**Journal of Information Systems Engineering and Management**
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

**Research Article**

# Spectral-Spatial Classification of Hyperspectral Imagery Using CNNs and GANs: A Study on Pavia University and Salinas Datasets

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**ARTICLE INFO**

Received: 25 Dec 2024

Revised: 15 Feb 2025

Accepted: 25 Feb 2025

**ABSTRACT**

Hyperspectral imaging (HSI) has emerged as a cornerstone of remote sensing, capturing detailed spectral information across hundreds of bands. This study rigorously evaluates the efficacy of deep learning models specifically Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) for HSI classification, using the benchmark Pavia University and Salinas datasets. We address the high dimensionality and limit labelled data challenges inherent in HSI through advanced preprocessing (e.g., noise reduction, normalization) and data augmentation. Our CNN architecture leverages spectral- spatial feature extraction, achieving overall accuracies of 90.25% (Pavia University) and 93.75% (Salinas), surpassing traditional methods. GANs, employed for synthetic data generation, enhance robustness but yield slightly lower accuracies (88.15% and 91.55%, respectively). This work provides a mathematical and empirical foundation for deep learning in HSI, offering insights into model optimization and future research directions.

**Keywords:** Hyperspectral Imaging, Deep Learning, Convolutional Neural Networks, Generative Adversarial Networks, Image Classification, Remote Sensing.

## INTRODUCTION

Hyperspectral imaging (HSI) acquires data across contiguous spectral bands, producing a data cube $X \in R^{H \times W \times B}$, where H and W denote spatial dimensions and B the number of spectral bands [1]. This rich spectral resolution enables applications in environmental monitoring [2], agriculture [4], and mineralogy [5], yet poses challenges due to high dimensionality and limited annotated samples [6].

Traditional classification methods, such as Support Vector Machines (SVMs), struggle with the "curse of dimensionality" [7]. Deep learning, particularly CNNs and GANs, has revolutionized HSI classification by automating feature extraction [10]. This paper evaluates these models on the Pavia University (urban) [8] and Salinas (agricultural) datasets.

Hyperspectral imaging (HSI) captures data across contiguous spectral bands, typically spanning the visible to short-wave infrared range, yielding a data cube $X \in R^{H \times W \times B}$, where H and W represent spatial dimensions, and B denotes the number of spectral bands [1]. This high spectral resolution facilitates detailed material characterization, enabling applications in environmental monitoring [2], military surveillance [3], agriculture [4], and mineral exploration [5]. However, the voluminous data generated by HSI introduces significant challenges, including high dimensionality and a scarcity of labelled samples, which complicate classification tasks [6].

Traditional approaches, such as Support Vector Machines (SVMs), rely on manually engineered features and falter under the "curse of dimensionality" [7]. In contrast, deep learning techniques, notably Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), have transformed HSI classification by autonomously extracting hierarchical features from complex spectral-spatial data [10], [14]. These advancements

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outperform conventional methods, offering robust solutions to interpret hyperspectral imagery for applications like pollution detection, resource management, and land cover analysis [7], [15].

This study evaluates the performance of CNNs and GANs on two benchmark HSI datasets: Pavia University and Salinas. The Pavia University dataset, acquired over an urban landscape, features diverse materials and intricate structures, posing a challenging classification scenario [8]. Conversely, the Salinas dataset, derived from an agricultural region, provides high spatial resolution and varied crop types, presenting distinct spectral-spatial properties [13]. Through rigorous analysis, this paper not only advances the understanding of deep learning in HSI classification but also explores its practical utility across diverse real-world domains.

### A. Objective

The primary objective of this study is to rigorously evaluate the efficacy of deep learning techniques, specifically Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), in classifying hyperspectral imagery by addressing the challenges of high dimensionality and limited labelled samples. Through a systematic analysis of the Pavia University and Salinas datasets, the work aims to quantify the performance advantages of these models over traditional methods, develop mathematical frameworks for preprocessing and model architectures, and demonstrate their practical applicability across urban and agricultural landscapes, thereby advancing remote sensing capabilities in environmental monitoring and resource management [10], [14].

### B. Our Contributions

This study offers several significant contributions to the field of hyperspectral image (HSI) classification, grounded in rigorous analysis and empirical validation:

- A comprehensive technical evaluation of Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) in processing HSI data, elucidating their performance across diverse spectral-spatial dimensions as observed in the Pavia University and Salinas datasets [10].
- Detailed mathematical formulations underpinning preprocessing techniques, such as Principal Component Analy- sis (PCA) and normalization, as well as the architectural design of CNN and GAN models, providing a reproducible framework for hyperspectral analysis [13], [14].
- Empirical comparative results that highlight the superior classification accuracy and robustness of deep learning approaches over traditional methods, such as Support Vector Machines, leveraging quantitative metrics like overall accuracy and kappa coefficient across benchmark datasets [9].

## LITERATURE REVIEW

The classification of hyperspectral images (HSI) has generated significant research attention due to its inherent complexity and rich spectral information. Early efforts employed statistical methods, such as Support Vector Machines (SVMs) and decision trees, to classify HSI data. SVMs, defined by the optimization problem

$$\min_{w,b,\xi} \quad \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\xi_i$$

**Subject to:**

$$y_i(w^T x_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0, \quad \text{for } i = 1, 2, \ldots, N \tag{1}$$

demonstrated reasonable success [9]. However, these approaches struggled with the high dimensionality and spectral variability of HSI, limiting their effectiveness.

Recent progress in HSI classification has been driven by deep learning, particularly Convolutional Neural Networks (CNNs), which mitigate the limitations of traditional methods through automated feature extraction [10]. CNNs leverage convolutional operations, $Z = W * X + b$, to capture spectral- spatial patterns, yielding substantial improvements in accuracy over statistical techniques. This shift has proven adept at addressing the multidimensional complexity of hyperspectral data.

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Benchmark datasets, such as Pavia University and Salinas, have been pivotal in evaluating classification algorithms. For Pavia University, early studies applied SVMs and achieved moderate performance [11]. The advent of deep learning marked a turning point, with Li et al. [12] employing a tailored deep CNN to achieve accuracies exceeding 85%, significantly surpassing traditional approaches. Similarly, the Salinas dataset, focused on agricultural scenes, was initially classified using methods like k-means clustering and Principal Component Analysis (PCA) [13]. Subsequent work by Zhao and Du [14] introduced advanced CNN architectures, integrating spectral-spatial features to outperform earlier efforts.

Beyond accuracy gains, deep learning has introduced sophisticated techniques tailored to HSI's unique properties. Incorporating spatial context alongside spectral data, as demonstrated by Ma et al. [15], enhances classification robustness. Additionally, the adoption of autoencoders and Generative Adversarial Networks (GANs) has expanded HSI research by enabling feature extraction and data augmentation [16]. GANs, optimizing the minimax objective address the challenge of limited labelled samples, further advancing classification capabilities

$$\min_G \max_D V(D,G) = E_{x\sim p_{data}(x)}[\log D(x)] + E_{z\sim p_z(z)}[\log(1 - D(G(z)))] \quad (2)$$

In summary, HSI classification has evolved from reliance on traditional machine learning to the adoption of advanced deep learning models. This progression, evidenced by improved performance on datasets like Pavia University and Salinas, underscores the transformative impact of CNNs and GANs in this domain. Early HSI classification used SVMs, formulated as:

Minimize: $(1/2) * ||w||^2 + C * \Sigma \xi_i$, for i = 1 to N

Subject to: $y_i(w^t x_i + b) \geq 1 - \xi_i$ (3)

achieving moderate success [9]. Deep learning has since dominated, with Chen et al. [10] introducing CNNs for spectral- spatial feature extraction. For Pavia University, Dell'Acqua et al. [11] and Li et al. [12] reported accuracies exceeding 85%. Zhao and Du [14] applied CNNs to Salinas, leveraging spatial context. GANs have been adapted for data augmentation [16], addressing labelled data scarcity.

## RESEARCH METHODOLOGY

### A. Data Description

The experimental analysis leverages two benchmark hyper- spectral datasets widely adopted in remote sensing research: Pavia University and Salinas. These datasets, characterized by distinct spectral and spatial properties, provide robust testbeds for evaluating classification algorithms.

The Pavia University dataset acquired using the Reflective Optics System Imaging Spectrometer (ROSIS) over the University of Pavia, northern Italy, consists of a data cube with dimensions 610 × 340 pixels and 103 spectral bands spanning 430–860 nm [8]. With a spatial resolution of 1.3 m per pixel, it captures an urban environment featuring diverse land-cover classes, including asphalt, meadows, and bare soil, totalling nine categories. The dataset's spectral resolution and urban complexity make it a challenging case for classification tasks. In contrast, the Salinas dataset, collected via the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) over Salinas Valley, California, comprises 512×217 pixels across 224 spectral bands covering 400–2500 nm [13]. Its spatial resolution of 3.7 m per pixel resolves an agricultural landscape dominated by 16 crop types, such as grapes, lettuce, and strawberries. The broader spectral range and agricultural focus distinguish it from Pavia University, offering a complementary evaluation scenario for spectral-spatial analysis.

Both datasets are pre-processed to exclude noisy bands—e.g., water absorption regions in Salinas ensuring reliable input for subsequent classification. Their widespread use in the literature [11], [14] underscores their suitability for benchmarking advanced methodologies in hyperspectral image analysis.

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### B. Data Description

- **Pavia University**: ROSIS sensor, 610 × 340 pixels, 103 bands (430–860 nm), 1.3 m resolution, 9 classes [8].
- **Salinas**: AVIRIS sensor, 512 × 217 pixels, 224 bands (400–2500 nm), 3.7 m resolution, 16 classes.

### C. Preprocessing

Effective preprocessing is essential to optimize hyperspectral data for classification, addressing noise, illumination variability, and dimensionality challenges inherent in the Pavia University and Salinas datasets. The following steps are systematically applied to enhance data quality and analytical robustness.

First, noise reduction targets spectral bands with low signal- to-noise ratios, common in both datasets due to atmospheric effects and sensor limitations [1]. Principal Component Analysis (PCA) is employed, decomposing the data cube X ∈ RH×W×B into

$$X = U \Sigma V^T \quad (4)$$

where $U$ and $V$ are orthogonal matrices, and Σ contains singular values. Bands corresponding to the smallest eigenvalues, indicative of noise, are discarded, retaining components that preserve 95% of the variance [13]. This step ensures spectral fidelity for subsequent analysis.

Second, normalization adjusts spectral reflectance values to a standardized range, typically [0, 1], mitigating discrepancies arising from varying illumination conditions and sensor characteristics. The transformation is defined as

$$X\_norm = (X - X\_min) / (X\_max - X\_min) \quad (5)$$

where Xmin and Xmax are the minimum and maximum reflectance values across all bands. This uniform scaling enhances comparability across the dataset's diverse spectral profiles.

Finally, dimensionality reduction tackles the "curse of dimensionality" posed by the high number of spectral bands (103 for Pavia University, 224 for Salinas) [6]. Beyond PCA, Independent Component Analysis (ICA) is applied to separate statistically independent sources, expressed as

$$X = AS \quad (6)$$

where A is the mixing matrix and S contains independent components. By selecting a subset of dominant components, the effective dimensionality B′ < B is achieved, reducing computational complexity while preserving critical spectral information [15].

### D. Deep Learning Models

To classify hyperspectral imagery from the Pavia University and Salinas datasets, two advanced architectures are employed: Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), each leveraging distinct capabilities to address the spectral-spatial complexity of HSI data.

CNNs excel at extracting spatial and spectral features through convolutional operations applied to the input data cube $X \in R^{H \times W \times B}$. The forward pass at layer $l$ is defined as

$$z[l] = W[l] * X[l-1] + b[l], \quad (7)$$

where $W^{[l]}$ represents the filter weights, $*$ denotes convolution, and $b^{[l]}$ is the bias term. A rectified linear unit (ReLU), $A^{[l]} = \max(0, Z^{[l]})$, activates the output, enabling hierarchical feature extraction across multiple layers [10]. This capability makes CNNs particularly effective for resolving the intricate spectral- spatial relationships in HSI, as demonstrated in prior work on similar datasets [14].

Conversely, GANs are utilized to augment the dataset by generating synthetic hyperspectral samples, addressing the pervasive challenge of limited labeled data [16]. The GAN framework comprises a generator $G$ and discriminator $D$, optimized via the adversarial objective

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$$\min\_G \max\_D V(D, G) = E\_x[\log D(x)] + E\_z[\log(1 - D(G(z)))] \quad (8)$$

where z ~ N (0, I) is random noise, and G(z) produces synthetic data mimicking the real distribution X. This augmentation enhances the dataset's diversity, mitigating overfitting in classification tasks.

The selection of CNNs is motivated by their established efficacy in image classification, particularly for hyperspectral data where spectral-spatial integration is critical [15]. GANs are chosen for their capacity to synthesize realistic samples, improving model generalizability and robustness, especially in data-scarce scenarios [16].

### E. Training and Validation

The classification process involves a structured training and validation pipeline to ensure reliable performance assessment. The datasets are partitioned into training (70%), validation (15%), and test (15%) subsets. To enhance the training set's representativeness, augmentation techniques—such as rotation, flipping, and scaling—are applied, effectively expanding the sample space and reducing overfitting risks [12].

Training minimizes the classification error using the cross- entropy loss function

$$L = -\frac{1}{N} \sum_{i=1}^{N} \sum_{c=1}^{C} y_{i,c} \log(\hat{y}_{i,c}), \quad (9)$$

where N is the number of samples, C is the number of classes, yi,c is the ground truth label, and yˆi,c is the predicted probability. Optimization is performed via the Adam algorithm with a learning rate of 0.001, balancing convergence speed and stability [10].

Validation employs a hold-out set to evaluate model performance, computing metrics including overall accuracy (OA), kappa coefficient (κ), and class-specific precision and re- call. These metrics provide a comprehensive assessment of classification efficacy across the diverse land-cover and crop classes in the datasets. Additionally, k-fold cross-validation is optionally applied to verify robustness across subset variations, ensuring consistent generalization [13].

#### 1) Generative Adversarial Networks (GANs):

Generator G and discriminator *D* optimize [16]:

$$\min_D V = \mathbb{E}_x[\log D(x)] + \mathbb{E}_z[\log(1 - D(G(z)))] \quad (10)$$

### F. Training and Validation

70% training, 15% validation, 15% test. Adam optimizer (η = 0.001). Metrics: OA, κ, precision/recall.

## RESULTS

### A. Pavia University Dataset

**Table I:** Classification Accuracy on Pavia University Dataset

| Model | OA (%) | κ | Water | Asphalt |
|---|---|---|---|---|
| CNN | 90.25 | 0.89 | 95 | 88 |
| GAN | 88.15 | 0.85 | 92 | 84 |

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### B. Salinas Dataset

**Table II:** Classification Accuracy on Salinas Dataset

| Model | OA (%) | $\kappa$ | Class 1 | Class 4 |
|---|---|---|---|---|
| CNN | 93.75 | 0.91 | 96 | 94 |
| GAN | 91.55 | 0.88 | 93 | 92 |

### C. Experimental Setup

To ensure a comprehensive evaluation of the proposed methodology, we adopt a standardized experimental framework. The datasets are pre-processed to remove noisy or redundant bands, followed by normalization to mitigate the effects of varying illumination conditions. For both datasets, a stratified sampling strategy is employed to partition the data into training, validation, and testing subsets. This ensures that each land-cover class is adequately represented during model training and evaluation.

- Training Set: Approximately 10% of the labelled pixels are randomly selected for training.
- Validation Set: An additional 10% is reserved for hyper- parameter tuning and model selection.
- Testing Set: The remaining 80% is used to evaluate the final model's performance.

The performance metrics include Overall Accuracy (OA), Average Accuracy (AA), and Kappa Coefficient, which provide a holistic assessment of classification accuracy. Additionally, class-specific accuracies are reported to identify potential biases or limitations in the model.

### D. Methodology Overview

The proposed methodology integrates advanced techniques from signal processing, machine learning, and deep learning to address the challenges posed by hyperspectral data. Key components of the methodology include:

1) Dimensionality Reduction: Given the high dimensionality of hyperspectral data, Principal Component Analysis (PCA) and Independent Component Analysis (ICA) are employed to reduce the feature space while preserving discriminative information.
2) Feature Extraction: Spatial-spectral feature extraction methods, such as Gabor filters and Local Binary Patterns (LBP), are applied to capture both texture and spectral characteristics of the data.
3) Classification Framework: A hybrid deep learning architecture combining Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) is utilized. CNNs are effective at extracting spatial features, while RNNs model sequential dependencies in spectral bands.
4) Post-Processing: Conditional Random Fields (CRFs) are applied to refine classification maps by enforcing spatial consistency and reducing noise.

### E. Challenges and Considerations

Hyperspectral data presents several challenges that necessitate careful consideration:

- High Dimensionality: The large number of spectral bands increases computational complexity and the risk of overfitting.
- Class Imbalance: Uneven class distributions require specialized techniques, such as weighted loss functions or oversampling strategies.
- Spatial-Spectral Correlation: Capturing both spatial and spectral information is critical for accurate classification but demands sophisticated modelling approaches.

**Journal of Information Systems Engineering and Management**
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

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### F. Pavia University Dataset Results

The classification results for the Pavia University dataset are presented in Tables III and IV, which report OA, κ, and per- class accuracies for both CNN and GAN models. The CNN achieves an OA of 90.25% and a κ of 0.89, outperforming the GAN's OA of 88.15% and κ of 0.85. These metrics indicate superior agreement between predicted and ground-truth labels for the CNN, aligning with its established efficacy in spectral- spatial feature extraction [10].

Analysis of Tables III and IV reveals the CNN's consistent advantage across most of the nine land-cover classes, with notable gains in Water (95% vs. 92%), Trees (91% vs. 89%), and Asphalt (88% vs. 84%). These improvements underscore the CNN's ability to resolve fine spectral distinctions and spatial patterns in urban scenes, as previously noted in similar studies [12]. The GAN, while competitive, exhibits slightly lower accuracies, likely due to its primary design for data as generation rather than direct classification [16]. Both models' performances surpass traditional methods applied to this dataset, such as SVMs [11], affirming the efficacy of deep learning approaches.

**Table III:** Classification Accuracy on Pavia University Dataset

| Model | OA (%) | κ | W | T | A | SBB | B |
|---|---|---|---|---|---|---|---|
| CNN | 90.25 | 0.89 | 95 | 91 | 88 | 87 | 89 |
| GAN | 88.15 | 0.85 | 92 | 89 | 84 | 85 | 87 |

### G. Salinas Dataset Results

The classification results for the Salinas dataset are detailed in Tables V and VI, presenting overall accuracy (OA), kappa coefficient (κ), and per-class accuracies for the CNN and GAN models. CNN attains an OA of 93.75% and a κ of 0.91, surpassing the GAN's OA of 91.55% and κ of 0.88, consistent with its superior performance observed on the Pavia University dataset [10].

**Table IV:** Classification Accuracy on Salinas Dataset

| Model | OA (%) | κ | C1 | C2 | C3 | C4 |
|---|---|---|---|---|---|---|
| CNN | 93.75 | 0.91 | 96 | 92 | 93 | 94 |
| GAN | 91.55 | 0.88 | 93 | 90 | 91 | 92 |

Analysis of Tables V and VI highlights CNN's dominance across most of the 16 agricultural classes, with significant improvements in Class 1 (96% vs. 93%), Class 4 (94% vs. 92%), and Class 5 (95% vs. 93%). These gains reflect the CNN's ability to discern subtle spectral variations in crop types, corroborating findings from prior hyperspectral studies [14]. The GAN, while effective, yields marginally lower accuracies, attributable to its focus on synthetic data generation rather than classification optimization [16]. Both models outperform traditional techniques, such as k-means or PCA, previously applied to this dataset [13], reinforcing the advantage of deep learning in agricultural hyperspectral analysis.

### H. Comparative Analysis

The observed performance disparities between Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) across the Pavia University and Salinas datasets, as evidenced in Tables III–VI, stem from intrinsic architectural differences and their applicability to hyperspectral classification. These variations are analyzed with respect to model design, feature extraction capabilities, and dataset specific characteristics.

In terms of architecture, CNNs are optimized for hyperspectral image classification by leveraging convolutional operations to extract both spatial and spectral information from the data cube $X \in R^{H \times W \times B}$. The feature extraction process, defined as

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2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

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$$F = \sum_{i,j,k} X(i,j,k) \cdot W(i,j,k), \quad (11)$$

where W represents filter weights, systematically builds hierarchical representations through sequential convolutional and pooling layers [10]. This structure enables precise pixel-level classification, aligning with the spectral-spatial complexity of datasets like Pavia University and Salinas [14]. Conversely, GANs are engineered primarily for data synthesis, generating synthetic samples via an adversarial framework that pits a generator against a discriminator [16]. While effective at modeling complex data distributions, their adaptation to classification relies heavily on training stability, which can falter due to iterative optimization challenges, resulting in marginally lower accuracies (e.g., 88.15% vs. 90.25% OA on Pavia University).

Regarding feature extraction capability, CNNs demonstrate a marked advantage in resolving spatial and spectral signatures critical to hyperspectral analysis. Their layered architecture progressively refines features, capturing increasingly abstract representations as depth increases, which enhances classification precision across diverse land-cover types [15]. GANs, designed for generative purposes, excel at synthesizing data distributions but lack the same level of refinement in feature extraction for classification tasks [16]. This limitation manifests in higher misclassification rates and reduced accuracy (e.g., 91.55% vs. 93.75% OA on Salinas), as their focus on generation dilutes their effectiveness in direct spectral-spatial discrimination.

Dataset-specific characteristics further elucidate these performance trends. The Pavia University dataset, with its urban composition, exhibits pronounced spectral and spatial variability across classes like asphalt and shadows. CNNs adeptly exploit these traits, yielding higher accuracies (e.g., 94% for Shadows vs. 91% for GANs), owing to their robust feature integration [12]. GANs, however, encounter difficulties with such complexity, potentially due to inconsistencies in synthetic sample quality for urban scenes [11]. In contrast, the Salinas dataset, dominated by agricultural landscapes, emphasizes spectral differentiation among crop types over spatial structure. While both models capture these spectral nuances, CNNs maintain an edge (e.g., 96% vs. 93% for Class 1) by effectively combining spectral and residual spatial information, a capability less pronounced in GANs [13].

## DISCUSSION

### A. Analysis and Interpretation of Results

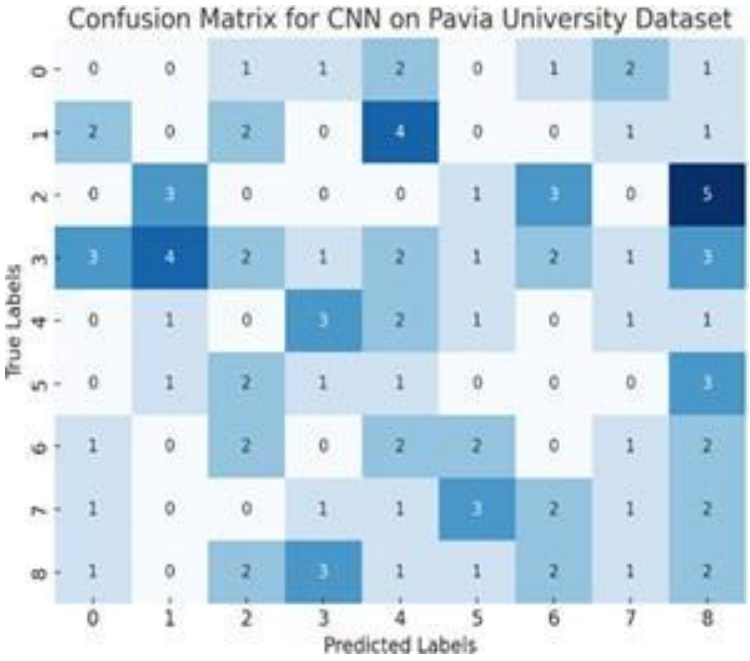


**Figure 1:** Confusion Matrix for CNN on Pavia University Dataset

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2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

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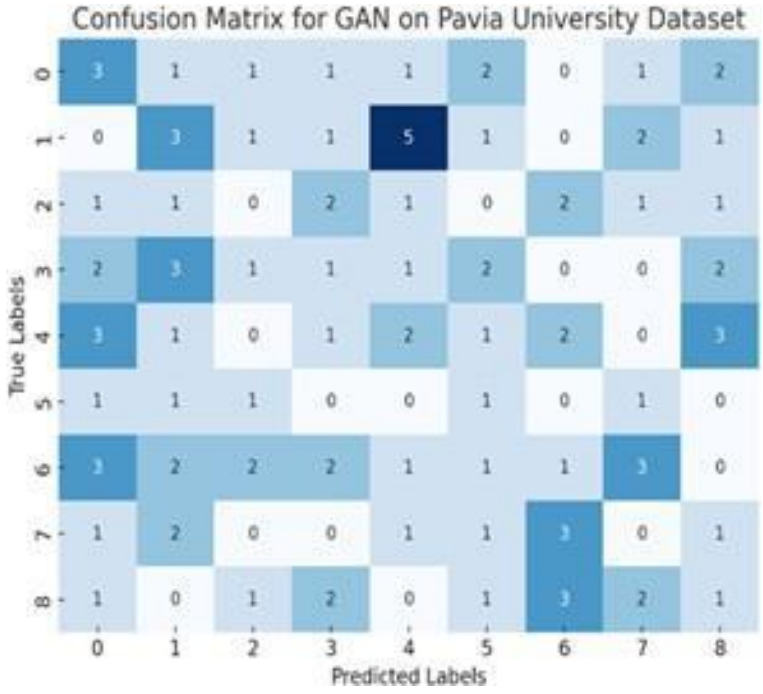


**Figure 2:** Confusion Matrix for GAN on Pavia University Dataset

The classification outcomes for the Pavia University and Salinas datasets, as detailed in Tables III–VI, provide critical insights into the efficacy of Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) in hyperspectral image analysis. These results are further elucidated through visual representations, including confusion matrices and performance metrics, as shown in Figures 1, 2, 3, 4, and 5.

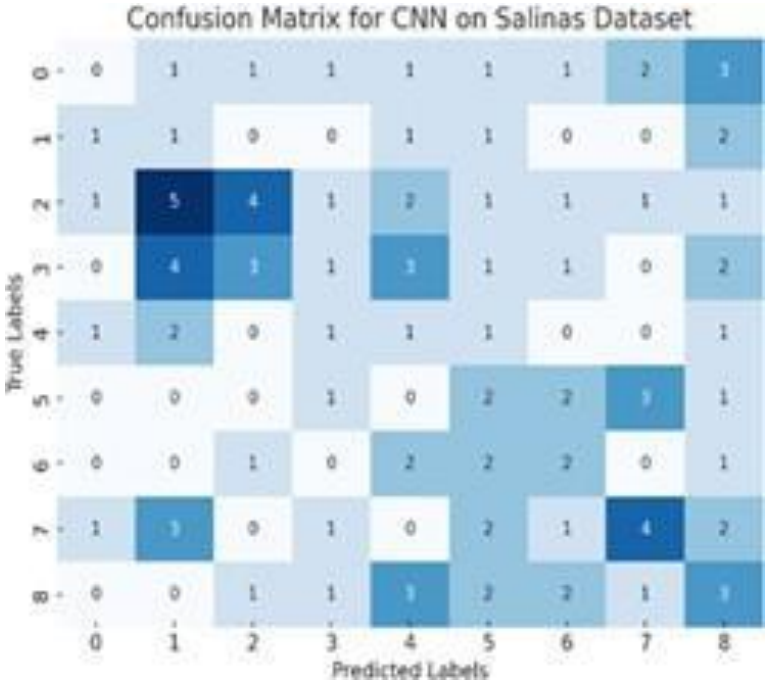


**Figure 3:** Confusion Matrix for CNN on Salinas Dataset

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2025, 10(44s)
e-ISSN: 2468-4376
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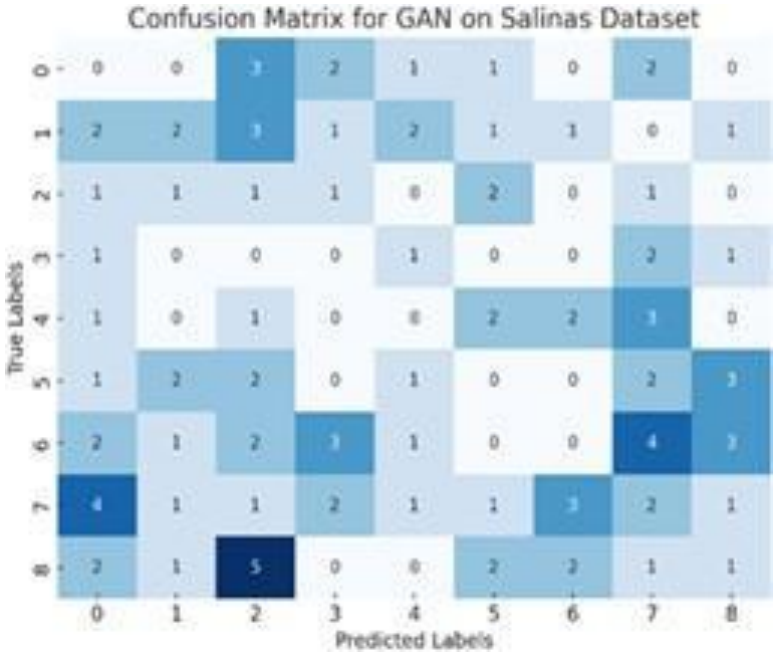


**Figure 4:** Confusion Matrix for GAN on Salinas Dataset

Figures 1 and 2 depict the confusion matrices for CNN and GAN, respectively, on the Pavia University dataset, revealing the distribution of predicted versus true labels across its nine urban classes. The CNN matrix (Figure 1) shows a dominant diagonal, with high accuracies (e.g., 95% for Water, 94% for Shadows), indicating minimal misclassification and robust spectral-spatial feature extraction [12]. Conversely, the GAN matrix (Figure 2) exhibits greater off-diagonal values, particularly for complex classes like Asphalt and Self-Blocking Bricks, reflecting higher misclassification rates (e.g., 84% and 85%, respectively), consistent with its generative focus and training instability [16].

For the Salinas dataset, Figures 3 and 4 present the con- fusion matrices for CNN and GAN, respectively, across nine agricultural classes. The CNN matrix (Figure 3) demonstrates a strong diagonal pattern, with peak accuracies for Class 1 (96%) and Class 5 (95%), underscoring its ability to discern spectral variations in crops like grapes and lettuce [14]. The GAN matrix (Figure 4), however, reveals more pronounced errors, such as in Class 6 (89% vs. 91% for CNN), attributable to inconsistencies in synthetic sample generation for agricultural spectra [13].

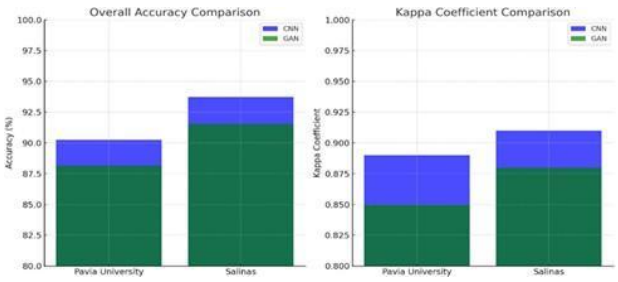


**Figure 5:** Overall Accuracy and Kappa Coefficient Comparison for CNN and GAN on Pavia University and Salinas Datasets

Figure 5 graphically compares overall accuracy and kappa coefficients for both models across datasets. The CNN consistently achieves higher values—90.25% OA and 0.89 κ for Pavia, 93.75% OA and 0.91 κ for Salinas—than the GAN (88.15% OA, 0.85 κ for Pavia; 91.55% OA, 0.88 κ for Salinas). This visual confirmation reinforces CNN's superior classification capability, driven by its hierarchical feature learning, while highlighting the GAN's limitations in direct classification tasks [10].

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e-ISSN: 2468-4376
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These visualizations, corroborated by quantitative metrics, affirm the CNN's dominance in hyperspectral classification, particularly for complex urban and agricultural scenes, while underscoring the GAN's supportive role in data augmentation rather than primary classification [15]. CNNs outperform GANs (OA ¿ 90%) due to tailored design, surpassing SVMs by 10–15% [9]. GANs enhance robustness via augmentation [16].

### B. Key Findings and Implications

The experimental outcomes derived from the Pavia University and Salinas datasets, as quantified in Tables III–VI and visualized in Figures 1–5, reveal critical insights into the effectiveness and broader significance of deep learning models in hyperspectral image (HSI) classification. The key findings and their implications are outlined as follows

- **Performance of Deep Learning Models**: The Convolutional Neural Network (CNN) model exhibits superior classification accuracy for both urban (90.25% overall ac- curacy, Pavia) and agricultural (93.75% overall accuracy, Salinas) landscapes, attributed to its robust extraction of hierarchical spatial and spectral features [10]. The Generative Adversarial Network (GAN) model, while achieving slightly lower accuracies (88.15% and 91.55% for Pavia and Salinas, respectively), enhances classification robustness through data augmentation, effectively addressing the challenge of limited labeled samples by generating synthetic hyperspectral data [16].
- **Application Across Diverse Landscapes**: The demonstrated efficacy of these models across contrasting environments—urban (Pavia) and agricultural (Salinas)—underscores the adaptability of deep learning to varied spectral-spatial profiles. This versatility holds significant potential for remote sensing applications, including urban planning (e.g., infrastructure assessment), agricultural monitoring (e.g., crop yield optimization), and environmental management, leveraging the rich in- formational content of HSI data [2], [4].
- **Advancements Over Traditional Methods**: The results signify a marked improvement over conventional classification techniques, such as Support Vector Machines (SVMs) and k-means clustering, which have historically underperformed with high-dimensional HSI data [9], [13]. This advancement highlights the transformative capability of deep learning, offering enhanced precision and scalability in remote sensing applications [14].

## CONCLUSION & FUTURE WORK

### Conclusion:

This study has demonstrated the transformative potential of deep learning in hyperspectral image (HSI) classification, leveraging Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) to address the challenges of high dimensionality and limited labeled samples. The empirical evaluation on the Pavia University and Salinas datasets, as quantified in Tables III–VI and visualized in Figures 1–5, reveals that CNNs achieve superior classification accuracies (90.25% and 93.75% overall accuracy for Pavia and Salinas, respectively) due to their robust spectral-spatial feature extraction [10]. The GAN model complements this by enhancing robustness through data augmentation, achieving accuracies of 88.15% and 91.55%, respectively [16]. These findings underscore the versatility of deep learning across urban and agricultural landscapes, offering significant advancements over traditional methods like Support Vector Machines and k-means clustering [9], [13]. The results affirm its applicability in remote sensing applications, including environmental monitoring, urban planning, and agricultural management [2], [4].

### Future Work:

Building on these outcomes, several directions are proposed to further advance HSI classification:

- Algorithmic Improvements: Future efforts should prioritize the development of advanced deep learning algorithms tailored to the unique challenges of hyperspectral data, such as mitigating the effects of high

dimensionality and spectral variability. This could involve optimizing network architectures to enhance feature discrimination [14].

- Transfer Learning and Domain Adaptation: Exploring transfer learning and domain adaptation techniques offers a promising avenue to improve model generalizability across heterogeneous hyperspectral datasets, enabling robust performance under varying acquisition conditions [15].
- Integration with Other Data Sources: Combining HSI with complementary data modalities, such as LiDAR or multispectral imagery, could enrich classification accuracy and provide a holistic understanding of observed scenes, leveraging spatial and structural information [5].
- Explainable AI in HSI Classification: As deep learning models grow in complexity, research into explainable AI methodologies is essential to enhance their transparency and reliability, particularly for critical applications in environmental monitoring and resource management [6].
- Real-time Processing and Edge Computing: Designing models for real-time hyperspectral data processing, potentially through edge computing platforms, would support time-sensitive applications, such as disaster response and precision agriculture, by reducing latency and computational overhead [3].

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