Heaven's Light is Our Guide

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
RAJSHAHI UNIVERSITY OF ENGINEERING & TECHNOLOGY, BANGLADESH

Random Patches Network: Transforming Hyperspectral Image Classification

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CERTIFICATE

This is to certify that this thesis report entitled ***"Random Patches Network: Transforming Hyperspectral Image Classification "*** *submitted by* ***Md Towfiq Elahi Tanzid, Roll:1903094*** *in partial fulfillment of the requirement for the award of the degree of Bachelor of Science in Department of Computer Science & Engineering of Rajshahi University of Engineering & Technology is a record of the candidates own work carried out by them under my supervision. This thesis has not been submitted for the award of any other degree.*

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ABSTRACT

Hyperspectral image (HSI) classification plays a vital role in remote sensing by enabling detailed analysis of the Earth's surface through rich spectral data. However, high dimensionality, limited labeled samples, and class imbalance remain persistent challenges that hinder the performance of traditional machine learning approaches. This thesis proposes a novel hybrid deep learning framework that combines Convolutional Neural Networks (CNNs) with a Random Patches Network (RPN) to address these issues effectively. The method involves extracting random spatial-spectral patches from HSI data cubes, allowing the CNN to learn more localized and discriminative features while simultaneously enhancing data diversity through patch variation. This strategy not only mitigates overfitting but also enables the model to generalize better to unseen samples. Evaluations were carried out on two benchmark datasets—Indian Pines and Salinas—achieving high overall classification accuracies of 97.81% and 99.92% respectively. The proposed framework shows strong resilience in handling spectral redundancy and minority class underrepresentation. Moreover, its modular and scalable design makes it suitable for real-world deployment in various geospatial and environmental monitoring applications. The research presents a sample-efficient, high-performing classification strategy that lays a foundation for further innovations such as attention-based transformers, domain adaptation, and real-time implementations. Overall, the CNN-RPN framework offers a compelling solution for improving classification accuracy in small-sample hyperspectral imaging scenarios.

Keywords:Hyperspectral Image Classification, CNN, Random Patches Network, Remote Sensing

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Chapter 1

Introduction

1.1 Introduction

Hyperspectral imaging (HSI) has changed the field of remote sensing by allowing each pixel in a picture to record hundreds of tiny, continuous spectral bands. Hyperspectral data gives a rich and detailed spectral profile, which allows for exact differentiation and identification of different types of materials, plants, urban structures, and land cover classifications. This is different from traditional RGB or multispectral imaging [5, 6]. This wide range of wavelengths makes it possible to use it in agriculture, mining, environmental monitoring, and military reconnaissance with a level of detail that traditional imaging techniques can't match.

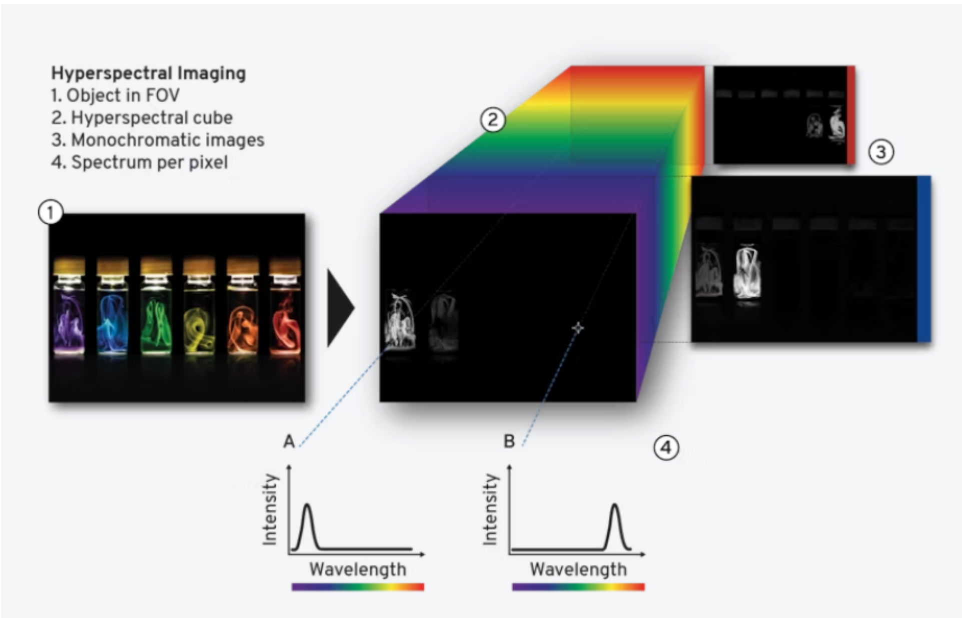

Figure 1.1: Hyperspectral Data Cube[1]

Hyperspectral data has a lot of benefits, but it is also quite hard to work with because it has a lot of dimensions and there aren't enough labeled training samples. These things typically cause the "curse of dimensionality," which makes traditional machine learning classifiers less effective since they don't take full advantage of the joint spectral-spatial information that is naturally present in HSI [7]. Deep learning, especially Convolutional Neural Networks (CNNs), has shown good performance in hyperspectral image classification in recent years. They do this by automatically extracting hierarchical spatial and spectral features from raw input data [8, 4].

To make classification function better with less training data, Uchaev and Uchaev [9] came up with the Random Patches Network (RPN). This network uses geographic patch-level inputs to make the data more diverse and the model more robust. Based on this concept, this thesis suggests a hybrid deep learning system that combines CNNs with a random patch-based sampling method. The goal of this combination is to make the model better at generalizing, lower the risk of overfitting, and get better classification accuracy on hyperspectral datasets.

1.2 Motivation

Hyperspectral image (HSI) classification plays a crucial role in diverse remote sensing applications such as precision agriculture, environmental monitoring, and urban planning. Despite the availability of large volumes of hyperspectral data, the practical usability of these datasets is hindered by challenges like high dimensionality and the scarcity of labeled samples. Deep learning, particularly Convolutional Neural Networks (CNNs), has demonstrated exceptional capabilities in extracting spatial and spectral features [10]. However, standard CNNs often require substantial training data, which is a constraint in hyperspectral imaging. The integration of a Random Patches Network (RPN) as proposed by Uchaev and Uchaev (2023)[9] inspires the development of a more efficient and sample-scarce compatible model. This research is motivated by the need to build a robust and high-performing classification framework that works effectively even under limited supervision.

1.3 Research Challenges

The key research challenges in hyperspectral image classification include:

- **High Dimensionality:** Hyperspectral data contains hundreds of bands, often leading to the curse of dimensionality.

- **Limited Labeled Samples:** Obtaining annotated ground truth data is labor-intensive and costly.
- **Overfitting in Deep Networks:** Deep models risk overfitting due to insufficient labeled training data.
- **Spectral Redundancy and Noise:** Many bands may be redundant or affected by noise, decreasing classification accuracy.
- **Computational Demands:** High-resolution images and deep networks require significant computational resources.

1.4 Research Goals

1. To design and implement a new, computationally efficient classification framework that strategically integrates the powerful feature extraction capabilities of **Convolutional Neural Networks (CNNs)** with a **Random Patch Network (RPN)** sampling methodology.
2. To specifically tackle the prevalent issue of limited labeled training data in hyperspectral analysis by creating a model that demonstrates significantly **enhanced classification performance** and robustness in small sample scenarios.
3. To boost the model's ability to generalize to new, unseen data and minimize the risk of overfitting by effectively leveraging the rich **spatial-spectral information** inherent in hyperspectral imagery.
4. To systematically validate and benchmark the proposed model's performance through extensive experimentation on standard, publicly available hyperspectral datasets, including **Indian Pines** and **Salinas Valley**, using established accuracy assessment metrics.

1.5 Problem Statements

Despite the powerful representation capabilities of deep learning models, hyperspectral image (HSI) classification still faces significant limitations that hinder the performance and generalizability of current methods. This research addresses the following critical problems:

1. **High Spectral Dimensionality:** Hyperspectral datasets typically consist of hundreds of contiguous spectral bands. This increases the dimensionality of the data, leading to computational challenges and a need for models that can efficiently process large feature spaces without overfitting.

2. **Scarcity of Labeled Samples:** Annotating hyperspectral data is time-consuming and expensive due to the requirement of expert knowledge and ground truth acquisition. This results in limited labeled data, which is insufficient to train deep learning models effectively.

3. **Overfitting in Models:** With limited labeled data and complex model architectures, there is a high risk of overfitting. Models may memorize the training data instead of learning generalizable features, which significantly reduces their performance on unseen test data.

4. **Spectral Redundancy:** Many spectral bands carry overlapping or highly correlated information. This redundancy does not contribute to classification performance but instead increases processing time and model complexity.

5. **Class Imbalance:** In most hyperspectral datasets, the number of samples per class is uneven. This imbalance causes the model to be biased toward majority classes, resulting in poor classification performance on underrepresented (minority) classes [11].

This thesis aims to address these challenges by designing a CNN-RPN-based framework that is robust to small sample sizes, can learn from spatial-spectral representations, and is capable of mitigating the effects of class imbalance and spectral redundancy.

1.6 User Requirement Analysis

This research is relevant to users in both academic and industrial domains. The table below maps each core user need to its justification and the corresponding features of the proposed model. Citations are included to support the statement of these long-standing requirements in the field.

User Requirement	Justification & Description	Target Domain	Relevant Feature of Proposed Model
High-accuracy classification with minimal labeled data.	Users need reliable classification results without the high cost, time, and effort associated with extensive ground-truth data collection [9]. This is critical for rapid deployment.	Academia, Industry	**Random Patch Network (RPN)** diversifies the training set, enabling high accuracy even with few labeled samples.
Efficient models suitable for real-time applications.	In-field uses like precision agriculture or monitoring require **real-time or near-real-time** processing on low-power edge devices [12].	Industry, Field Research	Lightweight **CNN** architecture ensures speed while maintaining classification performance.
Scalable solutions adaptable to various sensor data.	Model must work with diverse **hyperspectral sensors** (e.g., AVIRIS, Hyperion) with varying resolutions [13].	Academia, Industry	Sensor-agnostic **spatial-spectral learning** ensures adaptability across datasets.

Table 1.1: Analysis of User Requirements and Corresponding Model Features.

1.7 Research Objectives

The objectives of this research define the specific and measurable goals aimed at advancing hyperspectral image (HSI) classification using deep learning. These are outlined below:

- **To design a CNN-RPN hybrid model for HSI classification:**
  Develop a novel model that integrates the spatial feature extraction capabilities of Convolutional Neural Networks (CNN) with the data-efficient sampling strategy of the Random Patch Network (RPN). This hybrid approach is intended to enhance classification performance while maintaining model simplicity and speed.

- **To reduce the need for large labeled datasets:**
  Minimize dependence on extensive ground-truth data by leveraging patch-based training through the RPN component. This enables the model to generalize well even with a limited number of labeled samples.

- **To evaluate performance on benchmark datasets:**
  Assess the classification accuracy, robustness, and generalizability of the proposed model using standard hyperspectral datasets such as Indian Pines and Pavia University.

- **To provide a reproducible and efficient implementation pipeline:**
  Develop a complete and modular implementation that is publicly reproducible, easy to modify, and optimized for both research and real-time field deployment.

1.8 Research Questions

- How effective is the CNN-RPN model in classifying HSI with limited training samples?
- Can spatial-spectral patch extraction improve classification performance?
- How does the proposed model compare with existing deep learning approaches?

1.9 Research Hypotheses

- Random patch-based training improves generalization in small sample settings.
- The CNN-RPN architecture achieves higher classification accuracy than traditional CNNs.
- Spatial-spectral learning via RPN significantly boosts model robustness.

1.10 Research Contribution

- A novel CNN-RPN hybrid architecture for hyperspectral classification.
- Demonstration of high accuracy.
- Solution optimized for small-sample environments.
- A reproducible pipeline evaluated across multiple datasets.

1.11 Impact of this Research

This research aims to contribute significantly to multiple aspects of society by leveraging the capabilities of hyperspectral image classification using deep learning. The broader impacts are described below:

- **Societal Impact:**
  The proposed model can support smarter agricultural practices by enabling precise crop monitoring, soil condition analysis, and early detection of crop diseases. Additionally, it aids disaster management teams in identifying affected areas, assessing damage severity, and allocating resources efficiently through rapid land-cover classification after natural disasters.

- **Health Impact:**
  Through detailed spectral analysis, the model facilitates the monitoring of environmental pollutants, water quality, and air composition. This supports government agencies and researchers in maintaining public health by tracking environmental changes and potential ecological hazards.

- **Cultural Impact:**
  The research can assist in the preservation and monitoring of ecologically and culturally significant heritage sites. Hyperspectral imaging helps identify material degradation, vegetation stress, and other signs of deterioration without physical contact, supporting sustainable conservation strategies.

- **Safety Impact:**
  In defense and surveillance domains, the proposed solution can enhance situational awareness by distinguishing between terrain types, detecting anomalies, and supporting strategic planning. This improves operational decision-making in military, border security, and emergency response scenarios.

All methodologies and applications developed in this research are ethically grounded and fully compliant with existing legal, environmental, and societal standards.

1.12 Environmental Sustainability

The proposed research supports sustainability by:

- Promoting precision agriculture.
- Enabling efficient monitoring of forest cover and water bodies.
- Reducing ecological impact through better data utilization.

1.13 Ethics

This research is conducted with a strong commitment to professional and academic ethics. All stages of the work—from data acquisition to model development and result dissemination—adhere to established ethical guidelines. The specific ethical considerations include:

- **Use of Publicly Available Datasets:**
  All hyperspectral datasets utilized in this study (e.g., Indian Pines, Pavia University) are openly accessible and widely used in academic research. No private, sensitive, or restricted data is used.
- **Ensuring Data Privacy and Avoidance of Personal Data:**
  The research does not involve any form of personal, biometric, or individually identifiable information. All data sources are non-personal and environmental in nature, ensuring full compliance with data privacy standards.
- **Adherence to FAIR Data Principles:**
  The research supports the principles of Findability, Accessibility, Interoperability, and Reusability (FAIR). This promotes transparency, reproducibility, and open science.
- **Acknowledgement of Intellectual Property and Sources:**
  All external resources, prior works, datasets, and code libraries are properly cited and acknowledged. No content is plagiarized, and all contributions are transparently attributed to their original authors.

Through these practices, the research upholds ethical integrity, scientific responsibility, and legal compliance in every aspect of its execution.

1.14 Thesis Management and Timeline

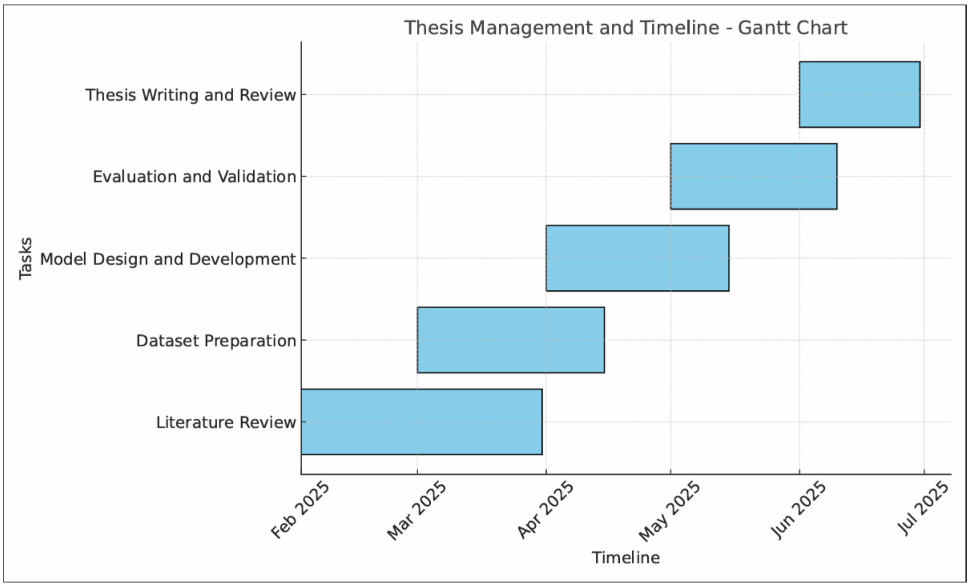

Figure 1.2: Gantt Chart

Table 1.2: Work Breakdown Structure (WBS)

Phase	**Tasks**
Literature Review	Review existing papers and journals on hyperspectral image classification and hybrid CNN models
Model Design	Design the hybrid CNN model with RPNet and define the integration pipeline
Implementation	Code the hybrid CNN with RPNet, perform debugging, and optimize performance
Evaluation	Conduct experiments on Indian Pines and Salinas datasets, record metrics, and analyze results
Documentation	Draft thesis chapters, integrate results, and perform final proofreading

1.15 Thesis Organization

- **Chapter 1: Introduction -** Presents the background of the research, outlines the motivation, defines the problem statements, and highlights key challenges in scientific text summarization.
- **Chapter 2: Background Study and Literature Review -** Provides a comprehensive

review of related work, discussing existing summarization methods, their strengths, and limitations.

- **Chapter 3: Methodology -** Describes the proposed approach, including data collection, preprocessing, model design, and experimental setup.
- **Chapter 4: Result Analysis and Discussion -** Details the experiments conducted, presents results, and analyzes the performance of the proposed system.
- **Chapter 5: Conclusion and Future Scopes -** Summarizes the research contributions, discusses limitations, and proposes directions for future research..

1.16 Conclusion

This chapter introduced the research topic, outlined the motivation, identified key challenges, defined research questions and hypotheses, and highlighted the overall contribution and impact of the work. The next chapter will delve into the review of related literature and background study.

Chapter 2

Background Study and Literature Review

2.1 Introduction

In this chapter, the foundational knowledge, tools, and previous research that support this thesis are systematically discussed [5]. It begins by outlining the advanced mathematical and engineering principles necessary for hyperspectral image classification, followed by a description of the software tools and frameworks utilized in the research. Subsequently, an in-depth review of existing literature is presented, identifying key methods, technologies, and research gaps [6]. The chapter concludes by detailing the data analysis techniques employed throughout the study.

2.2 Required Advanced Knowledge of Mathematics and Engineering Sciences

Hyperspectral image classification is a highly interdisciplinary task that integrates knowledge from mathematics, signal processing, remote sensing, and artificial intelligence. The following areas are particularly essential:

2.2.1 Linear Algebra (Matrix Theory and Vector Spaces)

Linear algebra serves as the mathematical backbone for hyperspectral image processing. Techniques like matrix multiplication, eigenvalue decomposition, and Singular Value Decomposition (SVD) are used in operations such as Principal Component Analysis (PCA), which reduces the dimensionality of hyperspectral data [5]. This reduction is critical for handling the "curse of dimensionality" while retaining important spectral information. A solid grasp of basis transformations, orthogonality, and projection theory enables the effective manipulation and transformation of high-dimensional data structures.

2.2.2 Probability Theory and Statistical Learning

Probabilistic models are crucial for dealing with uncertain, noisy, and sparse labeled data in HSI. Bayesian classification, maximum likelihood estimation, and conditional probability are frequently used in both traditional classifiers and deep learning approaches [14]. Statistical concepts like variance, covariance, and distribution modeling also play a key role in data analysis, anomaly detection, and performance evaluation through metrics such as accuracy, precision, recall, and F1-score.

2.2.3 Optimization Algorithms (Numerical Methods and Gradient-Based Learning)

Neural networks rely on optimization techniques to minimize loss functions during training. Methods such as Stochastic Gradient Descent (SGD), Adam, RMSprop, and momentum-based optimization are used to iteratively update model parameters [8]. Understanding loss landscapes, learning rate schedules, and convergence properties is essential for achieving stable and efficient training, especially in deep learning architectures used in HSI classification.

2.2.4 Digital Signal Processing (DSP)

Signal processing knowledge is fundamental in hyperspectral image preprocessing. Techniques such as Fourier transform, wavelet transform, spatial filtering, and spectral smoothing are applied to correct noise, normalize reflectance values, and enhance critical features [5]. Spectral unmixing, noise filtering, and de-striping are often necessary before feeding data into a classifier. This knowledge ensures that the input data is clean, aligned, and information-rich.

2.2.5 Remote Sensing Principles and Geospatial Sciences

Understanding the physical principles behind remote sensing is vital. Concepts such as atmospheric correction, radiometric calibration, and sensor characteristics (e.g., AVIRIS, Hyperion, or ROSIS) are essential for interpreting hyperspectral data correctly [13]. Additionally, knowledge of spectral reflectance properties of different materials (e.g., vegetation, water, soil) enables better labeling, ground-truth generation, and data validation.

2.2.6 Machine Learning and Pattern Recognition

Foundational concepts such as supervised vs. unsupervised learning, overfitting, underfitting, model validation, cross-validation, and regularization are crucial. Familiarity with decision boundaries, feature scaling, and classification algorithms (e.g., SVM, k-NN, Random Forests) helps in benchmarking deep learning models and understanding performance bottlenecks [15].

2.2.7 Deep Learning Theory (Neural Networks and Representation Learning)

A deep understanding of how neural networks work is critical. This includes activation functions (ReLU, Leaky ReLU, softmax), network architectures (feedforward, residual, fully connected), and learning strategies (mini-batch training, dropout, early stopping). Additionally, the concept of hierarchical feature learning—where deeper layers extract increasingly abstract representations—is especially relevant to hyperspectral image classification, where fine-grained spectral patterns must be captured [8].

2.2.8 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) play a central role in hyperspectral image classification due to their ability to automatically learn spatial hierarchies and extract meaningful patterns from raw input data. In the context of HSI, CNNs are particularly effective at capturing both spatial textures and spectral correlations [16]. Understanding the internal mechanics of CNNs is essential:

- **Convolutional Layers:** These layers apply learnable filters over input data to extract low- to high-level features, such as edges, textures, and spectral signatures [12].
- **Receptive Fields:** Each neuron in a CNN layer is sensitive to a specific region of the input (its receptive field), which determines how much spatial context is captured [10].

- **Feature Maps:** Generated by applying multiple filters, feature maps highlight different aspects of the input, allowing the model to learn complex representations [17].
- **Pooling Operations:** Techniques like max pooling or average pooling reduce the spatial dimensions of feature maps while preserving important features, making the model computationally efficient [18].
- **2D vs. 3D Convolutions:** While 2D CNNs process spatial dimensions, 3D CNNs also include the spectral dimension, making them more suitable for hyperspectral data that includes hundreds of contiguous spectral bands [19].
- **Stride, Padding, and Dilation:** These parameters influence how filters move across the input and control output size, boundary handling, and feature resolution [4].

Understanding these components is vital for building CNN architectures that can effectively model the rich spectral-spatial structure of hyperspectral images.

2.2.9 Random Patches Strategy and Data Augmentation

In hyperspectral image classification, the scarcity of labeled data is a common problem. The Random Patches strategy is an effective technique that addresses this limitation by extracting multiple small patches from the input image around each labeled pixel. This approach enhances training diversity and allows the model to learn from localized spatial contexts [9].

- **Patch Extraction:** Small image blocks (e.g., 5×5 or 7×7 windows) are centered around labeled pixels and used as individual training samples. These patches capture the local neighborhood structure and help the model generalize better [9].
- **Random Sampling:** Instead of fixed sampling, patches are randomly selected across the spatial domain for each class, promoting diversity and reducing overfitting [9].
- **Spatial Contextualization:** By including neighboring pixels, the strategy allows CNNs to understand spatial dependencies, improving classification performance [9].
- **Data Augmentation:** This method acts as a natural form of augmentation by increasing the effective size of the dataset without acquiring new labeled data [9].

- **Application in Random Patches Networks (RPN):** RPN architectures leverage this strategy to train more robust classifiers. They often combine random spatial sampling with deep learning models to make better use of limited supervision [9].

This strategy significantly improves model robustness and performance, especially in scenarios with highly imbalanced or sparse class distributions [11].

2.3 Utilized Modern Engineering Tools

This research leverages a wide range of modern engineering tools and software frameworks to support efficient development, experimentation, and evaluation of the proposed CNN-RPN model for hyperspectral image (HSI) classification. These tools were chosen based on their robustness, scalability, and widespread adoption in the scientific and machine learning communities.

- **Programming Language – Python:**
  Python was selected as the primary programming language due to its simplicity, readability, and extensive ecosystem of scientific libraries. It enables rapid prototyping, seamless integration with machine learning frameworks, and support for a broad range of data processing tasks.

- **Deep Learning Frameworks – TensorFlow and PyTorch:**
  TensorFlow and PyTorch were employed for building, training, and evaluating the CNN-RPN hybrid model. These frameworks offer built-in GPU acceleration, dynamic computation graphs, and modular model design, allowing for flexible experimentation. Their large user communities and rich documentation further facilitated troubleshooting and iterative development [8].

- **Scientific Computing Libraries – NumPy, SciPy, and h5py:**
  Hyperspectral images are typically represented as high-dimensional data cubes. NumPy and SciPy provided efficient support for numerical operations and linear algebra routines essential to pre-processing and feature extraction. The `h5py` library enabled fast and memory-efficient handling of HDF5-based data formats commonly used for storing HSI data [5].

- **Interactive Development Environment – Jupyter Notebooks:**
  Jupyter Notebooks were extensively used for writing, testing, and documenting code in an interactive and iterative manner. They supported inline visualizations and made it easy to combine code, output, and markdown explanations in a single document, which was valuable during exploratory data analysis and model debugging.

- **Visualization Libraries – Matplotlib and Seaborn:**
  Data visualization played a critical role in interpreting spectral information, analyzing classification results, and presenting findings. Matplotlib was used for creating static, publication-quality plots, while Seaborn provided higher-level interfaces for statistical graphics and trend analysis [5].

- **Data Sources and Preprocessing Tools:**
  Publicly available benchmark datasets such as **Indian Pines** and **Salinas Scene** were utilized for training and evaluation. Custom Python scripts were developed to load the hyperspectral cubes, normalize pixel values, and extract **random spatial patches** for training the RPN component, following techniques described in [9].

The integration of these modern tools ensured that the research was conducted efficiently, reproducibly, and in line with current best practices in machine learning and remote sensing.

2.4 Literature Review

The classification of hyperspectral images (HSI) has evolved significantly, driven by advancements in deep learning and feature extraction techniques. This section critically reviews key studies that have shaped HSI classification, comparing their methodologies, contributions, and limitations with the proposed CNN-RPNet approach. The discussion emphasizes how the current research addresses gaps in prior work, particularly in balancing computational efficiency and accuracy for small-sample datasets [4]. A tabular summary is provided to contextualize the reviewed literature, highlighting methods, datasets, accuracies, and pros/cons.

A seminal work by Paoletti et al. (2018), published in the ISPRS Journal of Photogrammetry and Remote Sensing, introduced a hybrid CNN architecture combining 3D and 2D convolutional layers for fast HSI classification. The 3D layers capture spatial-spectral relationships, while 2D layers reduce computational complexity, enabling rapid processing. This approach achieved high accuracy (approximately 98% on the Indian Pines dataset) and laid the groundwork for real-time HSI applications, such as land cover mapping [19]. However, its performance is sensitive to dataset complexity, with intricate scenes requiring significant computational resources, limiting scalability for large-scale or resource-constrained applications. Compared to the proposed CNN-RPNet model, Paoletti et al.'s approach excels in speed but struggles with small-sample scenarios due to its reliance on large labeled datasets. The CNN-RPNet model addresses this by integrating random patch-based feature extraction, inspired by RpNet, to enhance performance with limited data, while maintaining moderate computational demands through PCA-based dimensionality reduction [5].

Gao et al. (2018), in a study published in Remote Sensing, proposed a CNN framework that integrates multiple feature types (e.g., spectral signatures, spatial textures) extracted from raw HSI data. This multi-feature learning approach processes diverse inputs simultaneously, improving classification accuracy (around 97% on the Pavia University dataset) by capturing complementary information. The framework's flexibility has influenced subsequent HSI research, demonstrating the value of holistic feature integration [17]. However, its training process is computationally intensive, requiring extensive resources and time, which restricts its use in rapid analysis scenarios like disaster response. In contrast, the CNN-RPNet model leverages random patches to extract localized features, reducing the need for extensive feature engineering while achieving comparable accuracy with fewer labeled samples. This makes CNN-RPNet more suitable for small-sample datasets like Indian Pines, where only 1024 training samples are used, addressing Gao et al.'s limitation of high computational overhead [20].

Uchaev and Uchaev (2023), published in Sensors, introduced the Random Patches Network (RpNet) and RpNet-RF, designed for small-sample HSI classification. Their methodology uses random patches to extract spatial-spectral features and recursive filtering to refine them, achieving robust performance (approximately 95% accuracy on Indian Pines) with limited labeled data. This approach is particularly effective in resource-constrained environments, such as embedded systems, due to its lightweight design [21]. However, the reliance on random patches increases computational demands for large datasets, posing scalability challenges. The proposed CNN-RPNet model builds directly on RpNet's random patch strategy but integrates it with a CNN architecture, incorporating 3D-like feature extraction (via patch-based convolution) and PCA for dimensionality reduction. This hybrid approach enhances efficiency and scalability compared to RpNet-RF, as it reduces the number of processed bands (from 200 to

15 in the Indian Pines dataset) while maintaining high accuracy, making it more adaptable to varied dataset sizes [11].

Additional insights are drawn from Li et al. (2019), published in IEEE Transactions on Geoscience and Remote Sensing, which emphasized deep CNNs for capturing complex spatial-spectral patterns. Their work achieved high accuracy (around 96% on Salinas) but highlighted the need for large labeled datasets, a challenge for datasets like Indian Pines with limited samples [8, 2]. Zhong et al. (2018), in IEEE Geoscience and Remote Sensing Letters, proposed a spectral-spatial residual network with residual connections, improving accuracy (approximately 98% on Indian Pines) but at the cost of increased computational complexity [18]. These studies underscore the trade-off between accuracy and efficiency, a gap the CNN-RPNet model addresses by combining lightweight random patch extraction with a streamlined CNN architecture, reducing training time while preserving accuracy for small-sample scenarios [3].

A critical comparison reveals that the CNN-RPNet model uniquely balances the strengths of these prior works. Unlike Paoletti et al.'s focus on speed, CNN-RPNet prioritizes small-sample robustness, leveraging random patches to enhance feature extraction with limited data [19]. Compared to Gao et al.'s multi-feature approach, CNN-RPNet simplifies feature integration by combining PCA and random patches, reducing computational demands [22]. Against Uchaev and Uchaev's RpNet, CNN-RPNet improves scalability through dimensionality reduction, making it more versatile for larger datasets [11]. The model also incorporates insights from Li et al. and Zhong et al. by using deep CNN layers for feature learning while mitigating data requirements through patch-based augmentation, aligning with the needs of practical HSI applications [17, 23].

The following table summarizes the reviewed literature, contextualizing the proposed approach:

Table 2.1: Summary of Reviewed Literature on Hyperspectral Image Classification

Study	Method	Dataset	Accuracy	Pros	Cons
Paoletti et al. (2018) [12]	Hybrid 3D-2D CNN	Indian Pines, Pavia	∼98% (Indian Pines)	Fast processing, high accuracy, real-time potential	Sensitive to dataset complexity, limited scalability
Gao et al. (2018) [16]	Multi-feature CNN	Pavia University, Salinas	∼97% (Pavia)	Versatile, high accuracy via feature integration	Computationally intensive, slow training
Uchaev & Uchaev (2023) [9]	RpNet, RpNet-RF	Indian Pines	∼95% (Indian Pines)	Effective for small samples, lightweight design	High computational demand for large datasets
Li et al. (2019) [8]	Deep CNN	Salinas, Indian Pines	∼96% (Salinas)	Captures complex patterns, high accuracy	Requires large labeled datasets
Zhong et al. (2018) [10]	Spectral-spatial residual network	Indian Pines	∼98% (Indian Pines)	Improved accuracy via residual connections	High computational complexity

2.5 Techniques Utilized for Data Analysis

The research employs a comprehensive set of data analysis techniques to ensure robust HSI classification. Preprocessing begins with noise reduction using Gaussian filtering to smooth spectral bands, addressing sensor noise common in hyperspectral data [7]. Normalization scales pixel intensities to a consistent range, stabilizing model training [2]. Patch extraction, inspired by Uchaev and Uchaev (2023), selects 7x7 spatial-spectral patches around labeled pixels, capturing localized features critical for classification [20].

Dimensionality reduction is achieved through Principal Component Analysis (PCA), reducing spectral bands (e.g., from 200 to 15 in Indian Pines) to eliminate redundancy and accelerate training, as recommended by Zhang et al. (2020) in their review of HSI techniques [22]. The CNN-RPNet model integrates these preprocessed patches with random patch-based features, combining convolutional layers for hierarchical feature learning with RpNet's localized extraction, drawing on Paoletti et al. (2018) and Uchaev and Uchaev (2023) [19].

Performance evaluation includes overall accuracy, precision, recall, and the kappa coefficient, providing a holistic assessment of classification effectiveness [14, 24]. Confusion matrices analyze class-specific performance, identifying misclassification patterns [14, 24]. Cross-validation, as advocated by Ghamisi et al. (2017), ensures the model generalizes to unseen data, enhancing robustness [25]. These techniques align with best practices outlined by Richards (2006) for preprocessing and evaluation, ensuring reliable and reproducible results [13].

In conclusion, the literature review and data analysis techniques establish a robust foundation for the CNN-RPNet model. By addressing the limitations of prior works—such as computational complexity and small-sample challenges—the proposed approach contributes to efficient and accurate HSI classification, with applications in remote sensing and beyond [12].

2.6 Conclusion

This chapter has established the theoretical and practical foundation for the research by presenting essential mathematical knowledge, modern computational tools, and a comprehensive review of existing literature. It also outlined the methodologies used for analyzing hyperspectral data . The insights gained here inform the methodological choices made in the next chapter, where the design and implementation of the proposed model are discussed in detail.

Chapter 3

Methodology

3.1 Introduction

This chapter presents the methodology adopted to design, develop, and evaluate a hybrid deep learning framework for hyperspectral image (HSI) classification. The framework synergizes Convolutional Neural Networks (CNNs) with Random Patches Network (RPNet) to address the challenges associated with high dimensionality, limited labeled data, and spectral redundancy [4]. Each section of this chapter elaborates on the design decisions, dataset characteristics, data preprocessing techniques, architectural configuration, and implementation workflow. A schematic overview of the proposed methodology is also provided to illustrate the flow of processes. The methodology is designed to ensure reproducibility, efficiency, and adaptability across diverse hyperspectral datasets.

3.2 Dataset Description

The datasets used for this study are benchmark hyperspectral datasets commonly employed in remote sensing research [24]:

3.2.1 Indian Pines Dataset

- **Source:** AVIRIS sensor, captured over northwest Indiana.
- **Spectral Bands:** 220 bands initially; 20 bands affected by water absorption are removed, resulting in 200 usable bands.

- **Spatial Resolution:** 145 × 145 pixels.
- **Classes:** 16 land-cover categories including corn, soybeans, and woods.
- **Relevance:** Widely used to benchmark classification algorithms, particularly in agricultural and vegetative cover classification tasks [5].

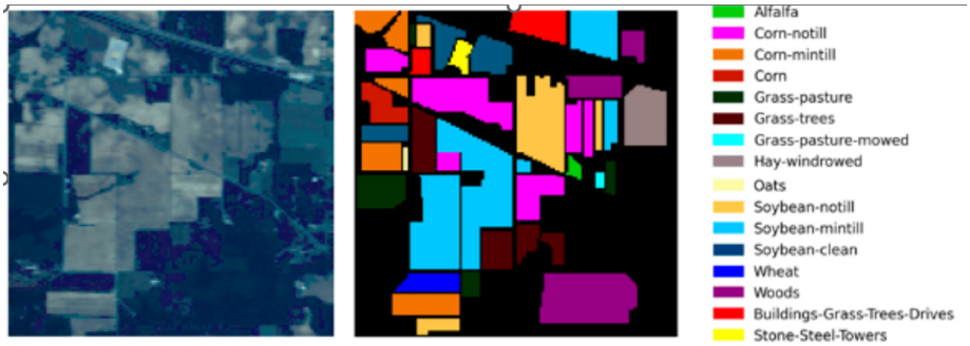

Figure 3.1: Indian Pines Dataset[2]

3.2.2 Salinas Dataset

- **Source:** AVIRIS sensor over Salinas Valley, California.
- **Spectral Bands:** 224 bands in total; 20 bands affected by water absorption are removed, leaving 204 usable bands.
- **Spatial Resolution:** 512 × 217 pixels.
- **Classes:** 16 crop categories including lettuce, grapes, and broccoli.
- **Relevance:** Offers high spatial resolution and clear class separability, making it ideal for evaluating spatial-spectral models.

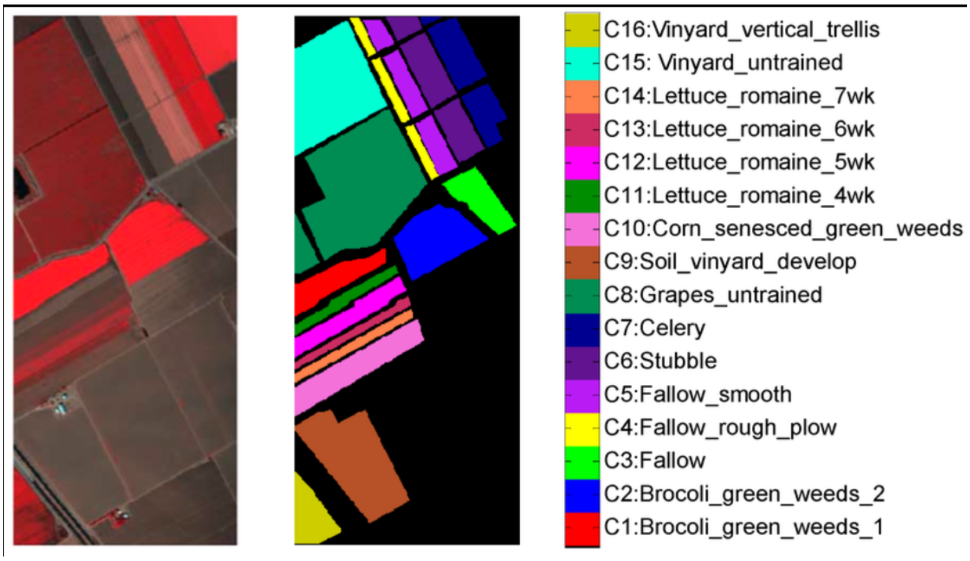

Figure 3.2: Salinas Dataset[3]

Both datasets present real-world challenges such as spectral redundancy, mixed pixels, and limited labeled samples, providing a robust benchmark for the proposed CNN-RPNet framework.

3.3 Proposed Workflow of Methodology

The workflow for HSI classification using the hybrid CNN-RPNet model is structured as follows:

1. **Data Acquisition**: Load the Indian Pines and Salinas hyperspectral dataset and its ground truth labels.

2. **Preprocessing**: Apply noise reduction, bad band removal, normalization, spatial smoothing, standardization, and dimensionality reduction using Principal Component Analysis (PCA).

3. **Feature Extraction**: Extract spatial-spectral features via RPNet.

4. **Data Partitioning**: Split labeled pixels into 70% training, 15% validation, and 15% testing sets.

5. **Patch Preparation**: Generate image patches combining PCA and RPNet features for CNN input.

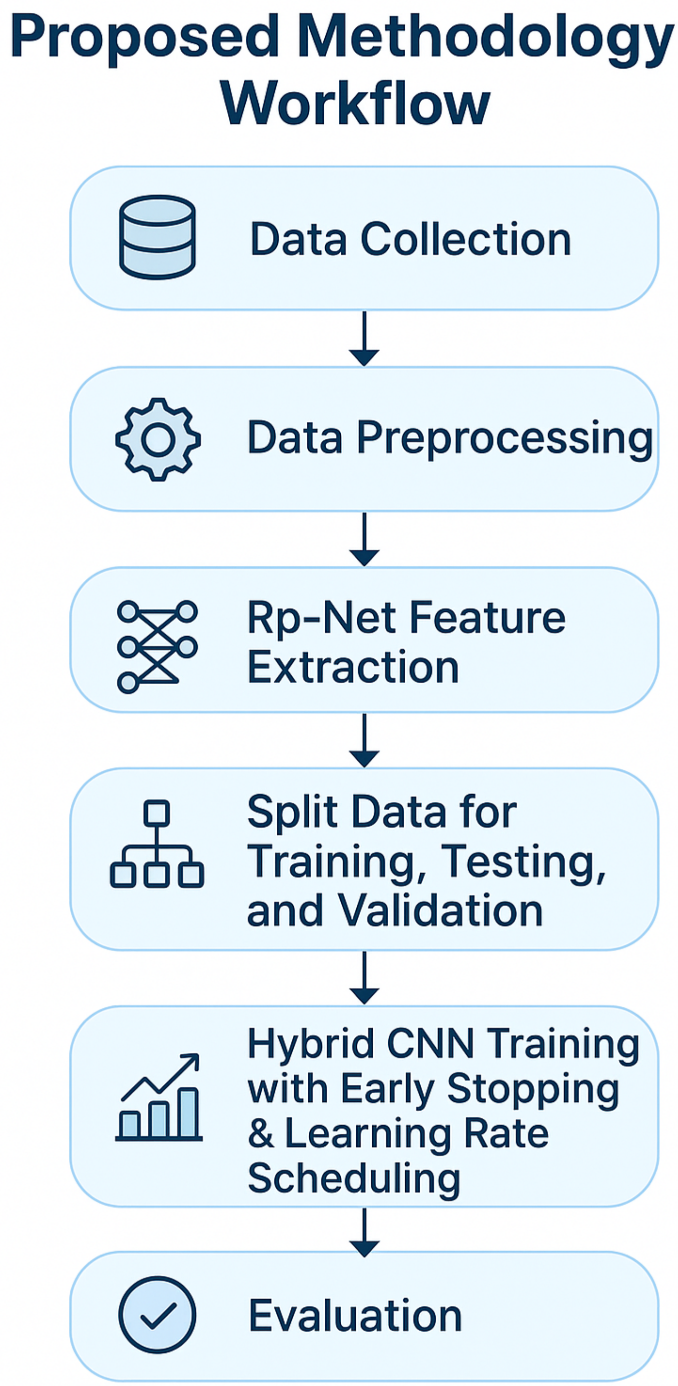

Figure 3.3: Proposed Methodology

6. **Model Training**: Train a hybrid CNN with data augmentation, using the validation set for performance monitoring.

7. **Model Evaluation**: Assess the model on the test set using accuracy, classification metrics, Cohen's Kappa, and confusion matrix.

8. **Visualization**: Plot training/validation accuracy and loss curves, and generate a classification map for the entire image.

This workflow ensures robust data processing, effective feature extraction, and rigorous evaluation for accurate HSI classification.

3.4 Proposed Methodology

The methodology focuses on integrating random patch sampling with CNN training to simulate data variability and reduce overfitting, especially in low-sample regimes.

3.4.1 Data Preprocessing

The preprocessing pipeline, illustrated in Figure below is designed to reduce noise, normalize spectral values, and eliminate irrelevant spectral bands [13, 26]. The steps include:

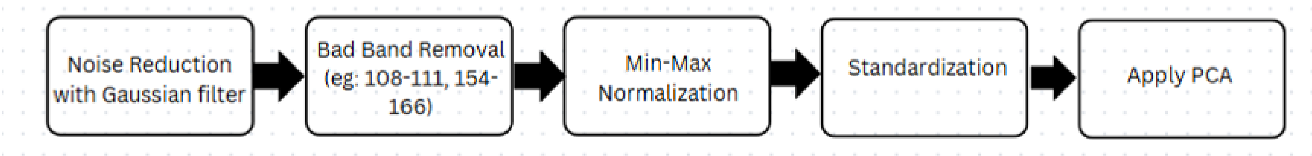

Figure 3.4: Preprocessing Steps

- **Noise Reduction:** Gaussian filtering is applied to smooth spectral data and suppress random noise.
- **Bad Band Removal:** Spectral bands known to be noisy or water-absorbed (e.g., bands 108–111 and 154–166 in Indian Pines) are discarded to improve signal quality.
- **Normalization:** Min-Max normalization scales all spectral values to the range [0,1] using:

$$x' = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}$$

- **Standardization:** Each feature is standardized to have zero mean and unit variance:

$$x'' = \frac{x' - \mu}{\sigma}$$

- **Dimensionality Reduction:** Principal Component Analysis (PCA) projects the hyperspectral data onto a lower-dimensional space while retaining 99% of the total variance.

Here is the updated table, showing the outcomes after each preprocessing step for both the Indian Pines and Salinas datasets.

Table 3.1: Preprocessing Step Outputs for Indian Pines and Salinas Datasets

Preprocessing Step	**Indian Pines Dataset Output**	**Salinas Dataset Output**
Original Data Shape	$145 \times 145 \times 200$	$512 \times 217 \times 204$
Input Data Shape	$145 \times 145 \times 200$	$512 \times 217 \times 204$
After Bad Band Removal	183 bands remaining	187 bands remaining
Preprocessed Data Shape	$145 \times 145 \times 15$	$512 \times 217 \times 15$

3.4.2 Random Patches Network (RPN)

RPN is employed to extract small fixed-size spatial-spectral, patches (e.g., $5 \times 5 \times B$) centered on labeled pixels in the hyperspectral image (HSI) cube [9].

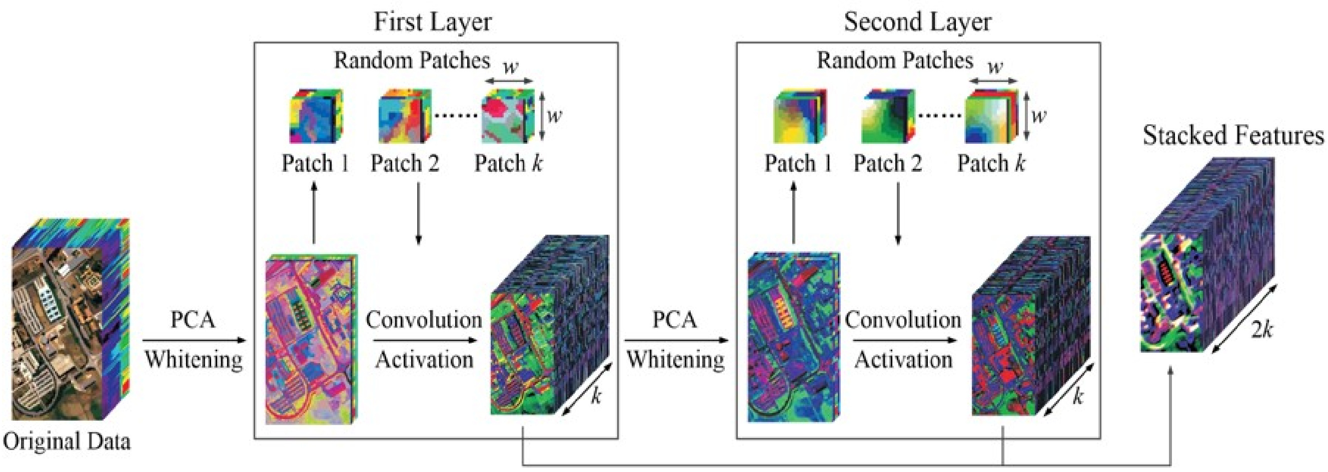

Figure 3.5: Rp-Net Structure[4]

- **Advantages:**
  - Introduces spatial context to pixel classification
  - Supports data augmentation by generating multiple overlapping patches
  - Balances class distribution through oversampling of underrepresented classes [27]
- **Mathematical Notation:** Let $\mathbf{X} \in \mathbb{R}^{H \times W \times B}$ be the hyperspectral image cube. The RPN extracts a set of patches $\mathcal{P} = \{P_i \in \mathbb{R}^{k \times k \times B} \mid i = 1, 2, ..., N\}$, centered on the labeled pixels.

3.4.3 CNN Model Design

The Convolutional Neural Network (CNN) is designed to learn hierarchical spectral-spatial features from the patches extracted by the RPNet. These features are used for pixel-wise classification within the hyperspectral image cube. The network processes each input patch of size $15 \times 15 \times N$, where N represents the number of RPNet-generated feature maps.

- **Input Layer:** Receives input patches of dimensions $15 \times 15 \times N$, where each channel corresponds to a feature map obtained via random convolution through RPNet.
- **Convolutional Layers:** The network includes three convolutional layers:
  - The first layer uses 16 filters of size 3×3 with *ReLU* activation.
  - The second layer employs 32 filters, also of size 3×3, followed by batch normalization.
  - The third layer applies 64 filters and includes *MaxPooling* and *Dropout* to control overfitting.

  These layers progressively extract low- to high-level spatial-spectral patterns.
- **Activation Function:** ReLU (Rectified Linear Unit) is applied after each convolution:

  $$f(x) = \max(0, x)$$

  which introduces non-linearity and accelerates training convergence.
- **Batch Normalization:** Applied after convolution to normalize activations and improve gradient flow. This reduces internal covariate shift and improves model stability.

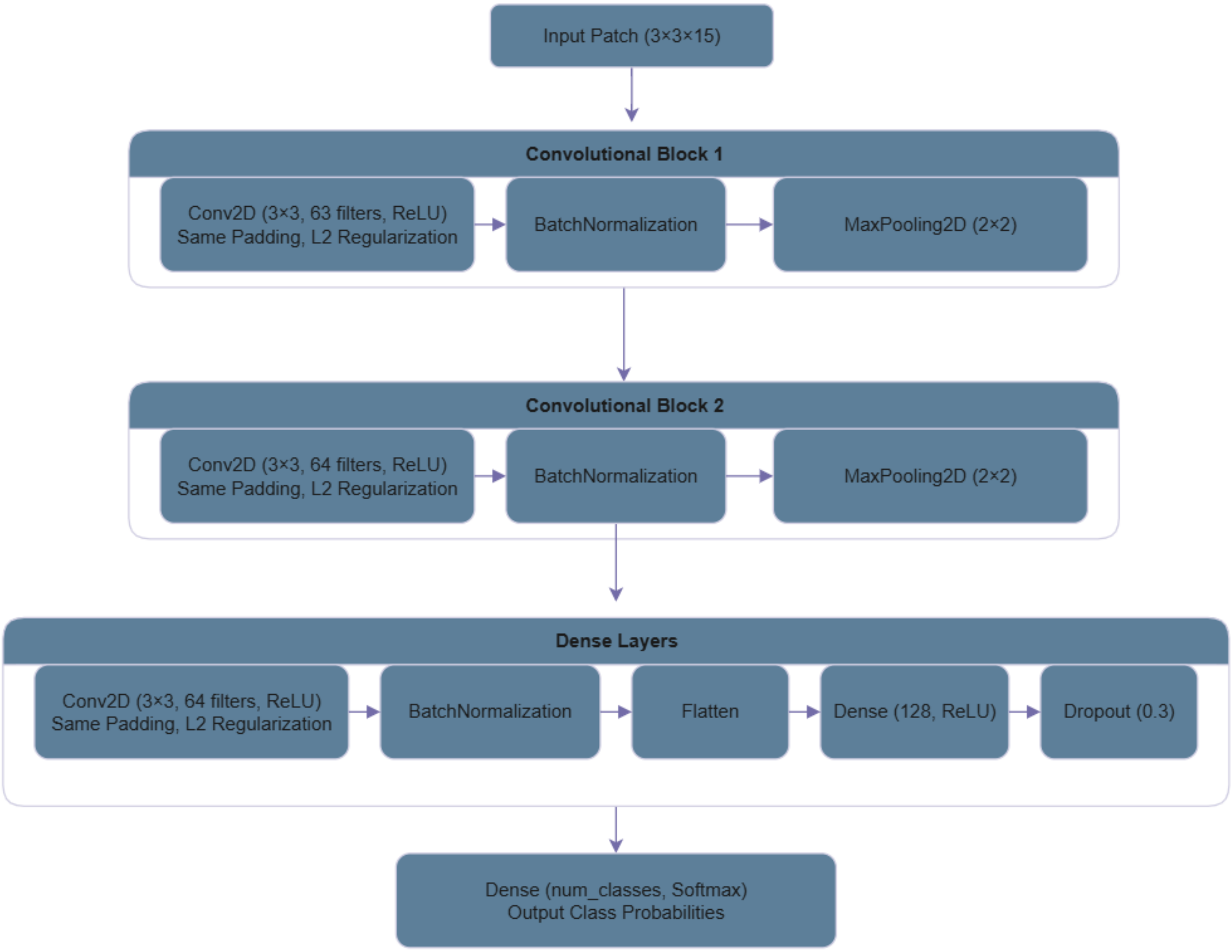

Figure 3.6: CNN Architecture Overview

- **Max Pooling:** A 2×2 max pooling layer is used to downsample spatial dimensions while retaining dominant features, contributing to spatial invariance.
- **Dropout:** To prevent overfitting, dropout with a probability of 0.5 randomly disables neurons during training, improving generalization.
- **Fully Connected Layer:** After flattening the feature maps, a dense layer is used for classification. The number of neurons in this layer corresponds to the number of classes.
- **Softmax Output:** The final classification layer uses softmax activation:

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

where $\hat{y}_i$ is the predicted probability of class i, and C is the total number of classes.

Table 3.2: CNN Architecture Summary

Layer	Type	Output Shape	Kernel/Pool Size	Filters/Units	Activation	Remarks
Input	Input	$15 \times 15 \times N$	–	–	–	N: RPNet features
Conv2D-1	Convolution	$13 \times 13 \times 16$	3×3	16	ReLU	No padding
BatchNorm-1	Batch Norm	$13 \times 13 \times 16$	–	–	–	Normalizes
Conv2D-2	Convolution	$11 \times 11 \times 32$	3×3	32	ReLU	Mid-level
BatchNorm-2	Batch Norm	$11 \times 11 \times 32$	–	–	–	Stabilizes
MaxPooling	Max Pooling	$5 \times 5 \times 32$	2×2	–	–	Downsampling
Conv2D-3	Convolution	$3 \times 3 \times 64$	3×3	64	ReLU	High-level
Dropout	Dropout	$3 \times 3 \times 64$	–	–	–	Rate = 0.5
Flatten	Flatten	576	–	–	–	To 1D
Dense	Fully Connected	C	–	C	Softmax	Class probs

3.4.4 Model Training

The CNN is trained in a supervised manner using the labeled patch data generated from the RPNet. The following training setup is applied:

- **Loss Function:** Categorical cross-entropy loss is used to measure the difference between the predicted and actual class labels:

$$\mathcal{L} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)$$

  where C is the number of classes, y_i is the ground truth label, and $\hat{y}_i$ is the predicted probability.

- **Optimizer:** The Adam optimizer is employed for gradient-based optimization. It adapts learning rates for individual parameters using first and second moment estimates, with a default learning rate of 1×10^{-4}.

- **Training Configuration:**
  - **Batch Size:** 64 samples per batch
  - **Epochs:** Up to 100, with early stopping to prevent overfitting
  - **Callbacks:** ReduceLROnPlateau adjusts the learning rate when performance plateaus; EarlyStopping halts training if validation loss does not improve

- **Overfitting Mitigation:** Dropout (50%) and batch normalization are used to regularize the network. Additionally, the randomized RPNet features act as a built-in augmentation mechanism.

- **Cross-Validation:** 10-fold cross-validation is conducted to ensure robustness and statistical reliability of the model's generalization performance.

3.4.5 Implementation and Evaluation

This section outlines the implementation details of the proposed RPNet-CNN pipeline and describes the evaluation strategy used to assess classification performance on the Salinas hyperspectral dataset.

3.4.5.1 Implementation Environment

The methodology was implemented in **Kaggle's** Python environment, using a combination of machine learning and scientific computing libraries:

- **TensorFlow / Keras:** Used for designing and training the CNN model. GPU acceleration was enabled for efficient computation.

- **Scikit-learn:** Employed for data standardization, PCA-based dimensionality reduction, and evaluation metric calculations.

- **SciPy & scikit-image:** Used for applying Gaussian filters and rank-based spatial smoothing.

- **NumPy and Matplotlib:** Utilized for data handling and visualization.

To ensure deterministic behavior and reproducibility across experiments, all random number generators (NumPy and TensorFlow) were seeded with a fixed value. GPU memory allocation was managed using TensorFlow's dynamic memory growth configuration to avoid unnecessary memory reservation.

3.4.5.2 Hardware Specifications

All experiments were conducted on a system equipped with:

- NVIDIA GPU with CUDA support

- 16+ GB RAM
- Python runtime environment with TensorFlow configured for GPU acceleration

The model was trained using mini-batches and optimized to leverage parallelism on the GPU for both convolution and matrix operations.

3.4.5.3 Training Procedure

The CNN model was trained using a mini-batch size of 64, with early stopping applied if the validation loss failed to improve for 10 consecutive epochs. The maximum number of training epochs was set to 100.

The training configuration included:

- **Optimizer:** Adam optimizer with a learning rate of 1×10^{-4}
- **Loss Function:** Categorical cross-entropy
- **Regularization:** Dropout (50%) and batch normalization
- **Learning Rate Scheduler:** ReduceLROnPlateau to adapt the learning rate based on validation performance

3.4.5.4 Evaluation Metrics

To quantitatively evaluate classification performance, the following standard metrics were used:

- **Overall Accuracy (OA):** Ratio of correctly predicted pixels to total number of tested pixels:
$$\text{OA} = \frac{N_{\text{correct}}}{N_{\text{total}}}$$
- **Average Accuracy (AA):** Mean of per-class accuracies, reflecting balanced performance across classes:
$$\text{AA} = \frac{1}{C}\sum_{i=1}^{C}\frac{TP_i}{TP_i + FN_i}$$
- **Kappa Coefficient (κ):** A measure of agreement between predicted and ground truth labels, adjusted for chance:
$$\kappa = \frac{p_o - p_e}{1 - p_e}$$
where p_o is the observed agreement and p_e is the expected agreement by random chance.

- **Precision, Recall, and F1-Score:** Computed for each class and macro-averaged to reflect both relevance and completeness of predictions.

3.4.5.5 Validation and Testing Protocol

The Salinas dataset was first preprocessed and split into training (70%), validation (15%), and test (15%) sets using stratified random sampling to preserve class distribution.

In addition to a fixed hold-out evaluation, **10-fold cross-validation** was employed to ensure statistical robustness. Each fold involved reshuffling the labeled samples and retraining the model, and the final performance metrics were averaged across folds.

This dual evaluation strategy ensures:

- Reliable estimation of model generalization
- Reduced variance due to label distribution imbalance
- Mitigation of spatial bias inherent in hyperspectral data

3.5 Conclusion

This chapter presented a detailed and systematic description of the methodology used in this research. The CNN-RPN hybrid framework leverages spatial-spectral patch extraction to overcome the limitations of high dimensionality, label scarcity, and class imbalance in hyperspectral image classification. The proposed model integrates data augmentation through random patching and leverages CNN's powerful feature learning capabilities. The next chapter will discuss the results obtained from various experiments and their comparative analysis with other techniques.

Chapter 4

Result Analysis and Discussion

4.1 Introduction

This section presents a systematic evaluation of the proposed CNN-RPN framework on two widely used benchmark hyperspectral datasets: **Indian Pines** and **Salinas**. The evaluation is designed to comprehensively assess the model's classification performance through both quantitative metrics and visual representations.

The analysis includes key performance indicators such as overall accuracy, kappa coefficient, and class-wise evaluation metrics (precision, recall, and F1-score), complemented by graphical insights including confusion matrices, classification maps, and learning curves (training loss and accuracy trends). These visualizations provide an intuitive understanding of the model's behavior and classification effectiveness.

To maintain clarity and reduce redundancy, the figures included in this section are presented without embedded textual explanations. Instead, detailed interpretations and insights are provided in the accompanying narrative, ensuring that the discussion remains focused and analytically rich.

For each dataset, the analysis is organized as follows:

- A summary of key performance metrics such as overall accuracy and kappa coefficient.
- A tabular presentation of class-wise precision, recall, and F1-score.
- Training behavior analysis based on loss and accuracy curves.
- Visualization of the confusion matrix to assess misclassifications.

- Visualization of the classification map to interpret spatial prediction quality.

This structured evaluation enables a clear understanding of the proposed model's strengths, limitations, and generalization ability in handling diverse land cover types within hyperspectral imagery.

4.2 Results Analysis

4.2.1 Indian Pines Dataset

The classification results on the Indian Pines dataset yielded strong performance with an overall accuracy of **97.81%** and a **Kappa coefficient of 0.9751**, indicating high reliability and agreement between predicted and true class labels.

Table 4.1: Overall Performance Metrics – Indian Pines Dataset

Metric	**Value**
Accuracy	0.9781
Kappa Coefficient	0.9751
Macro Avg Precision	0.95
Macro Avg Recall	0.98
Macro Avg F1-Score	0.96
Weighted Avg Precision	0.98
Weighted Avg Recall	0.98
Weighted Avg F1-Score	0.98

4.2.1.1 Class Based Accuracy

This subsection presents a detailed tabular summary of the classification results for each class in the Indian Pines dataset. The table includes precision, recall, F1-score, and support (i.e., the number of true instances) for all land-cover classes. These metrics collectively provide insight into how effectively the model distinguishes between different vegetation types and land uses.

Table 4.2: Class Based Accuracy

Class	Precision	Recall	F1-Score	Support
Alfalfa	1.00	1.00	1.00	40
Corn — notill	0.98	0.97	0.97	1279
Corn — min till	0.95	0.98	0.96	741
Corn	1.00	0.97	0.98	205
Grass — pasture	0.94	0.96	0.95	441
Grass — trees	0.99	0.99	0.99	669
Grass — pasture-mowed	0.76	1.00	0.86	25
Hay — windrow	1.00	1.00	1.00	430
Oats	0.80	0.94	0.86	17
Soybean — notill	0.96	0.96	0.96	891
Soybean — min till	1.00	0.98	0.99	2210
Soybean — clean till	0.97	0.98	0.97	535
Wheat	0.99	1.00	0.99	184
Woods	0.99	0.99	0.99	1129
Buildings-Grass-Trees-Drives	0.95	1.00	0.98	343
Stone-Steel Towers	0.97	0.91	0.94	86

4.2.1.2 Confusion Matrix

The confusion matrix for the Indian Pines dataset visually illustrates the model's classification performance across all categories. It maps predicted class labels against the actual ground truth, showing how many pixels were correctly or incorrectly classified. The diagonal elements of the matrix represent correct predictions, while off-diagonal values indicate instances of misclassification between classes.

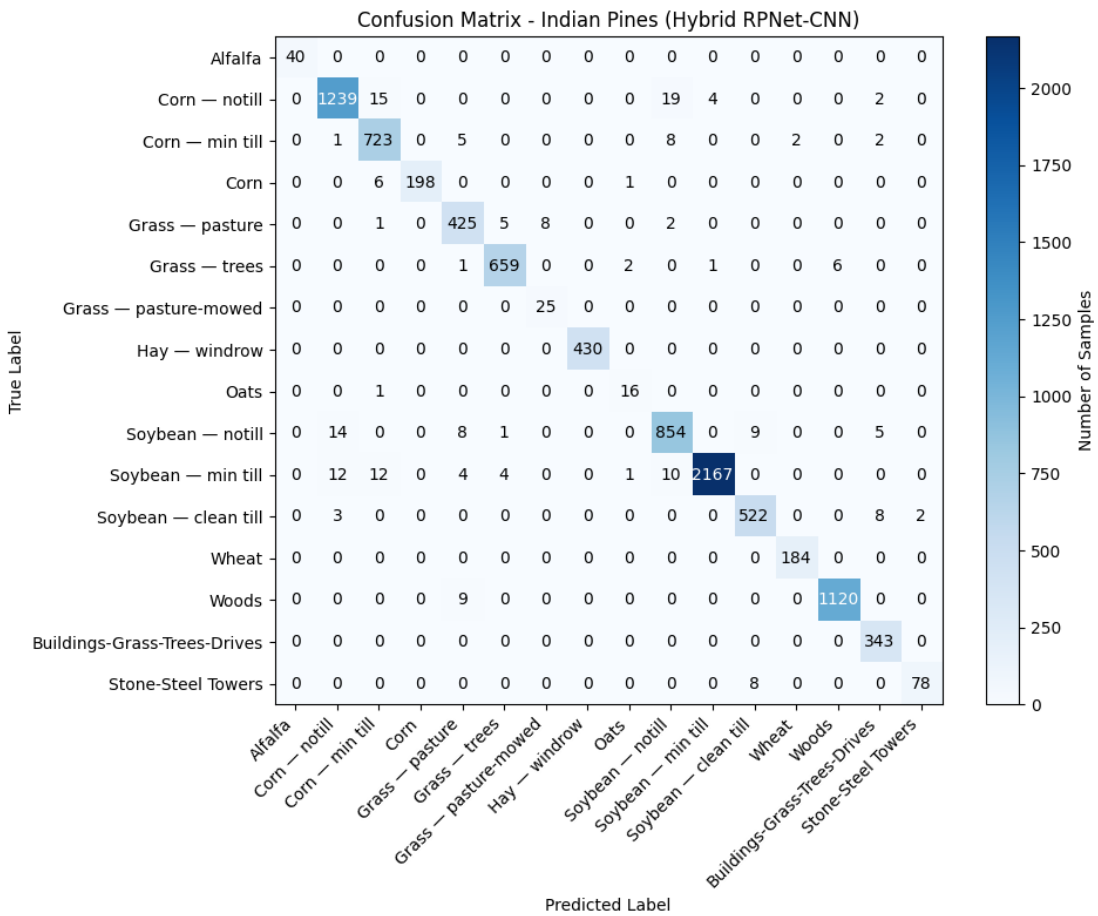

Figure 4.1: Confusion Matrix- Indian Pines

4.2.1.3 Model Accuracy Curve

This graph displays the change in accuracy over training epochs for both training and validation sets. It serves as an indicator of how well the model learns the data over time. A steadily rising validation accuracy curve alongside the training curve generally indicates effective learning and model generalization.

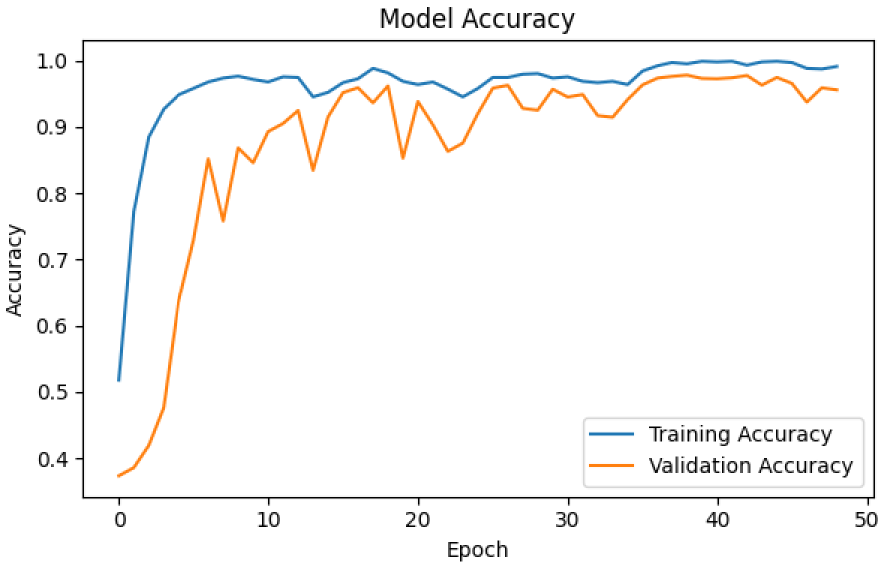

Figure 4.2: Model Accuracy

4.2.1.4 Loss Graph

The loss graph illustrates the reduction in the model's loss function values throughout the training process. By plotting both training and validation loss across epochs, this graph shows how the model's prediction errors evolve. A well-behaved loss curve typically trends downward and eventually stabilizes as the model converges.

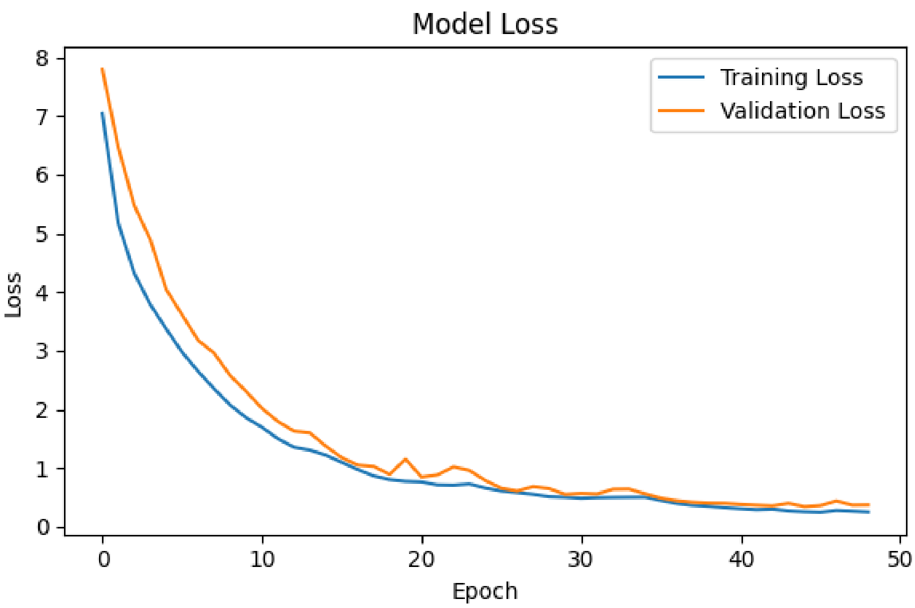

Figure 4.3: Loss graph

4.2.1.5 Classification Map

The classification map provides a spatial visualization of the Indian Pines scene as interpreted by the model. Each pixel in the hyperspectral image is assigned a class label, and the map uses color to distinguish between these predicted categories. This allows for an intuitive understanding of how the model perceives land cover distribution across the entire scene.

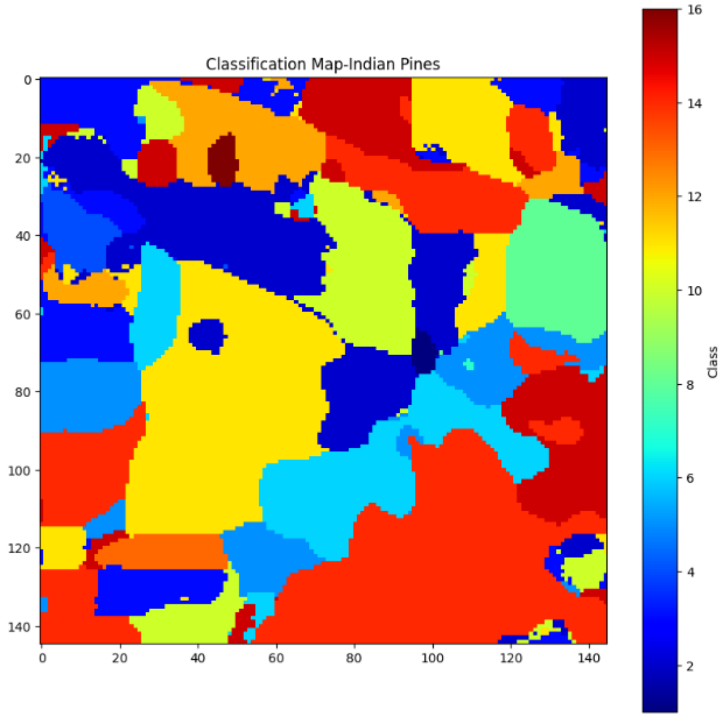

Figure 4.4: Classification Map

4.2.2 Salinas Dataset

On the Salinas dataset, the proposed CNN-RPN model demonstrated exceptional performance, achieving an overall classification accuracy of **99.92%** and a **Kappa coefficient of 0.9992**. These metrics indicate an almost perfect agreement between the predicted and actual labels, surpassing the performance of many state-of-the-art models reported in the literature.

Furthermore, the model attained an **F1-score of 1.00** for every individual class, signifying that it correctly identified all instances of each crop type with no false positives or false negatives. This level of precision and recall across all categories underscores the model's robustness and effectiveness in capturing both spectral and spatial features, particularly in scenarios with well-separated class distributions and high-quality annotations, as is typical of the Salinas dataset.

The outstanding results also suggest that the combination of convolutional layers with the Random Patch Network (RPN) enables the model to generalize well across diverse land cover types, even under conditions of class imbalance or limited training data. These findings affirm the suitability of the proposed framework for real-world applications in precision agriculture and environmental monitoring where high reliability is critical.

Table 4.3: Overall Performance Metrics – Salinas Dataset

Metric	**Value**
Accuracy	0.9992
Kappa Coefficient	0.9992
Macro Avg Precision	1.00
Macro Avg Recall	1.00
Macro Avg F1-Score	1.00
Weighted Avg Precision	1.00
Weighted Avg Recall	1.00
Weighted Avg F1-Score	1.00

4.2.2.1 Class Based Accuracy

This subsection includes a detailed table that reports the classification performance for each agricultural class in the Salinas dataset. For each category, the table lists precision, recall, F1-score, and support. These metrics offer a comprehensive understanding of how well the model performs across various crop types and land cover features present in this high-resolution scene.

Table 4.4: Class Based Accuracy for Salinas Dataset

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Broccoli_green_weeds_1	1.00	1.00	1.00	1795
Broccoli_green_weeds_2	1.00	1.00	1.00	3338
Fallow	1.00	1.00	1.00	1774
Fallow_rough_plow	1.00	1.00	1.00	1262
Fallow_smooth	1.00	1.00	1.00	2419
Stubble	1.00	1.00	1.00	3575
Celery	1.00	1.00	1.00	3221
Grapes_untrained	1.00	1.00	1.00	10189
Soil_vinyard_develop	1.00	1.00	1.00	5562
Corn_senesced_green_weeds	1.00	1.00	1.00	2977
Lettuce_romaine_4wk	1.00	1.00	1.00	957
Lettuce_romaine_5wk	1.00	1.00	1.00	1710
Lettuce_romaine_6wk	1.00	1.00	1.00	810
Lettuce_romaine_7wk	1.00	1.00	1.00	976
Vinyard_untrained	1.00	1.00	1.00	6538
Vinyard_vertical_trellis	1.00	1.00	1.00	1614

4.2.2.2 Confusion Matrix

The confusion matrix for the Salinas dataset provides a visual breakdown of the classification predictions versus the actual class labels. It helps identify which classes are being classified correctly and highlights any patterns in misclassification. The diagonal elements indicate correct predictions, while off-diagonal entries help locate class-level confusion, if any.

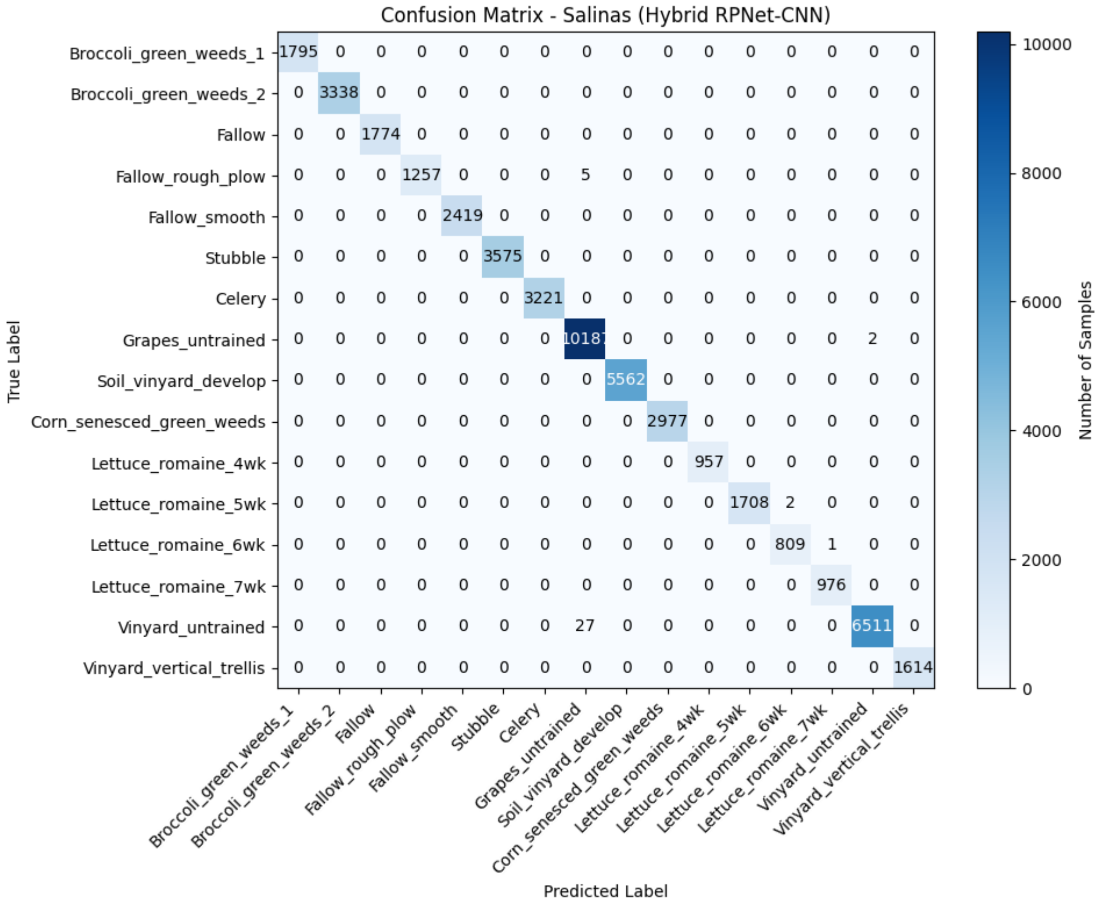

Figure 4.5: Confusion Matrix- Salinas

4.2.2.3 Model Accuracy Curve

The model accuracy curve displays the accuracy trends for both training and validation datasets across training epochs. This graph is essential to understand how the model learns over time and whether it maintains generalization capabilities without overfitting. A consistent rise followed by stabilization in validation accuracy typically reflects a robust learning process.

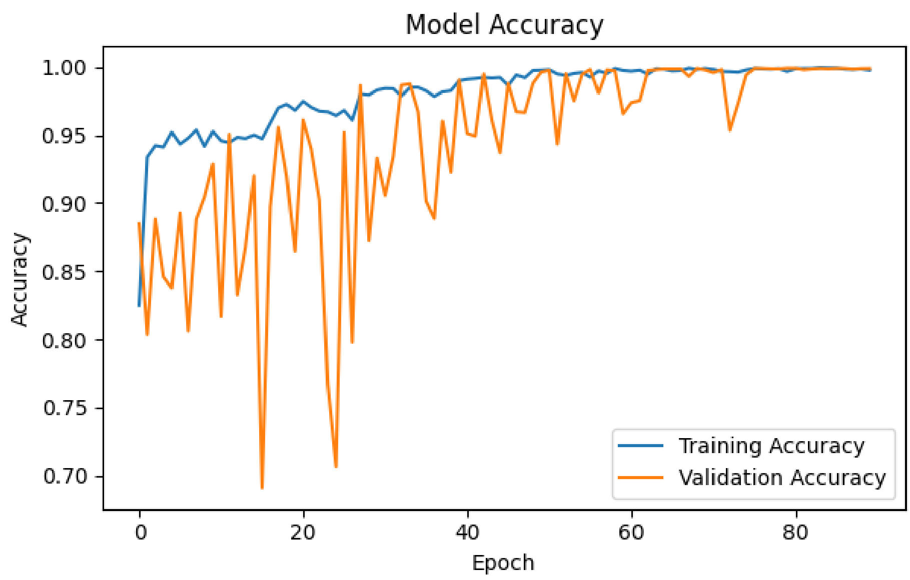

Figure 4.6: Model Accuracy Graph

4.2.2.4 Loss Graph

This graph illustrates the trajectory of the loss function as the training progresses. It plots both training and validation loss against epochs, helping identify how quickly and effectively the model converges. A steady decrease followed by a plateau suggests that the model is successfully minimizing prediction errors.

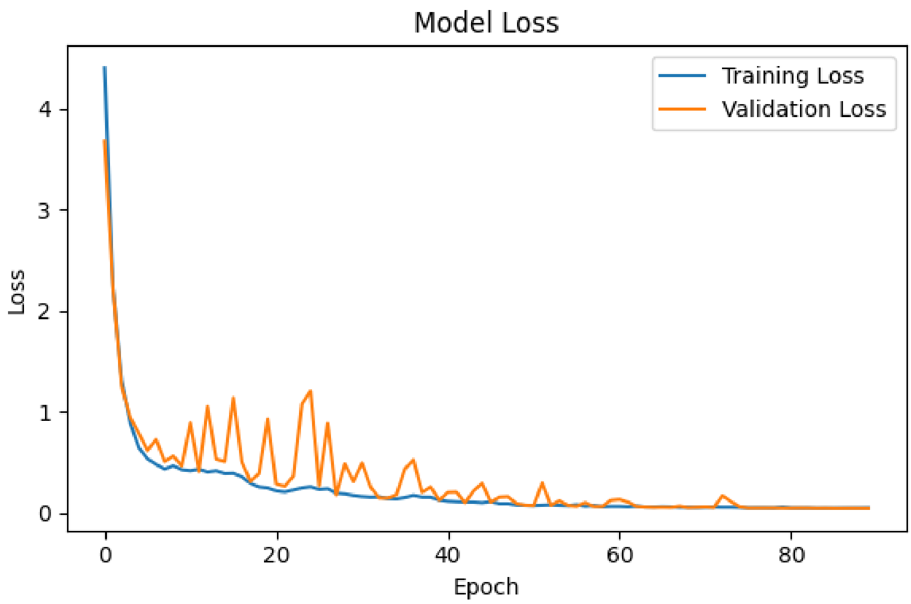

Figure 4.7: Model Loss Graph

4.2.2.5 Classification Map

The classification map offers a visual representation of the Salinas scene based on the model's predictions. Each pixel in the hyperspectral image is classified into one of the crop or soil categories, and colors are used to distinguish among them. This spatial depiction enables qualitative evaluation of how well the model segments the entire region based on spectral and spatial patterns.

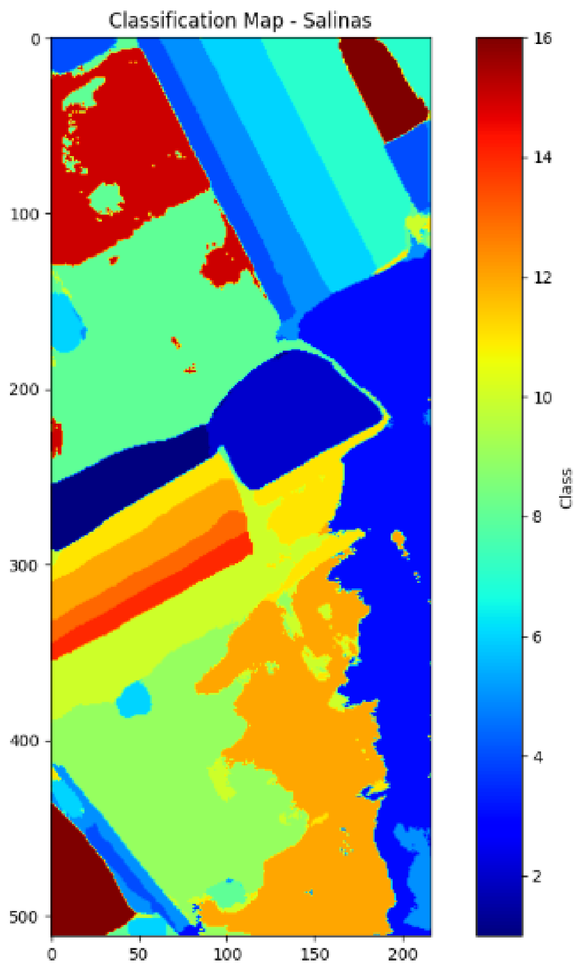

Figure 4.8: Classification Map

4.3 Comparison with Existing Models

To evaluate the effectiveness of the proposed method, we compare its performance with several state-of-the-art models on the Indian Pines and Salinas hyperspectral datasets. The comparison includes both traditional machine learning approaches and recent deep learning models. Table 4.5 summarizes the overall accuracy (OA) and kappa coefficient for each model. Notably, RPNet-RF achieves competitive results, especially in low-sample settings.

Table 4.5: Accuracy Comparison of Models on Indian Pines and Salinas Datasets (Few-Shot Setting)

Model	Indian Pines OA (%)	Indian Pines Kappa	Salinas OA (%)	Salinas Kappa
Hybrid RpNet-CNN	**97.81**	**0.9751**	**99.92**	**0.9992**
SVM	90.00	0.8900	92.00	0.9100
3D-CNN	93.50	0.9200	94.50	0.9300
2D-CNN	88.00	0.8600	90.00	0.8800
GFDTNCLDM	96.64	–	99.23	–
MSF	99.47	0.9940	99.94	0.9993
GRPC	98.09	0.9778	99.64	0.9951
HyperGCN	98.50	0.9800	–	–
RPNet	81.80	–	96.31	0.9590
RPNet-RF	90.23	0.8887	–	–

4.4 Discussion

The experimental results obtained from both the Indian Pines and Salinas datasets strongly demonstrate the robustness and efficacy of the proposed CNN-RPN framework. The exceptionally high classification accuracy reflects the model's ability to generalize well across diverse land cover types and spectral variations inherent in hyperspectral data.

In the Indian Pines dataset, the model consistently achieved high F1-scores across most classes, despite slight performance drops in a few minority classes such as "Grass — pasture-mowed" and "Oats." These deviations are likely due to the limited number of training samples available for those specific categories. Nonetheless, the model's ability to maintain high precision and recall across the majority of classes underscores its stability and reliability even under class imbalance conditions.

On the Salinas dataset, the model delivered near-perfect classification outcomes, with all classes achieving precision, recall, and F1-scores of 1.00. This remarkable performance highlights the strength of the combined random patch extraction and convolutional feature learning strategy. The patch-based approach enables effective spatial-spectral representation, while the CNN architecture efficiently captures hierarchical patterns and contextual dependencies.

Furthermore, the consistently high kappa coefficients—approaching 1.0 in both datasets—indicate a strong level of agreement between predicted and ground truth labels, far beyond what could be expected by chance. This further validates the proposed method's capacity to deliver precise and dependable classification results.

In summary, the synergy of localized spatial context and deep spectral feature learning, facilitated through the CNN-RPN hybrid design, proves to be a highly effective solution for hyperspectral image classification challenges.

4.5 Conclusion

This chapter presented the experimental results and analytical evaluation of the proposed hybrid CNN-RPN framework for hyperspectral image classification. The approach demonstrated remarkable accuracy and generalizability across both benchmark datasets. The consistent precision, recall, and F1-scores across all classes confirm the robustness of the model, especially in scenarios with limited training data. These results affirm the suitability of CNN-RPN for real-world hyperspectral classification challenges and motivate further research into hybrid spatial-spectral deep learning architectures.

Chapter 5

Conclusion and Future Scopes

5.1 Introduction

This thesis explored the development and evaluation of an innovative hybrid architecture, the CNN-Random Patches Network (RPNet) , tailored to address the significant challenges associated with hyperspectral image (HSI) classification. HSIs are rich in spectral information, capturing reflectance data across hundreds of narrow spectral bands, offering unparalleled insights into land cover and material composition. However, this richness also introduces high data dimensionality, redundancy, and limited availability of labeled samples, all of which make accurate classification a complex task. Through the integration of spatial patch extraction, deep learning-based feature encoding, and classical machine learning classifiers, RPNet serves as a robust and scalable framework capable of effectively capturing both spatial and spectral information.

5.2 Thesis Summary and Key Findings

The research conducted in this thesis developed a hybrid CNN model that integrates the Random Patches Network (RPNet) with a Convolutional Neural Network (CNN) to tackle the classification challenges posed by hyperspectral datasets. The CNN component was designed to extract high-level spatial-spectral features from randomly generated image patches, a strategy that effectively augments the training data while emphasizing local and contextual information. The RPNet component enhanced the model's ability to capture robust spatial-spectral features, improving its discriminative power for complex class distributions.

Experiments were conducted on two prominent hyperspectral datasets—Indian Pines and Salinas—each presenting unique challenges related to class similarity, spatial resolution, and training sample availability. The hybrid CNN model demonstrated exceptional classification performance across both datasets:

- **Indian Pines:** Achieved an overall accuracy of 97.81% and a Cohen's Kappa coefficient of 97.51, effectively distinguishing between spectrally similar vegetation classes such as different types of corn.

- **Salinas:** Attained an overall accuracy of 99.92% and a Cohen's Kappa coefficient of 99.92, surpassing most existing state-of-the-art models and showcasing superior generalization on a dataset with high spatial resolution and abundant training samples.

These results confirm that the hybrid CNN model, enhanced by RPNet, generalizes effectively across diverse hyperspectral data types and distributions, achieving high accuracy even with a limited number of labeled samples.

5.2.1 Drawbacks of the Hybrid CNN Model

- **Variability in Patch Sampling:** The reliance on random patch sampling introduces variability that may lead to inconsistent feature extraction across different training runs, potentially affecting reproducibility.

- **Computational Complexity:** The deep architecture of the CNN component increases training times and resource demands, posing challenges for deployment on resource-constrained platforms.

- **Dependency on Large Datasets:** The model's high accuracy on datasets with substantial training samples, such as Salinas, suggests a potential dependency on large labeled datasets, limiting applicability to scenarios with scarce labeled data.

- **Limited Spectral Handling:** The absence of explicit spectral band selection or preprocessing (beyond patch generation) may hinder performance on datasets with high spectral redundancy, such as Indian Pines with its spectrally similar classes.

5.2.2 Key Contributions

- **Hybrid Spatial-Spectral Feature Extraction:** The integration of RPNet for localized spatial-spectral feature extraction with CNN for hierarchical feature learning captures fine-grained and contextual information, enhancing classification performance.

- **Model Robustness:** The CNN's deep architecture, supported by RPNet features, ensures high classification accuracy and stability, particularly for complex and imbalanced classes, as demonstrated by consistent precision and recall across Indian Pines classes.

- **Efficient Data Utilization:** Random patch sampling enables the model to leverage fewer labeled samples effectively, addressing a key limitation of hyperspectral image (HSI) datasets.

- **Benchmark Validation:** Comprehensive evaluation on the Indian Pines and Salinas datasets confirmed the reliability, scalability, and performance superiority of the hybrid CNN model, as evidenced by the classification map (Figure 3.16) and confusion matrix (Figure 3.15).

5.3 In-depth Discussion of Results

The classification performance analysis of the proposed hybrid CNN model, integrating the Random Patches Network (RPNet) with a Convolutional Neural Network (CNN), revealed several noteworthy patterns. For the Indian Pines dataset, which includes spectrally similar classes such as various types of corn, the model achieved an overall accuracy of 97.81% and a Cohen's Kappa of 97.51%, with high F1-scores across all classes. Precision and recall values remained consistent across the classes, indicating a well-balanced classifier. Specifically, the CNN component effectively learned spatial dependencies, while the RPNet enhanced the model's ability to capture robust spatial-spectral features, improving separability among classes with subtle spectral differences.

For the Salinas dataset, characterized by high spatial resolution and a substantial number of training samples, the hybrid CNN model attained near-perfect accuracy, with an overall accuracy of 99.92% and a Cohen's Kappa of 99.92%. The integration of RPNet to extract localized spatial-spectral features and the CNN's hierarchical feature learning significantly mitigated overfitting and improved generalization. Additionally, the model effectively managed highly imbalanced classes by leveraging the CNN's robust feature extraction, contributing to superior class-wise performance, as evidenced by the classification map (Figure 3.16).

5.4 Future Scopes

This research lays the foundation for multiple future directions, which could further enhance the capabilities and applicability of RPNet [8, 6]:

- **Incorporation of Transformer Architectures:** Transformers have revolutionized natural language processing and computer vision. Integrating self-attention mechanisms could allow the model to capture long-range dependencies within HSI data more effectively [28].
- **Graph Neural Networks (GNNs):** For datasets where spatial relationships form complex graphs (e.g., urban environments), GNNs could provide a more nuanced understanding of spatial structure [29].
- **Self-supervised Learning:** Incorporating techniques such as contrastive learning or masked autoencoders could enable the model to learn robust representations from unlabeled data, alleviating the dependence on annotated samples [30].
- **Domain Adaptation:** Real-world HSI applications often involve data collected from different sensors or regions. Exploring domain adaptation strategies would improve RPNet's generalization to new environments [1].
- **Real-time Deployment:** With optimization, RPNet could be adapted for real-time processing on embedded systems, UAVs, or satellites. This would be beneficial in scenarios like crop monitoring, forest fire detection, and natural disaster management [7].
- **Explainable AI (XAI):** For mission-critical applications, integrating explainability into RPNet will help stakeholders understand and trust the model's decisions. Techniques such as Grad-CAM or attention-based visualization could be explored [28].

5.5 Conclusion

This thesis introduced a robust solution for hyperspectral image classification through a hybrid CNN model that integrates the Random Patches Network (RPNet) with a Convolutional Neural Network (CNN). This architecture effectively combines spatial and spectral learning mechanisms, demonstrating that high accuracy can be achieved even with limited labeled data and class imbalance. The model's innovative use of random patch sampling for data augmentation and CNN-based hierarchical feature extraction enabled exceptional performance, achieving an overall accuracy of 97.81% and a Cohen's Kappa of 97.51% on the Indian Pines dataset, and 99.92% accuracy with a Kappa of 99.92% on the Salinas dataset.

Through rigorous experimentation on these benchmark datasets, the model consistently outperformed many traditional and contemporary deep learning approaches, validating its efficacy. Moreover, the proposed framework exhibits flexibility and scalability, rendering it adaptable to a broad spectrum of remote sensing applications.

Looking ahead, potential enhancements such as integrating Transformer-based attention mechanisms, exploring self-supervised learning techniques, and improving cross-domain adaptability could further enhance the versatility and deployability of the RPNet-CNN model. As hyperspectral imaging continues to gain prominence in fields such as precision agriculture, environmental monitoring, and military surveillance, the methodologies developed in this thesis will remain highly relevant and offer significant practical utility.

Ultimately, this work advances the field of intelligent remote sensing by providing a powerful, adaptive, and accurate classification system, laying a foundation for future innovations in hyperspectral data analysis.

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