the regression or classification phases. This was an intentional design choice to ensure that the observed performance improvements originate solely from the proposed regression-based framework rather than from external feature engineering. Moreover, because the regression-derived probability maps were later used independently as compact, low-dimensional inputs to the classifiers, additional feature reduction was unnecessary.

Training and testing pixels were randomly selected from the ground-truth maps according to three train–test ratios (70–30, 60–40, and 50–50) as summarized in Table 1. Each ratio corresponds to a distinct experimental scenario, labeled as S#1, S#2, and S#3, respectively. This approach was adopted to evaluate the generalizability of the proposed method under different data distribution conditions. The exact numbers of training and testing samples for each dataset and scenario are presented in Table 2. A stratified random sampling strategy was adopted to preserve class balance and spectral diversity, consistent with standard practices in hyperspectral image classification.

3. Methodology

This section describes the proposed two-stage regression-based framework for hyperspectral image classification. First, we outline the overall workflow and the rationale for using class-wise regression to produce probabilistic feature maps. Next, we provide step-by-step details

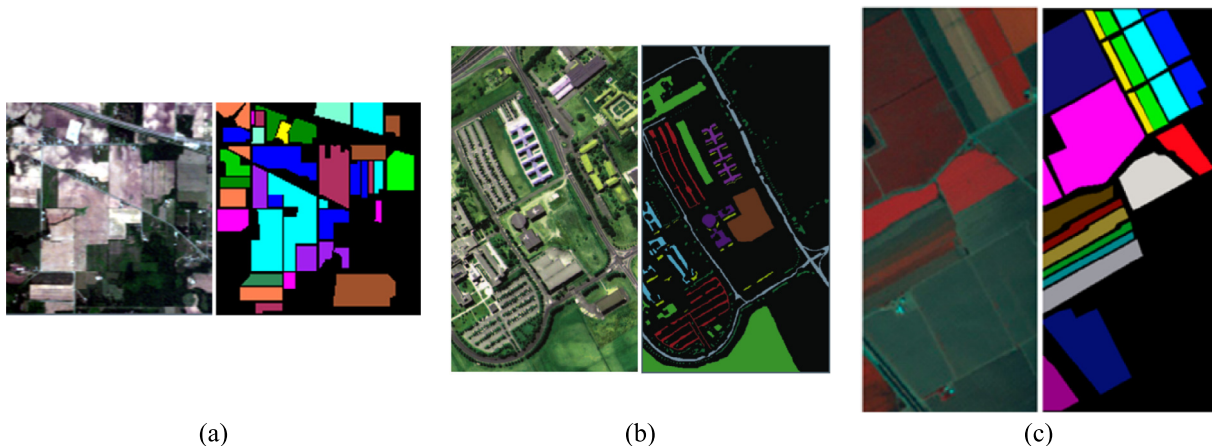


Fig. 1. RGB representation and ground truth maps of the three hyperspectral datasets: (a) Indian Pines (Dataset #1), (b) Pavia (Dataset #2), and (c) Salinas (Dataset #3).

Table 1
Different experimental scenarios.

Scenarios	Training data	Testing data
S#1	70%	30%
S#2	60%	40%
S#3	50%	50%

for data preparation, regression training and inference, the classification stage, algorithm selection and hyperparameter tuning, and the experimental scenarios used for evaluation.

3.1. Overview of the proposed framework

The proposed approach introduces a regression-based feature generation stage preceding the classification phase. Unlike conventional auxiliary-feature methods—such as pseudo-labeling, class-probability smoothing, or self-training—which rely on iterative label refinement or smoothing of discrete labels, our framework employs a direct, non-iterative strategy. For each class, a dedicated regression model learns a continuous mapping between spectral reflectance vectors and the probability of class membership. The resulting regression outputs form class-specific probability maps that quantitatively capture the spectral affinity of each pixel to every class. Importantly, these maps preserve fine-grained spectral variations between neighboring classes, providing richer discriminative information than discrete label-smoothing or pseudo-label approaches and enhancing class separability during classification.

Regression is particularly well-suited for hyperspectral data because pixel reflectance values exhibit strong nonlinear and continuous relationships with surface materials. Regressors such as SVR, RFR, and MLPR effectively model these nonlinearities, producing smooth and quantitative probability distributions. Although these three algorithms were used for demonstration, the framework is model-agnostic and can incorporate any regression function capable of producing continuous class-probability esti-

mates. This design yields a computationally lightweight, low-dimensional representation that avoids iterative pseudo-label refinement and remains effective even when labeled samples are limited.

3.2. Regression stage—class-wise model training

For each class c , an independent regression model was trained according to a series of steps. These steps involve constructing labels, selecting a model, optimizing hyperparameters, training the model, generating output, and performing inference on the full image. The details of these steps are illustrated in Fig. 3 below, which provides a visual representation of the process.

Label Construction. Pixels belonging to class c were assigned the target value 1, while all remaining pixels were assigned 0. This resulted in a continuous target vector representing class membership for training the regression model.

Model Selection and Design. To ensure methodological consistency with the subsequent classification stage, three regression families were employed: SVR, RFR, and MLPR. These regressors were chosen to illustrate the flexibility of the framework rather than to limit it, since any regression function capable of generating continuous class-probability estimates can be incorporated into the proposed workflow.

Hyperparameter Optimization. All models were tuned using grid search combined with 5-fold cross-validation on the training portion of each dataset. Parameter ranges included regularization coefficients, kernel parameters, number of trees, learning rate, and hidden-layer size. This procedure ensured dataset-specific adaptation while avoiding overfitting.

Training. Each regression model was trained on its corresponding class-specific labels using only the training samples. No information from the test set was introduced at any stage of training or parameter tuning.

Output Characteristics. Because each model was trained with binary target values (1 for the target class and 0 for all others), the resulting regression outputs naturally fall

Table 2
Number of training and testing datasets.

Datasets		Number of training data	Number of testing data
Dataset #1	70–30	7256	3110
	60–40	6220	4146
	50–50	5183	5183
Dataset #2	70–30	29,943	12,833
	60–40	25,666	17,110
	50–50	21,388	21,388
Dataset #3	70–30	77,773	33,331
	60–40	66,662	44,442
	50–50	55,552	55,552

within or very close to the $[0, 1]$ range. These outputs were interpreted directly as class-membership probabilities without any additional normalization step.

Inference on the Full Image. After training, each regression model was applied to all pixels of the input image (including both training and testing regions) to generate the probability map corresponding to that class. Since regression fitting and tuning were performed exclusively on the training data, this process strictly prevented data leakage and ensured unbiased prediction for test pixels.

3.3. Construction and use of regression-derived probability maps

After completing the regression stage for all classes, a set of K class-specific probability maps was obtained, where K denotes the number of classes in the dataset. Each map represents the estimated probability that each pixel belongs to its corresponding class. These maps were then stacked to construct a K -dimensional probabilistic feature vector for every pixel. Importantly, the classification algorithms used only these regression-derived probability maps as input features; no fusion with the original spectral bands was performed. This design isolates the contribution of the regression stage and enables an unbiased evaluation of its discriminative capability. Because the number of generated maps equals the number of classes (typically 9 or 16), the resulting feature space is inherently low-dimensional, and therefore no additional dimensionality reduction step is required.

3.4. Classification stage

Using the regression-derived probability maps as input, three classifiers—SVM, RF, and MLP—were trained to predict the final class labels. The same algorithmic families employed in regression were reused for classification to maintain methodological consistency and enable fair comparison. All classifier hyperparameters were independently optimized via grid search and 5-fold cross-validation on the training data, ensuring equal tuning rigor for both baseline and proposed models.

3.5. Experimental scenarios and evaluation protocol

To evaluate the robustness and generalizability of the proposed framework, three experimental scenarios were conducted for each dataset, corresponding to different train–test ratios: 70–30, 60–40, and 50–50. In each case, stratified random sampling was applied to select training and testing pixels while maintaining balanced class distributions. The overall workflow and evaluation pipeline are illustrated in Fig. 2.

Model performance was assessed using multiple complementary metrics, including Overall Accuracy (OA), Average Accuracy (AA), F1-score, and the Kappa coefficient,

all computed on the held-out test sets. In addition to these global indicators, per-class accuracies were also analyzed to provide a more detailed assessment of class-level performance variations.

To determine whether the observed performance improvements were statistically significant, paired t-tests and Wilcoxon signed-rank tests were performed across repeated experimental runs and datasets. These tests verified that the gains achieved by the proposed regression-based framework were not due to random variation.

Furthermore, average runtime and computational cost were recorded for each experimental setting to support the claim of computational efficiency. Comparative results confirmed that the proposed framework achieved its improvements with substantially lower computational demand than typical deep-learning-based baselines.

3.6. Computational considerations and scalability

The proposed regression-based framework is computationally lightweight and readily scalable to large hyperspectral datasets. Because the method generates only K class-specific probability maps—where K denotes the number of land-cover classes—the resulting feature representation is compact and memory-efficient compared with the hundreds of spectral bands in the original data.

During implementation, regression and classification models were trained independently for each class, and parallel processing was utilized to reduce overall runtime. The total computational cost mainly depends on the number of classes and the complexity of the selected regression algorithm. Even for large satellite scenes, the framework remained practical with respect to both memory usage and execution time.

For reference, the computational performance of the proposed regression-based framework was compared with that of deep-learning-based methods reported in the literature. The results demonstrated that the proposed approach achieved comparable or superior classification accuracy while maintaining substantially lower computational complexity. This confirms the scalability and efficiency of the regression-based framework for operational remote sensing applications.

4. Results

This section presents a comprehensive evaluation of the proposed regression-based classification framework in comparison with the conventional direct classification strategy. Experiments were conducted on three widely used hyperspectral datasets under three train/test configurations (70/30, 60/40, and 50/50) and across three representative classifiers: RF, SVM, and MLP. To ensure a fair and detailed comparison, multiple quantitative, statistical, and qualitative analyses were performed. The quantitative evaluation includes overall accuracy (OA), average accuracy (AA), F1-score, and Kappa coefficient, along with compu-

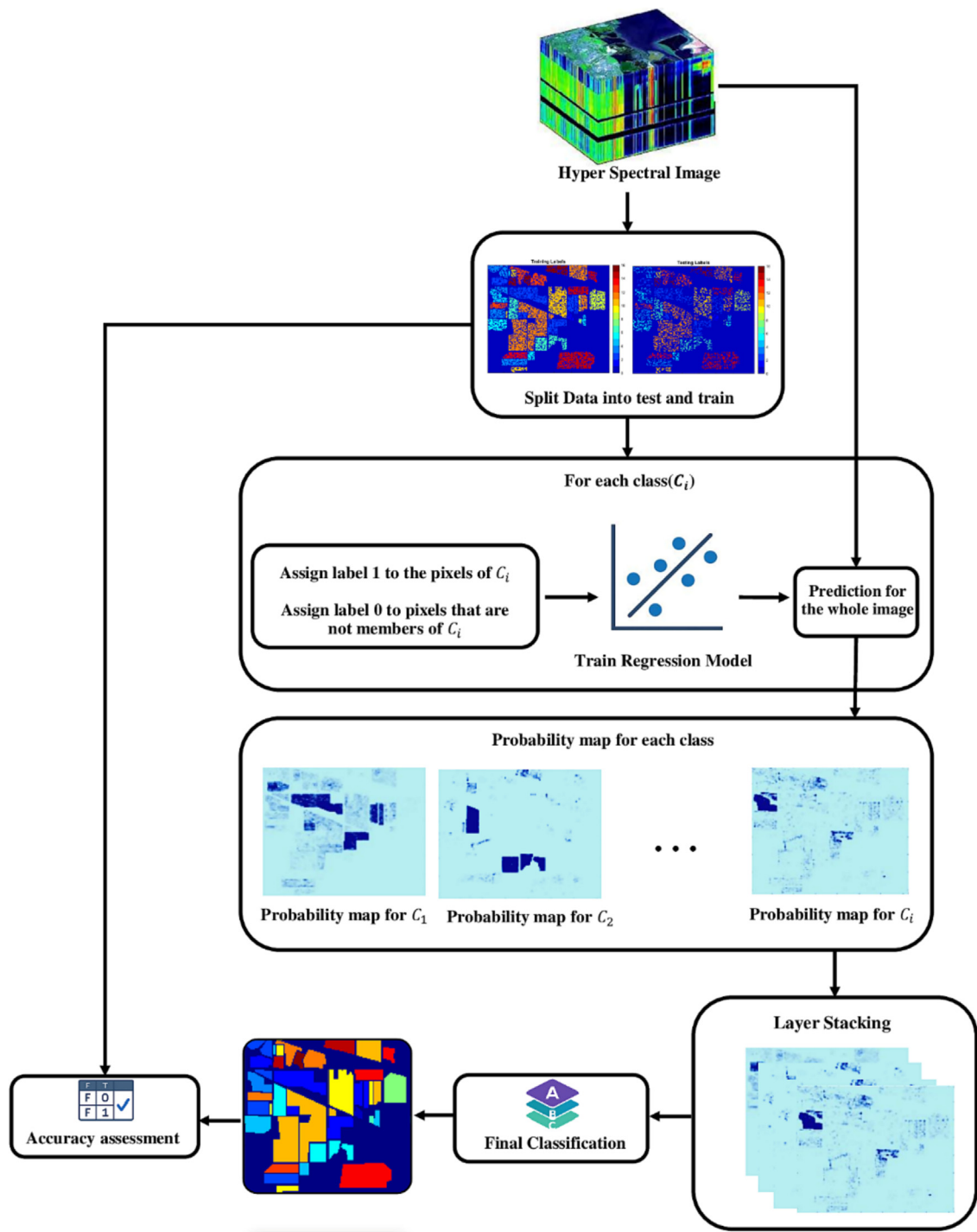


Fig. 2. Flowchart illustrating the execution process of the proposed method and the result evaluation procedure.

tational time to assess the trade-off between accuracy and efficiency. Furthermore, confusion matrices and visual classification maps were generated for representative cases to analyze class-level behavior, spatial consistency, and potential sources of misclassification. To validate the consistency and robustness of the observed improvements, statistical significance analyses were carried out using paired t-tests and Wilcoxon signed-rank tests across 10 random runs.

Finally, to assess the competitiveness of the proposed regression-based approach against modern alternatives, we conducted additional comparisons with recent light-weight deep-learning models, including 2D-CNN and 3D-CNN architectures. These comparisons evaluated whether the proposed framework preserves its advantages in accuracy, stability, and computational cost under contemporary baselines.

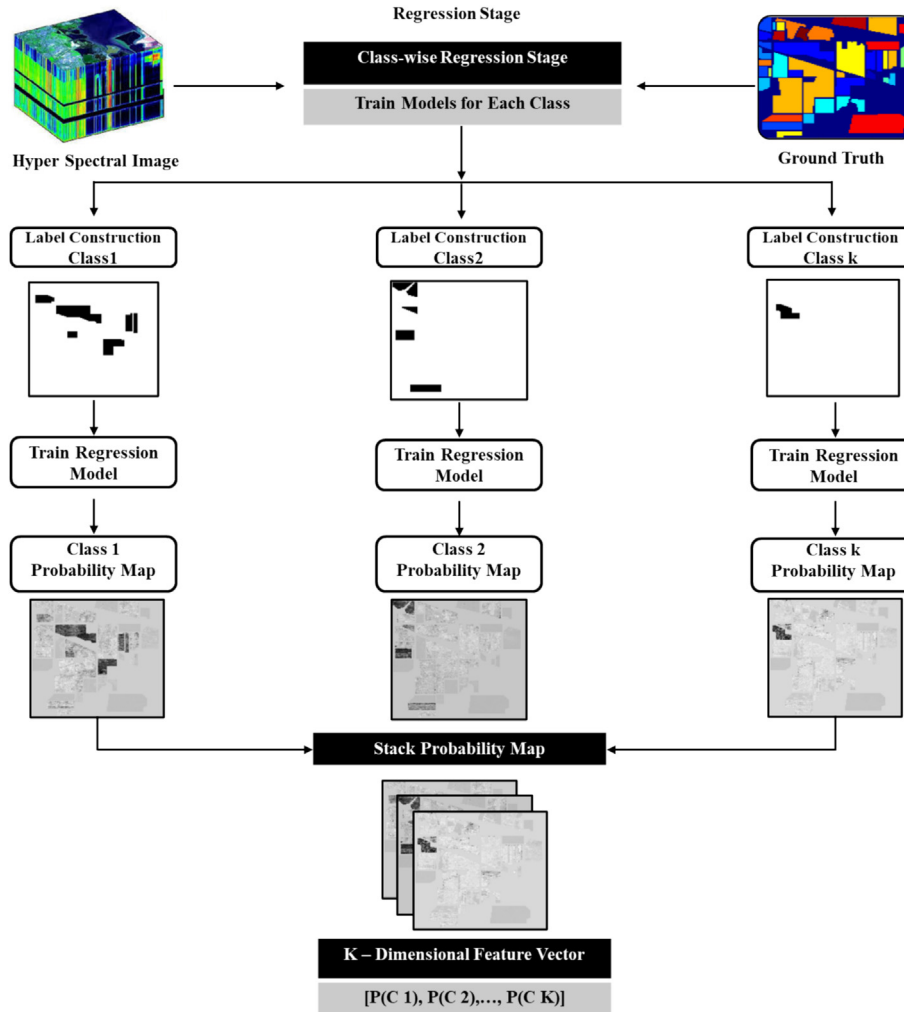


Fig. 3. Flowchart illustrating the steps of class-wise regression model training.

4.1. Quantitative evaluation

Tables 3–5 present the quantitative classification results obtained from the proposed regression-based and conventional direct classification strategies across the three hyper-spectral datasets using MLP, SVM, and RF classifiers under different train–test ratios (70/30, 60/40, and 50/50). Each table reports Overall Accuracy (OA), Average Accuracy (AA), F1-score, Kappa coefficient, and computational Time (in seconds) to summarize the numerical performance of each configuration.

4.2. Confusion matrices and class-level results

To complement the quantitative evaluation presented in Tables 3–5, both class-level confusion analysis and visual classification maps were employed to provide a comprehensive qualitative assessment of the proposed regression-based framework.

Confusion matrices were first used to examine class-wise behavior in detail. Each matrix summarizes the relationship between true and predicted labels, enabling iden-

tification of dominant confusion patterns, class imbalance effects, and improvements achieved through the regression-based preprocessing stage. Given that exhaustive visualization of all 54 experimental configurations (27 direct and 27 regression-based) would not be practical, three representative cases were selected to illustrate the general behavior of the framework. These configurations include: (i) Dataset #1 with the SVM classifier at 50% training, (ii) Dataset #2 with RF at 60% training, and (iii) Dataset #3 with MLP at 70% training. The corresponding confusion matrices for both direct and regression-based modes are presented in Fig. 4.

Beyond class-level statistics, visual inspection of the spatial classification patterns provides further validation of the proposed approach. Therefore, for the same representative configurations, classification maps were generated and are shown in Fig. 5. For each dataset, three maps are presented: (1) the direct classification result, (2) the regression-based classification result, and (3) a difference map highlighting pixel-wise changes between the two methods relative to the ground truth.

Table 3

Classification accuracy of the MLP algorithm for three different datasets under varying training-to-testing.

Dataset #1						
Scenarios	Method	OA (%)	AA (%)	F1 (%)	Kappa (%)	Time(s)
S#1	Direct	69.98	56.23	55.20	68.20	13.15 s
	Regression-Based	79.12	75.36	77.72	77.85	147 s
S#2	Direct	68.49	54.02	53.26	66.67	10.17 s
	Regression-Based	77.71	72.71	74.78	76.35	103.08 s
S#3	Direct	63.47	46.52	47.21	61.52	8.53 s
	Regression-Based	76.42	66.36	68.55	75.01	82.01 s
Dataset #2						
Scenarios	Method	OA (%)	AA (%)	F1 (%)	Kappa (%)	Time(s)
S#1	Direct	85.26	80.28	82.30	83.88	69.52 s
	Regression-Based	92.06	90.26	90.68	91.24	435.35 s
S#2	Direct	84.56	79.72	81.44	83.11	60.74 s
	Regression-Based	91.46	89.31	90.12	90.58	373.46 s
S#3	Direct	82.83	75.79	76.21	81.23	52.83 s
	Regression-Based	90.94	88.88	89.33	90.01	313.23 s
Dataset #3						
Scenarios	Method	OA (%)	AA (%)	F1 (%)	Kappa (%)	Time(s)
S#1	Direct	89.78	93.54	93.91	89.13	110.62 s
	Regression-Based	91.82	95.66	95.62	91.30	1301.84 s
S#2	Direct	88.89	93.11	93.19	88.20	96.77 s
	Regression-Based	91.53	95.48	95.44	90.99	1131.59 s
S#3	Direct	88.97	92.79	93.01	88.28	76.43 s
	Regression-Based	90.93	95.32	95.19	90.35	921.25 s

Table 4

Classification accuracy of the SVM algorithm for three different datasets under varying training-to-testing.

Dataset #1						
Scenarios	Method	OA (%)	AA (%)	F1 (%)	Kappa (%)	Time(s)
S#1	Direct	85.69	80.71	83.68	84.82	5.50 s
	Regression-Based	89.95	87.59	89.48	89.33	23.07 s
S#2	Direct	84.83	78.00	80.51	83.91	5.77 s
	Regression-Based	89.20	86.41	88.54	88.53	17.82 s
S#3	Direct	83.65	73.16	76.48	82.66	6.16 s
	Regression-Based	88.00	83.35	85.35	87.26	13.05 s
Dataset #2						
Scenarios	Method	OA (%)	AA (%)	F1 (%)	Kappa (%)	Time(s)
S#1	Direct	91.60	86.84	88.97	90.76	18.28 s
	Regression-Based	94.23	92.09	92.82	93.63	175.61 s
S#2	Direct	90.94	85.84	88.19	90.03	59.85 s
	Regression-Based	94.02	91.89	92.71	93.40	116.83 s
S#3	Direct	90.32	84.72	87.24	89.35	11.31 s
	Regression-Based	93.98	91.89	92.67	93.36	75.75 s
Dataset #3						
Scenarios	Method	OA (%)	AA (%)	F1 (%)	Kappa (%)	Time(s)
S#1	Direct	92.69	96.01	96.19	92.23	33.64 s
	Regression-Based	93.78	96.83	96.97	93.38	149.22 s
S#2	Direct	92.97	96.17	96.34	92.53	38.90 s
	Regression-Based	93.98	96.96	97.10	93.60	207.70 s
S#3	Direct	92.69	96.01	96.19	92.23	33.32 s
	Regression-Based	93.78	96.83	96.97	93.38	161.59 s

Table 5

Classification accuracy of the RF algorithm for three different datasets under varying training-to-testing.

Dataset #1						
Scenarios	Method	OA (%)	AA (%)	F1 (%)	Kappa (%)	Time(s)
S#1	Direct	84.93	78.96	82.21	84	2.53
	Regression-Based	85.12	81.84	82.59	84.21	41.37
S#2	Direct	85.89	81.14	83.81	85.01	2.32
	Regression-Based	86.28	81.53	84.39	85.43	35.07
S#3	Direct	82.47	75.81	76.75	81.40	2.42
	Regression-Based	83.22	77.06	78.74	81.92	29.91
Dataset #2						
Scenarios	Method	OA (%)	AA (%)	F1 (%)	Kappa (%)	Time(s)
S#1	Direct	93.30	91.02	92.07	92.62	8.04
	Regression-Based	93.75	92.17	92.48	93.10	74.97
S#2	Direct	93.03	90.82	91.87	92.32	7.86
	Regression-Based	93.56	92.11	92.44	92.89	62.10
S#3	Direct	92.84	90.58	91.64	92.11	6.06
	Regression-Based	93.23	91.70	91.91	92.52	51.05
Dataset #3						
Scenarios	Method	OA (%)	AA (%)	F1 (%)	Kappa (%)	Time(s)
S#1	Direct	94.7	97.27	97.29	94.37	9.9
	Regression-Based	95.04	97.48	97.48	94.72	230.1
S#2	Direct	94.37	97.06	97.04	94.01	8.19
	Regression-Based	94.58	97.09	97.12	94.24	185.23
S#3	Direct	94.01	96.72	96.71	93.63	7.29
	Regression-Based	94.14	96.91	96.93	93.77	149

The difference map is color-coded to explicitly visualize performance variation at the pixel level. Green pixels indicate locations where the regression-based method corrected misclassifications produced by the direct classifier (i.e., pixels incorrectly labeled in the direct mode but correctly classified in the regression-based mode). Red pixels denote the opposite case, where the regression-based approach misclassified pixels that were correctly labeled by the direct classifier. White pixels represent agreement between the two approaches, meaning that both methods assigned the same class label to the pixel, regardless of correctness.

This visualization enables pixel-wise validation against the ground truth and provides insight into how performance variations are spatially distributed across the scene. Overall, the visual evidence is consistent with the quantitative and statistical findings reported earlier. While localized degradations (red regions) indicate cases where the direct classifier performs better, the predominance of corrected pixels and improved spatial coherence suggests that the regression-based preprocessing stage generally enhances classification stability. Rather than uniformly improving every pixel, the proposed framework redistributes classification errors, leading to a net gain in global performance and more consistent spatial patterns across the scene.

4.3. Statistical significance analysis

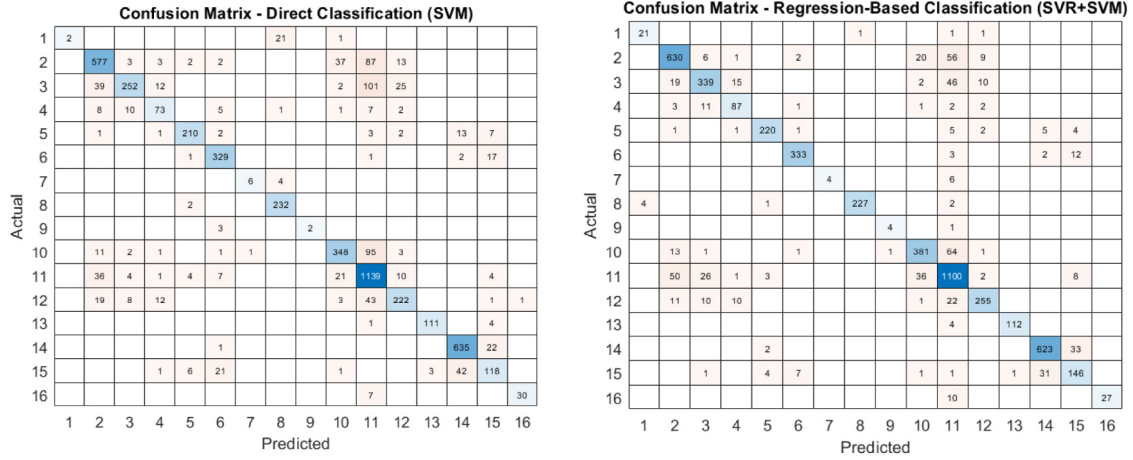
To ensure that the observed performance improvements of the proposed regression-based classification framework

are statistically reliable rather than the result of random variation, formal significance tests were conducted. Considering the large number of possible experimental combinations—27 in total, derived from three datasets, three classifiers, and three train/test ratios—a subset of representative cases was selected to assess statistical robustness while maintaining computational feasibility. These representative configurations include Dataset 1 with the Random Forest classifier at 60% training, Dataset 2 with SVM at 50% training, and Dataset 3 with MLP at 70% training.

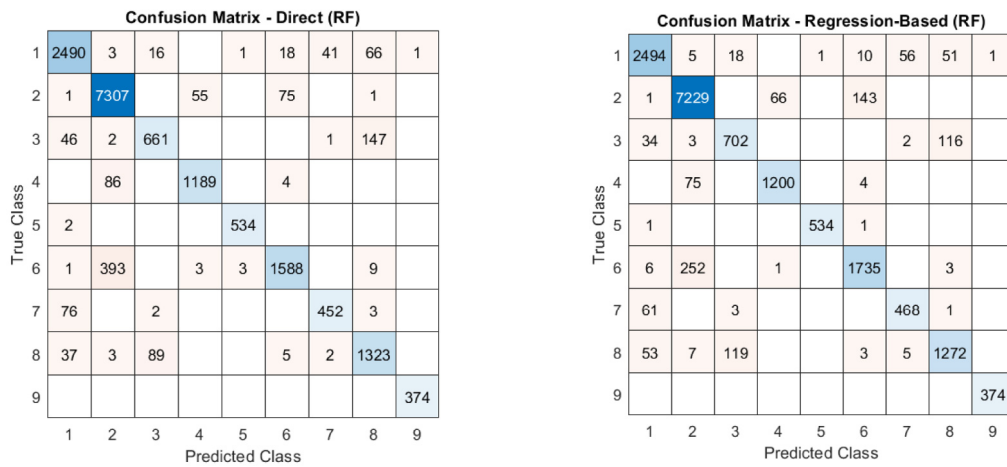
For each selected configuration, both paired *t*-tests and Wilcoxon signed-rank tests were applied using results from ten independent runs. These complementary tests account for both parametric and non-parametric distributions, providing a rigorous assessment of whether the observed differences between the direct and regression-based classification strategies are statistically significant. The outcomes of these tests are summarized in Table 6.

4.4. Comparison with lightweight deep learning approaches

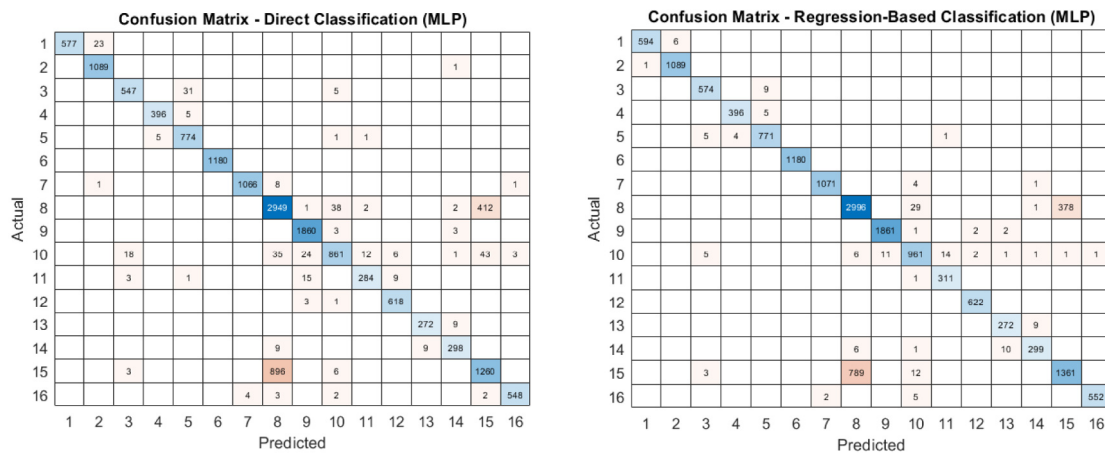
To further examine the competitiveness of the proposed regression-based classification framework under modern baselines, a comparative analysis was performed against several representative deep learning methods. Specifically, four architectures were considered: conventional CNN and Deep Belief Network (DBN) following the implementations reported by (Feng et al., 2019), as well as 2D-CNN



SVM | Dataset #1 | S#3



RF | Dataset #2 | S#2



MLP | Dataset #3 | S#1

Fig. 4. Confusion matrices for three selected representative cases.

and 3D-CNN models based on (Esmaceli et al., 2023). The comparison was conducted across the same three hyper-spectral datasets used in this study to ensure a consistent evaluation setting.

The results of this comparison are presented in Table 7, which summarizes the classification accuracies obtained by

the regression-based method and the deep learning approaches for each dataset. For each dataset, we report the best-performing regression-based configuration (SVM for Dataset #1 and Dataset #2; RF for Dataset #3) to provide a fair, dataset-wise comparison against the deep learning baselines. This extended comparison offers a broader

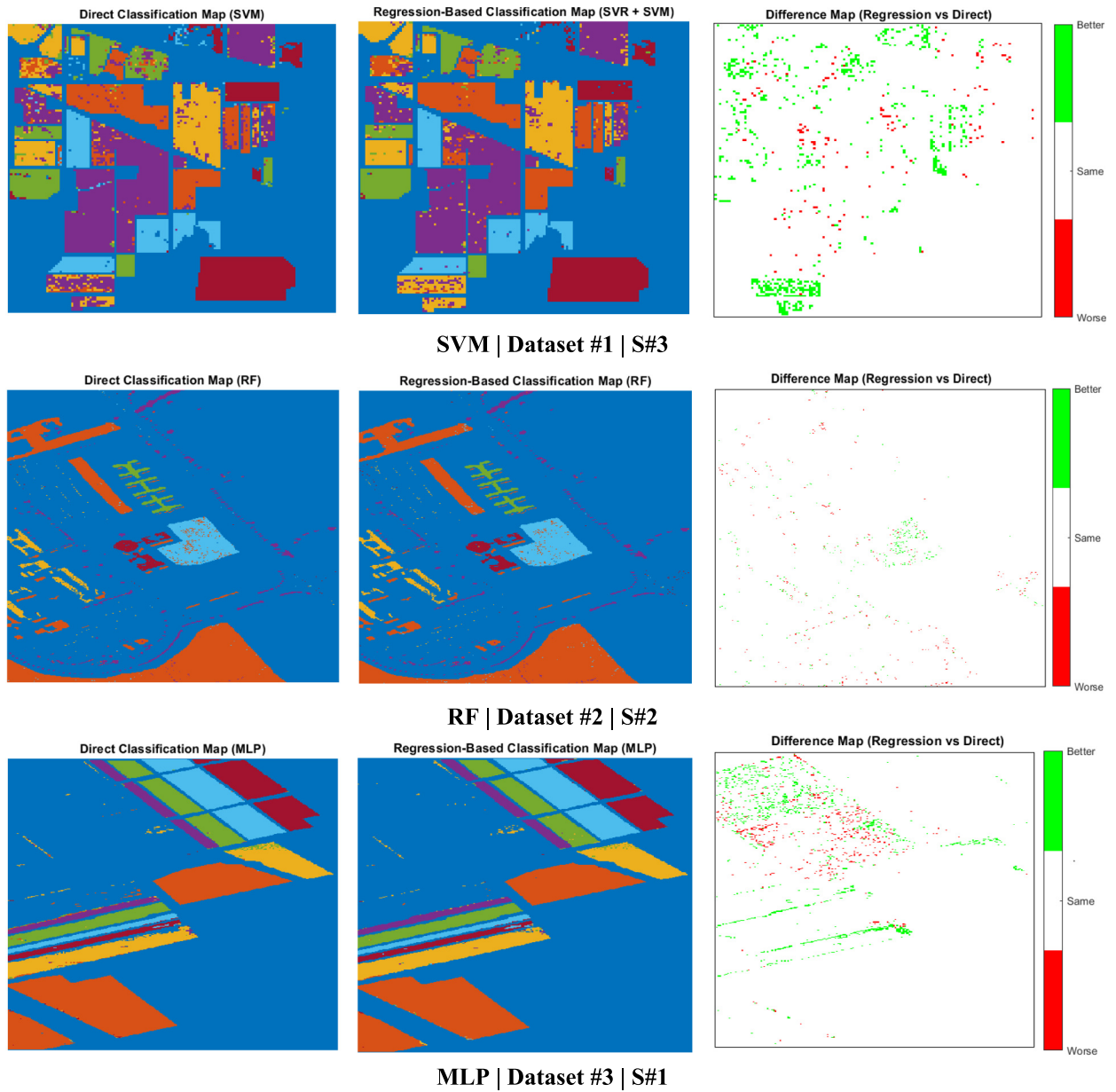


Fig. 5. Direct vs. regression-based classification maps with pixel-wise difference maps (green: improved; red: degraded; white: agreement).

benchmark for positioning the proposed framework relative to both convolutional and generative deep architectures commonly applied to hyperspectral image classification.

5. Discussion

5.1. Overview of findings

This study evaluated a regression-based two-stage framework for hyperspectral image classification across three benchmark datasets (Indian Pines, Pavia University, and Salinas), three classifiers (SVM, RF, and MLP), and three train–test ratios (70/30, 60/40, and 50/50). The quantitative results summarized in Tables 3–5 demonstrate that

the regression-based pipeline yields systematic and consistent improvements across all evaluation metrics—OA, AA, F1-score, and Kappa—when compared to the conventional direct classification baseline. Averaged over all 27 experimental configurations, the proposed method achieved approximately a 4% increase in OA, a 6% increase in AA, a 5% gain in F1-score, and about a 4% improvement in Kappa, confirming its overall superiority across different classifiers and data splits.

The observed performance gains were stable across all algorithms and sampling scenarios: improvements were present for SVM, RF, and MLP alike, and persisted under the three considered train–test ratios. Statistical analyses further supported the reliability of these improvements. As reported in Table 6, the paired t-tests yielded p -values

Table 6

Statistical significance analysis of direct and regression-based classification methods using paired *t*-test and Wilcoxon signed-rank test on three representative datasets.

Dataset #1						
Classifier	Scenarios	Metric	Direct (Mean $\pm$ SD)	Regression (Mean $\pm$ SD)	<i>t</i> -test <i>p</i> -value	Wilcoxon <i>p</i> -value
SVM	S#3	OA (%)	83.75 $\pm$ 0.59	88.17 $\pm$ 0.36	0.0000	0.0020
		AA (%)	73.28 $\pm$ 1.50	82.02 $\pm$ 1.77	0.0000	0.0020
		F1 (%)	76.43 $\pm$ 1.88	84.84 $\pm$ 1.58	0.0000	0.0020
		Kappa (%)	0.8277 $\pm$ 0.0063	0.8744 $\pm$ 0.0038	0.0000	0.0020
Dataset #2						
Classifier	Scenarios	Metric	Direct (Mean $\pm$ SD)	Regression (Mean $\pm$ SD)	<i>t</i> -test <i>p</i> -value	Wilcoxon <i>p</i> -value
RF	S#2	OA (%)	93.09 $\pm$ 0.15	93.49 $\pm$ 0.13	0.0000	0.0020
		AA (%)	90.73 $\pm$ 0.24	91.83 $\pm$ 0.29	0.0000	0.0020
		F1 (%)	91.80 $\pm$ 0.16	92.16 $\pm$ 0.21	0.0001	0.0020
		Kappa (%)	0.9238 $\pm$ 0.0016	0.9281 $\pm$ 0.0014	0.0000	0.0020
Dataset #3						
Classifier	Scenarios	Metric	Direct (Mean $\pm$ SD)	Regression (Mean $\pm$ SD)	<i>t</i> -test <i>p</i> -value	Wilcoxon <i>p</i> -value
MLP	S#1	OA (%)	89.41 $\pm$ 0.52	93.49 $\pm$ 0.13	0.0000	0.0020
		AA (%)	90.73 $\pm$ 0.24	91.83 $\pm$ 0.29	0.0000	0.0020
		F1 (%)	91.80 $\pm$ 0.16	92.16 $\pm$ 0.21	0.0001	0.0020
		Kappa (%)	0.9238 $\pm$ 0.0016	0.9281 $\pm$ 0.0014	0.0000	0.0020

Table 7

Classification accuracy of the proposed regression-based method compared with 2D-CNN and 3D-CNN deep learning models across the three hyperspectral datasets.

Dataset #1			
Method	OA (%)	Kappa (%)	F1 (%)
Regression-Based SVM	89.95	89.33	89.48
CNN	85.4	84.3	–
2D-CNN	87.98	85.39	86.54
3D-CNN	88.03	87.52	87.63
DBN	80.6	77.8	–
Dataset #2			
Method	OA (%)	Kappa (%)	F1 (%)
Regression-Based SVM	94.23	93.63	92.82
CNN	93	90.7	–
2D-CNN	93.22	92.16	92.54
3D-CNN	93.94	92.83	93.24
DBN	91.9	89.2	–
Dataset #3			
Method	OA (%)	Kappa (%)	F1 (%)
Regression-Based RF	95.04	94.72	97.48
CNN	92.3	91.4	–
2D-CNN	96.10	95.41	95.61
3D-CNN	94.53	93.32	93.78
DBN	90.8	89.7	–

close to zero (typically below 0.0001) for all evaluation metrics, while the non-parametric Wilcoxon signed-rank test consistently produced $p = 0.0020$, indicating highly significant differences in favor of the regression-based

approach. The representative confusion matrices shown in Fig. 4 complement these findings by illustrating that the proposed framework improves class-wise discrimination across most spectral categories.

Finally, the comparison with representative deep learning baselines, the conventional CNN and Deep Belief Network (DBN) from (Feng et al., 2019), as well as 2D-CNN and 3D-CNN reproduced from (Esmaili et al., 2023), provides an additional benchmark for positioning the proposed method under contemporary standards. As shown in Table 7, the regression-based framework achieved competitive or superior performance compared to most deep learning models across the three datasets. It consistently outperformed CNN and DBN, surpassed 3D-CNN in all datasets, and exceeded 2D-CNN in two datasets while remaining closely competitive in the third. These results indicate that the proposed probabilistic feature framework can deliver deep-learning-level accuracy without relying on complex hierarchical architectures or GPU-dependent training, further highlighting its robustness and practical efficiency.

5.2. Regression effects

The improvements observed across the experiments can be attributed to the effect of the regression-based feature generation stage introduced prior to classification. By regressing spectral responses onto class probability estimates, the proposed framework transforms the original high-dimensional spectral space into a smoother and more

discriminative representation. This transformation allows each classifier—SVM, RF, and MLP—to operate on features that better capture class separability while suppressing noise and redundancy among neighboring spectral bands.

The regression step effectively enhances inter-class distinction and reduces intra-class spectral variability, particularly in regions where raw spectral signatures of different materials exhibit significant overlap. As a result, the subsequent classifier can form more stable decision boundaries, improving generalization across varying training proportions. This effect is observed consistently in [Tables 3–5](#), where all classifiers benefit from the regression-derived feature space, although the magnitude of improvement varies depending on dataset characteristics and classifier type.

Overall, the regression-based mapping acts as a feature refinement mechanism that bridges the gap between spectral data and class-level decision functions. By capturing continuous relationships rather than discrete label boundaries, it provides a compact and informative representation that contributes to the improved performance verified in the statistical analyses of [Section 4.3](#).

5.3. Class-level analysis

To further understand the behavior of the proposed framework at the class level, the diagonal elements of the confusion matrices were compared between the direct and regression-based classification modes for the three representative experimental cases. These comparisons reveal that the regression-based approach generally improves the recognition accuracy for a majority of classes, while minor decreases are observed in a limited number of categories.

In Dataset #1 using SVM (Scenario 3), which contains 16 classes, improvements were observed in 12 classes, whereas 4 classes showed slightly lower accuracies. This indicates that most spectral categories benefited from the regression-derived representation, particularly those with complex or overlapping spectral signatures. For Dataset #2 using RF (Scenario 2) with 9 classes, 5 classes exhibited higher accuracies, 3 showed minor decreases, and 2 remained unchanged. The presence of both improved and stable classes suggests that the regression stage neither disrupts well-separated classes nor introduces instability across the classifier's decision boundaries.

Finally, for Dataset #3 using MLP (Scenario 1), which also contains 16 classes, the regression-based framework improved the accuracy of 11 classes, maintained equal performance in 4 classes, and showed a small decrease in only one class.

These results collectively demonstrate that the regression-based transformation enhances discrimination for most classes across different datasets and classifiers, with performance degradation confined to a small subset of categories. The observed pattern also indicates that classes with limited training samples or high spectral simi-

larity tend to show smaller gains, suggesting a mild sensitivity of the regression stage to class imbalance. Nevertheless, the overall dominance of positive improvements across multiple experimental conditions confirms that the proposed framework achieves a favorable class-level balance and preserves stability across diverse spectral categories.

5.4. Statistical robustness

To confirm that the performance differences between the regression-based and direct classification strategies are not attributable to random variation, statistical significance analyses were conducted using both paired *t*-tests and Wilcoxon signed-rank tests on the ten independent runs of the three representative experimental configurations. The detailed outcomes are summarized in [Table 6](#).

Across all cases and evaluation metrics (OA, AA, F1, and Kappa), the paired *t*-tests produced *p*-values close to zero (typically below 0.0001), confirming statistically significant improvements in favor of the regression-based approach. The non-parametric Wilcoxon signed-rank test produced *p*-values of 0.0020 for all cases, further corroborating the statistical significance of the observed improvements.

The combination of both parametric and non-parametric tests confirms that the observed gains are not data-specific artifacts or the result of stochastic fluctuations across runs. These findings provide quantitative evidence that the regression-based feature generation mechanism introduces a consistent and statistically reliable enhancement in classification performance.

5.5. Deep learning comparison

The comparative results in [Table 7](#) position the proposed regression-based framework relative to several representative deep learning architectures, including conventional CNN and DBN models, as well as 2D-CNN and 3D-CNN variants. While deep neural networks possess strong spatial-spectral feature learning capabilities, they generally require larger parameter spaces, GPU acceleration, extensive hyperparameter tuning, and substantial labeled samples to fully exploit their representational capacity. In contrast, the regression-based framework maintains a simple and interpretable pipeline while delivering highly competitive performance.

Across the three benchmark datasets, the proposed method consistently outperformed conventional CNN and DBN models. It also achieved higher accuracy than the 3D-CNN architecture in all datasets and surpassed the 2D-CNN baseline in two datasets, remaining closely competitive in the third. These results indicate that the probabilistic feature space generated by the regression models is sufficiently discriminative to match or exceed the performance of several deep learning approaches, despite not relying on convolutional spatial modeling.

Beyond raw accuracy, the regression-based approach offers additional advantages in transparency, modularity, and adaptability. Each class-wise regressor models an explicit mapping from spectral reflectance to class probability, providing a level of interpretability typically unavailable in deep neural architectures. Moreover, because the regressors operate independently per class, the framework can be readily extended to new classes or incrementally updated without requiring full retraining of a deep network. In terms of its mechanisms, the regression model excels in situations where labeled data is limited, which is common in many hyperspectral datasets. Deep learning models generally require large parameter spaces and extensive labeled data to fully leverage their representational power. This makes them more prone to overfitting, especially in data-scarce environments. In contrast, the regression-based approach, with its simpler structure and lower capacity, provides better generalization in such situations. Additionally, the framework first generates class-specific probability maps via regression, creating a compact, class-oriented feature space that reduces spectral noise while retaining key information. In comparison, deep learning models often require high-dimensional data and complex feature extraction, which can lead to unstable results when data is limited. Given the complexity and data requirements of deep learning models, regression-based models, with their reduced dimensionality and focus on class-specific features, demonstrate superior performance in data-limited conditions.

Collectively, these findings suggest that while deep learning models remain powerful in data-rich scenarios, the proposed regression-based framework constitutes a lightweight, interpretable, and computationally efficient alternative for hyperspectral image classification, particularly in resource-constrained or large-scale remote sensing applications.

5.6. Computational aspects

Although the regression-based framework introduces an additional stage before classification, its overall computational footprint remains moderate and practically manageable. The regression step produces only K class-specific probability maps, where K denotes the number of land-cover classes, resulting in a compact representation that replaces the original high-dimensional spectral space. This design drastically reduces the input dimensionality for the subsequent classifiers, lowering their memory requirements and improving numerical stability during training.

While the total runtime is naturally longer than that of the direct classification approach due to the extra regression stage, the framework still operates at a fraction of the computational cost required by deep-learning-based alternatives, including conventional CNN, DBN, and lightweight 2D/3D-CNN architectures. The deep models typically involve millions of parameters and require GPU acceleration for feasible training, whereas the regression-

based method can be executed efficiently on standard CPUs without specialized hardware.

Another practical advantage lies in the independence of the regression models trained for each class. Since these class-wise regressors are fully decoupled, they can be trained in parallel, significantly reducing total processing time on multi-core or distributed systems. This property enhances scalability and enables efficient deployment on large-scale hyperspectral scenes where the number of pixels is substantial.

Overall, the proposed framework offers a favorable trade-off between accuracy and computational efficiency. It achieves near-deep-learning-level performance with substantially lower resource demand, interpretable intermediate outputs, and straightforward parallelization capabilities—making it particularly suitable for operational or resource-constrained remote sensing applications.

6. Conclusion

This study introduced a regression-based two-stage framework for hyperspectral image classification that extends conventional machine learning by incorporating a regression-driven probabilistic feature generation stage. The proposed approach transforms original spectral reflectance data into a continuous class-probability space, enabling downstream classifiers to operate on smoother and more discriminative representations. By decoupling probabilistic estimation from final decision-making, the framework provides a flexible and model-agnostic preprocessing paradigm applicable to multiple classifiers.

Extensive experiments conducted on three widely used benchmark datasets under multiple training–testing scenarios demonstrated that the proposed framework consistently improves classification accuracy and stability compared to direct baseline implementations. The results confirmed its statistical reliability and robustness across different classifiers and sampling ratios. Notably, the method achieved performance superior to conventional CNN and DBN models across all datasets and outperformed lightweight 3D-CNN models in all cases. It also surpassed 2D-CNN baselines on two datasets while remaining highly competitive on the third. Importantly, these improvements were obtained without requiring GPU resources or complex deep architectures, highlighting the framework's balance between efficiency, interpretability, and performance.

Despite these strengths, several limitations should be acknowledged. The overall effectiveness of the framework depends on the quality of the regression-generated probability maps. In cases of spectral overlap or limited training samples, regression uncertainty may propagate to the classification stage, leading to minor fluctuations in class-wise performance. Furthermore, the current implementation operates purely in the spectral domain and does not explicitly exploit spatial–contextual relationships among neighboring pixels, which are known to enhance hyperspectral

image classification. Although the additional regression stage increases computational time relative to the direct baseline, it remains substantially more efficient than deep learning-based alternatives.

Future research may focus on improving regression robustness through uncertainty-aware or ensemble-based schemes, integrating spatial-spectral contextual modeling to enhance local consistency, and exploring hybrid regression-deep learning architectures that combine interpretability with higher representational capacity. Moreover, given that class-wise regression models operate independently, the framework naturally supports parallel implementation, offering promising potential for scalable and real-time remote sensing applications.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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