Hyperspectral Image Denoising Using Features Extraction and Attention Mechanism (AAFEHDN)

Project Supervisor

Fazle Basit

fazl.basit@nu.edu.pk

Project Co-Supervisor

Dr. Muhammad Amin

muhammad.amin@nu.edu.pk

Group Members

Muhammad Allah Rakha (P19-0006)

Farkhanda Saleem (P19-0004)

Mina Riaz (P19-0099)

Introduction

1. Hyperspectral images are obtained by airborne or satellite sensors imaging a target area.
2. That contains information on objects in tens to two hundred of continuous and segmented bands from visible light to the infrared (wavelength) spectral region.
3. Hyperspectral Images (HSIs), simultaneously acquire both spatial and spectral information.
4. The pixels are important features in hyperspectral data analysis. Therefore, the spatial and spectral information has been characterized into pixels.
5. Each pixel is a vector of values that specify the strength at a location **(x,y)** in **z** different bands.

Introduction (Continued)

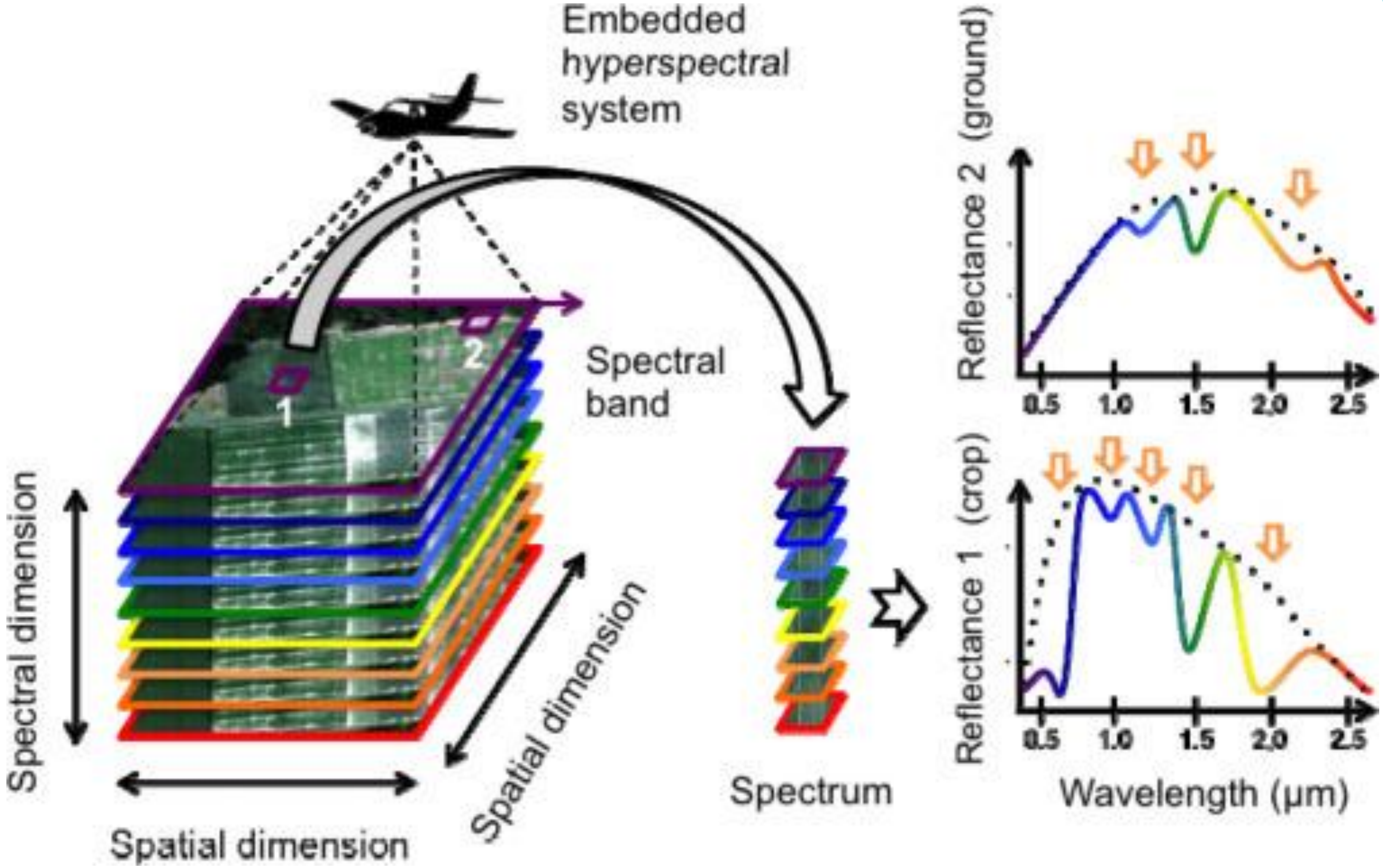


Figure-1: Hyperspectral Image structure [1].

Motivation

1. Hyperspectral images have many fields such as classification, denoising, and target detection.
2. Hyperspectral images have many applications in many fields, such as biomedical imaging, agriculture, water resources, disaster, and land use.
3. Because of the photon effects and atmospheric interference.
4. Hyperspectral images suffer from various types of noise such as random noise, gaussian noise, and dead pixels.
5. The procedure of de-noising is compulsory for enhancing the quality of the images.

Literature Review/ Related Work

Sr No	Year	Basic Idea	Methodologies	Results	Limitations
[3]	2023	Mixed Attention Network for Hyperspectral Image Denoising.	• Simultaneously considers the inter- and intra-spectral correlations • Interactions between low- and high-level spatial-spectral meaningful features.	• Simulated and real noise experiments outperform existing state-of-the-art methods. • Maintaining a low cost of parameters and running time.	• Efficiently integrates the inter-spectral features across all the spectral bands.
[4]	2022	Deep Spatial-Spectral Global Reasoning Network for Hyperspectral Image Denoising	• To address the issue of ignoring global contextual information. • That utilizes both local and global information for HSI noise removal.	• Efficiently considered both the spatial and spectral in synthetic and real HSIs data. • That outperforms other state-of-the-art HSI denoising methods.	• The global spatial relations between pixels in feature maps. • The global relations across the channels. • Tackle complex noise by exploiting multiple representations.
[5]	2022	Hyperspectral Image Denoising With Weighted Nonlocal Low-Rank Model and Adaptive Total Variation Regularization	That utilize some method for HSIs spatial-spectral data. • The non-independent and non-local similarity. • The edge-preserving total variation regularization. • The identically distributed.	• The ADMM network has extensive experiments on simulated data and real data. • That justifies the superiority of the proposed method beyond state-of-the-art.	• Exploit HSI's non-local similarity and spatial-spectral relation. • To characterize the non-local smooth property of HSI and complex noise.

Literature Review/ Related Work (Continued)

[6]	2022	Fast Hyperspectral Image Denoising and Inpainting Based on Low-Rank and Sparse Representations	• Fast hyperspectral denoising: to handle Gaussian and Poissonian noise. • Fast hyperspectral inpainting: to restore HSIs where some observations from known pixels in some known bands are missing.	• In experiments with simulated and real data, FastHyDe and FastHyIn compete with the state-of-the-art methods. • Lower computational complexity	• Fully exploit extremely compact and sparse HSI representations. • Utilized to low-rank and self-similarity characteristics.
[7]	2021	LR-Net: Low-Rank Spatial-Spectral Network for Hyperspectral Image Denoising	• The low-rank features are utilized to capture the latent semantic relationships of the HSIs to recover clean HSIs.	• Extensive experiments on simulated and real-world. • That LR-Net outperforms other state-of-the-art denoising methods in terms of evaluation metrics and visual assessments.	• The atrous blocks exploit spatial-spectral features. • Forwarded to a multi-atrous block to aggregate the context fields. • The contextual and spatial-spectral features are concatenated to a low-rank module (LRM).
[8]	2021	Hyperspectral Image Denoising Using a 3-D Attention Denoising Network	• The parallel separate processes of the spatial and spectral information. • That managed the global dependence and correlation between spatial and spectral.	• Experimental results on simulated and real data support the better quality of our method. • When compared with state-of-the-art methods visually and quantitatively.	• The position attention module to spatial feature map. • The channel attention module to the spectral combined branches. • The multiscale features to extract and fusion.

Literature Review/ Related Work (Continued)

[9]	2021	Hyperspectral Image Denoising via Low-Rank Representation and CNN Denoiser	• The sparse-based low-rank representation explores the global correlations of spatial and spectral. • The CNN-based denoiser represents the deep prior restoration models.	• Simulated experiments the achieves better denoising results for both additive noise in quantitative evaluation • Real data experiments show that the proposed model yields the best performance.	• Denoising model with low-rank representation. • CNN denoiser prior in the flexible and extensible plug-and-play framework.
[10]	2020	Spatial-spectral weighted nuclear norm minimization for hyperspectral image denoising	• The weighted Nuclear Norm Minimization to recover the spectral LR structure. • The multi-channel Weighted Nuclear Norm Minimization to recover spatial LR matrix.	• Experiments implemented on simulated and real HSIs data sets. • That validates the denoising visual quality and efficiency of the proposed method.	• Spatial domain nonlocal similar cubic patches are found. • Stacked into an LR matrix contains the local detailed spatial texture information.
[11]	2020	Enhanced Non-Local Cascading Network with Attention Mechanism for Hyperspectral Image Denoising	• That (ENCAM) extracts the joint spatial-spectral feature more effectively for Hyperspectral Image Denoising.	• The theoretical analysis and the experiments indicate. • That method is superior to the other state-of-the-art methods of HSIs denoising.	• The non-local structure enlarges to extract spatial features. • The multi-scale convolutions and channel attention module extracted multi-scale features.

Literature Review/ Related Work (Continued)

[12]	2020	A Single Model CNN for Hyperspectral Image Denoising	For spectral-spatial HSI denoising. • Convolutional neural networks (HSISDeCNN)	• Efficiently utilized both spatial and spectral data. • Synthetic and Real experiment results outperform other methods.	• High spectral correlation between adjacent bands in HSIs
[13]	2020	A Tensor Subspace Representation-Based Method for Hyperspectral Image Denoising (TenSRDe)	• Subspace-based methods can reduce computational complexity. • Matrix subspaces-based can't represent unfolding operations that destroy the tensor structure.	• Experiments implemented on simulated and real data sets. • That validates the denoising effect and efficiency of the proposed method.	• The low-tubal rankness of the HSI tensor. • The nonlocal self-similarity of the coefficient tensor.
[14]	2018	Hyperspectral Image Denoising Employing a Spatial–Spectral Deep Residual Convolutional Neural Network	• Nonlinear end-to-end mapping between the noisy and clean HSIs data. • The spatial-spectral deep convolutional neural network (HSID-CNN)	• The simulated and real-data experiments (HSID-CNN) outperform many of the methods. • In the case of evaluation indexes, visual effect, and classification accuracy.	The multiscale feature extraction is employed to capture. • Multiscale spatial feature. • Multiscale spectral feature.

Problem Statement

“State-of-the-art models for Hyperspectral Images (HSIs) can't utilize the features of spectral band correlation, geometrical characteristics, and eventually decompose high-frequency features. This inability degrades further processing of Target Detection and Classification.”

Objective

1. To develop novel HSIs denoising network.
2. To extract spatial-spectral features, suppress noise levels, and preserve real HSIs spatial-spectral information structure prior.
3. To perform well-constructed results than other proposed HSIs methods and decompose high-frequency features.
4. To have relatively low runtime complexity and high-quality results and a robust, flexible, cost-effective network.

System Design [1/4]

1. **Hyperspectral Images (HSI) Data:** The filtered dataset is given after applying some preprocess techniques such as Cropping, Simulated Noise, Data Augmentation, and Specified Batch Size Samples. The provided shape of the dataset is Training, Testing, and Matric.

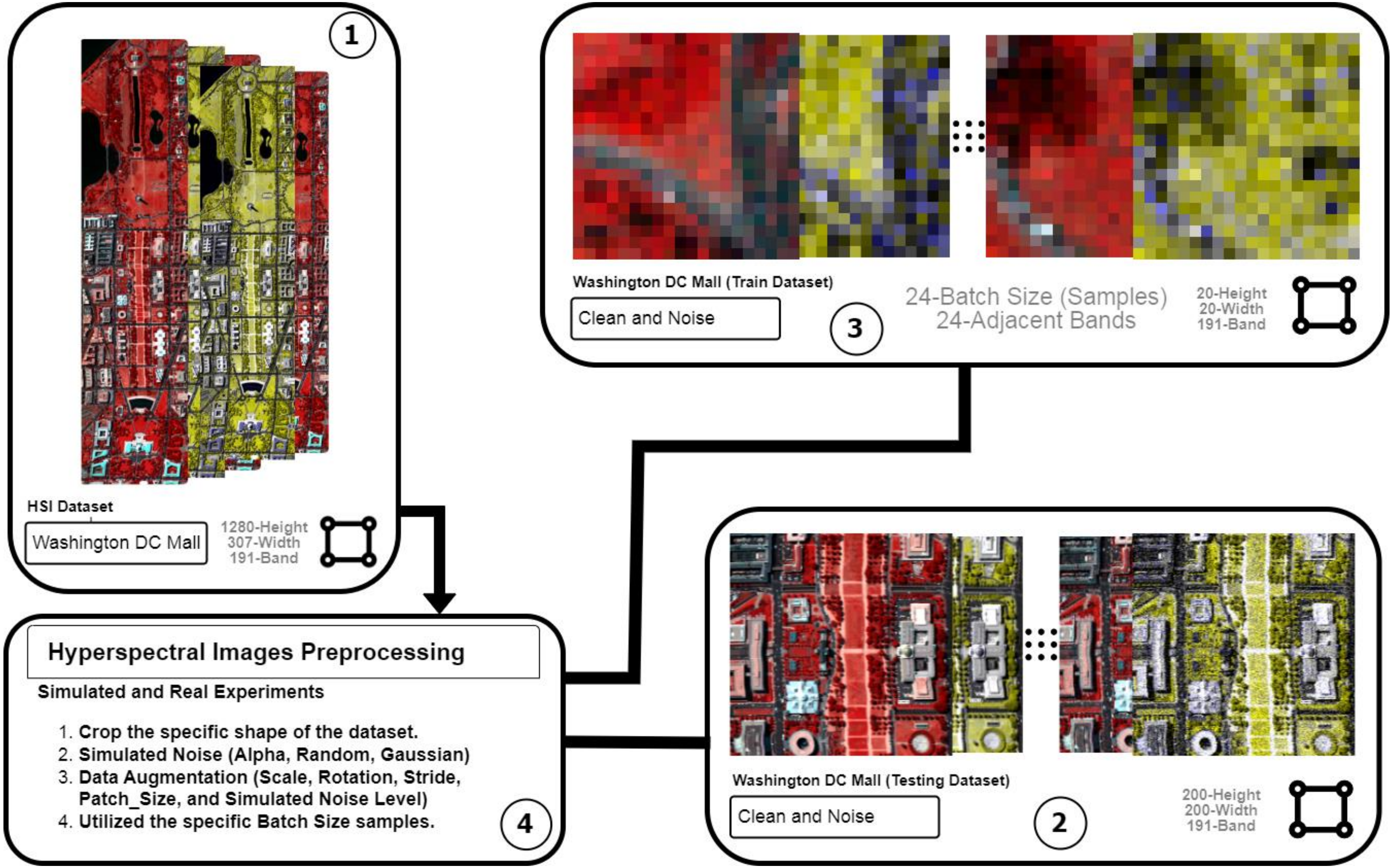
2. **Spectral Band Correlation:** The utilization of spectral bands in which correlation through K-Adjacent noisy bands.

3. **Geometrical Characteristics:** The utilization of feature extraction modules on both case of spatial and spectral to preserve geometrical characteristics in structured prior information.

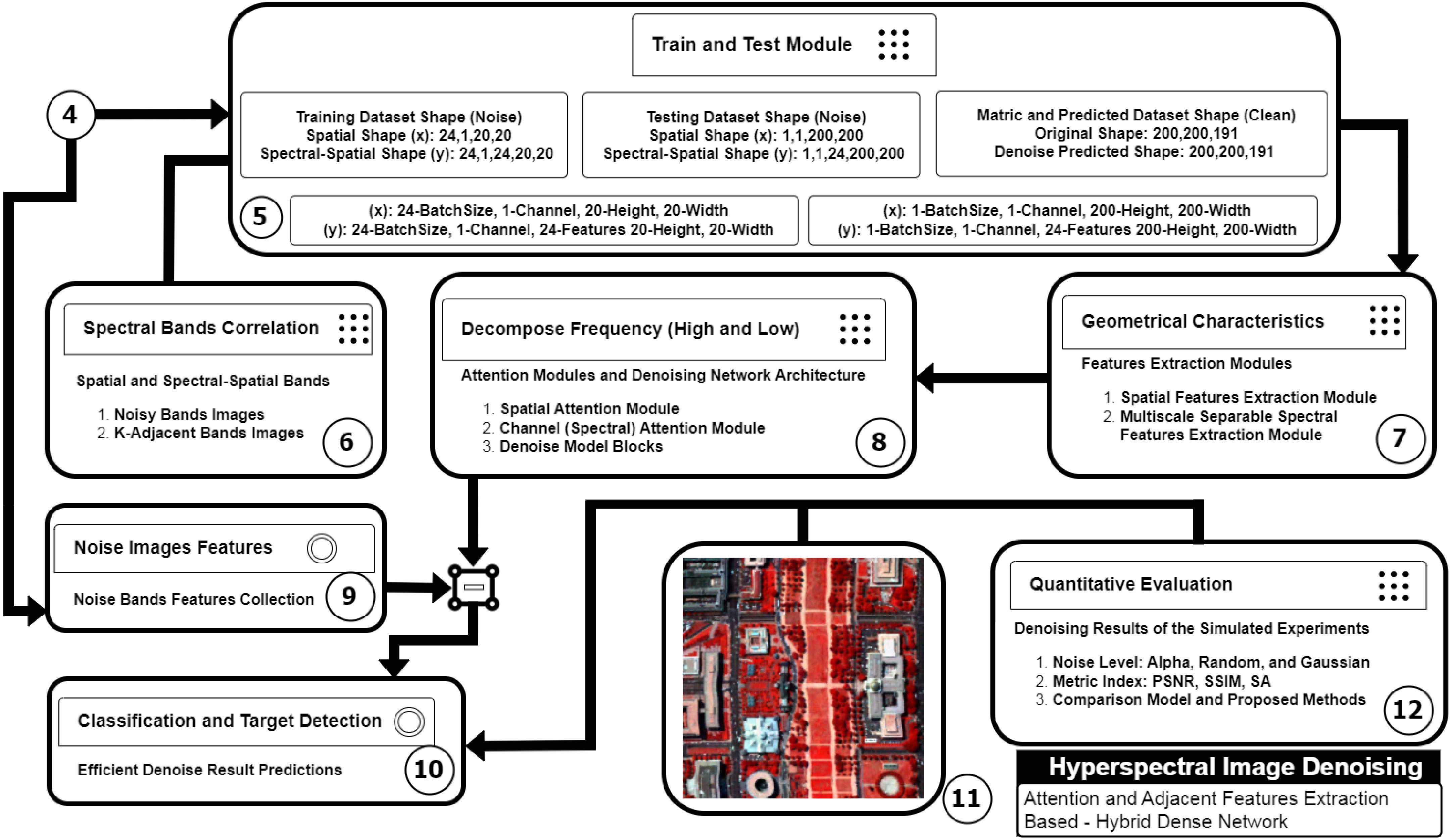
4. **Decompose Frequency (High & Low):** The hybrid dense network based on attention modules (spatial and channel) is used to decompose frequency of higher and lower noisy features.

5. **Classification and Target Detection:** The predicted denoise results (loss) are substituted by noisy band features.

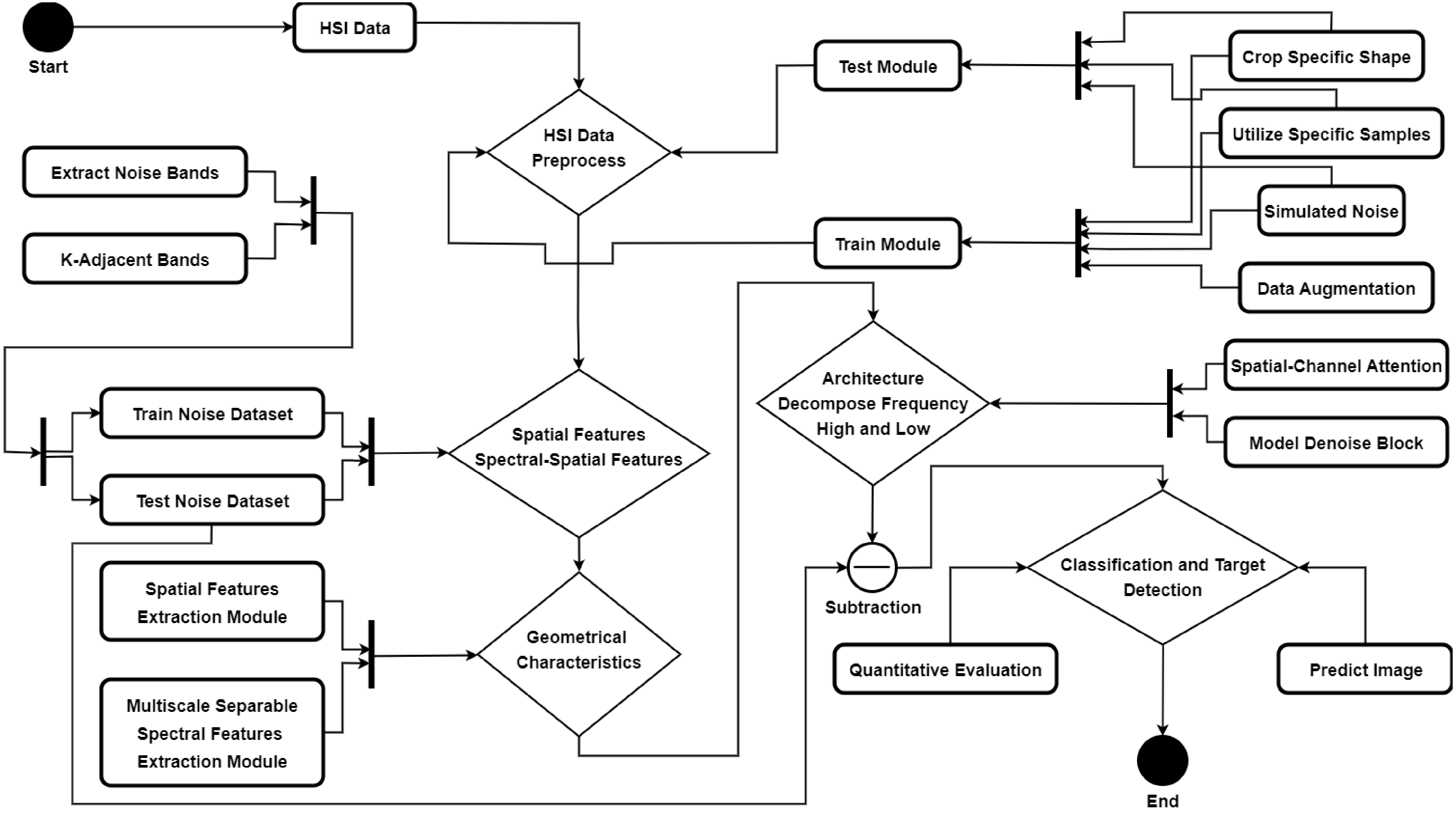
System Design (Component Diagram) [2/4]



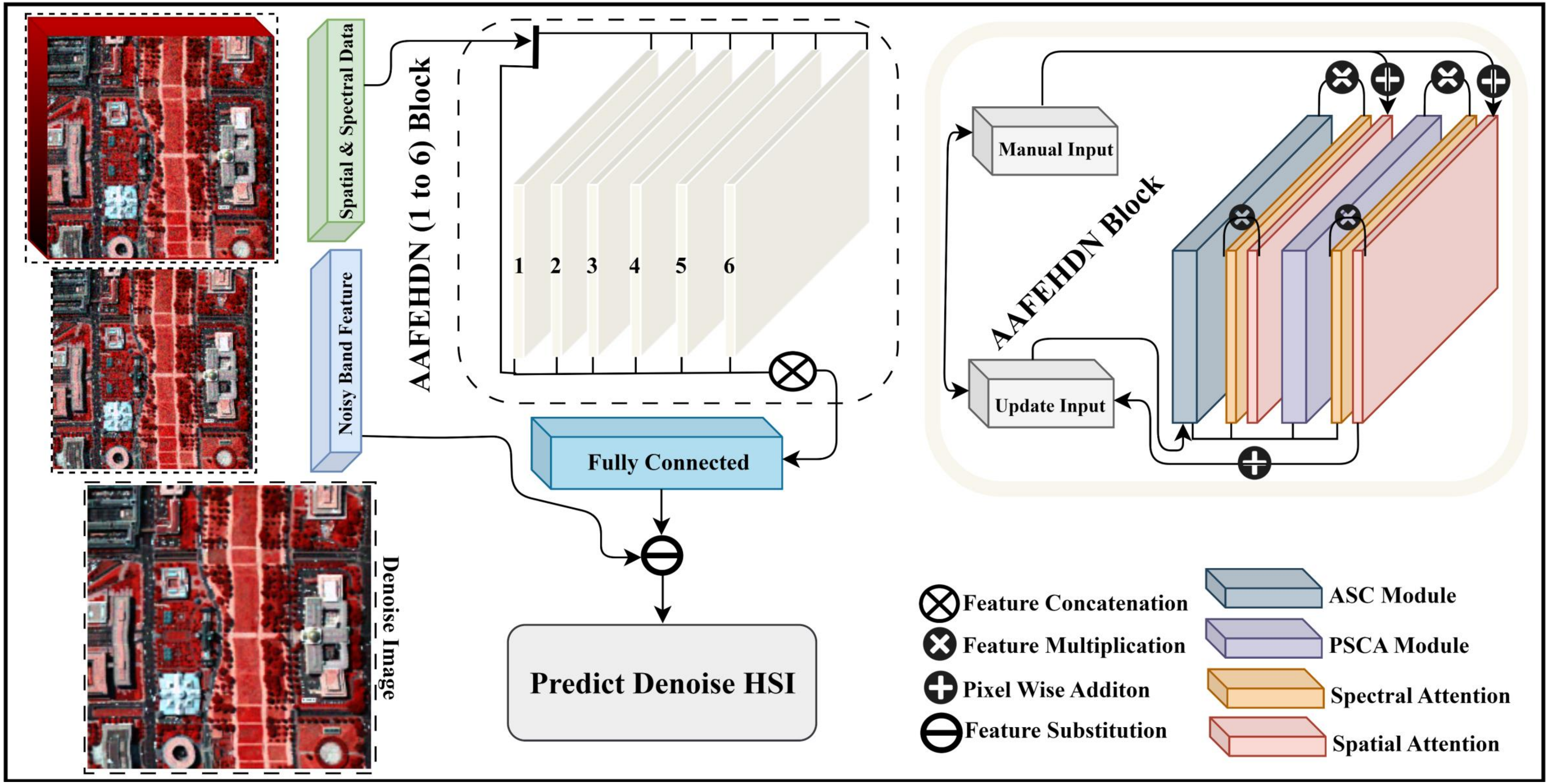
System Design (Component Diagram) [3/4]



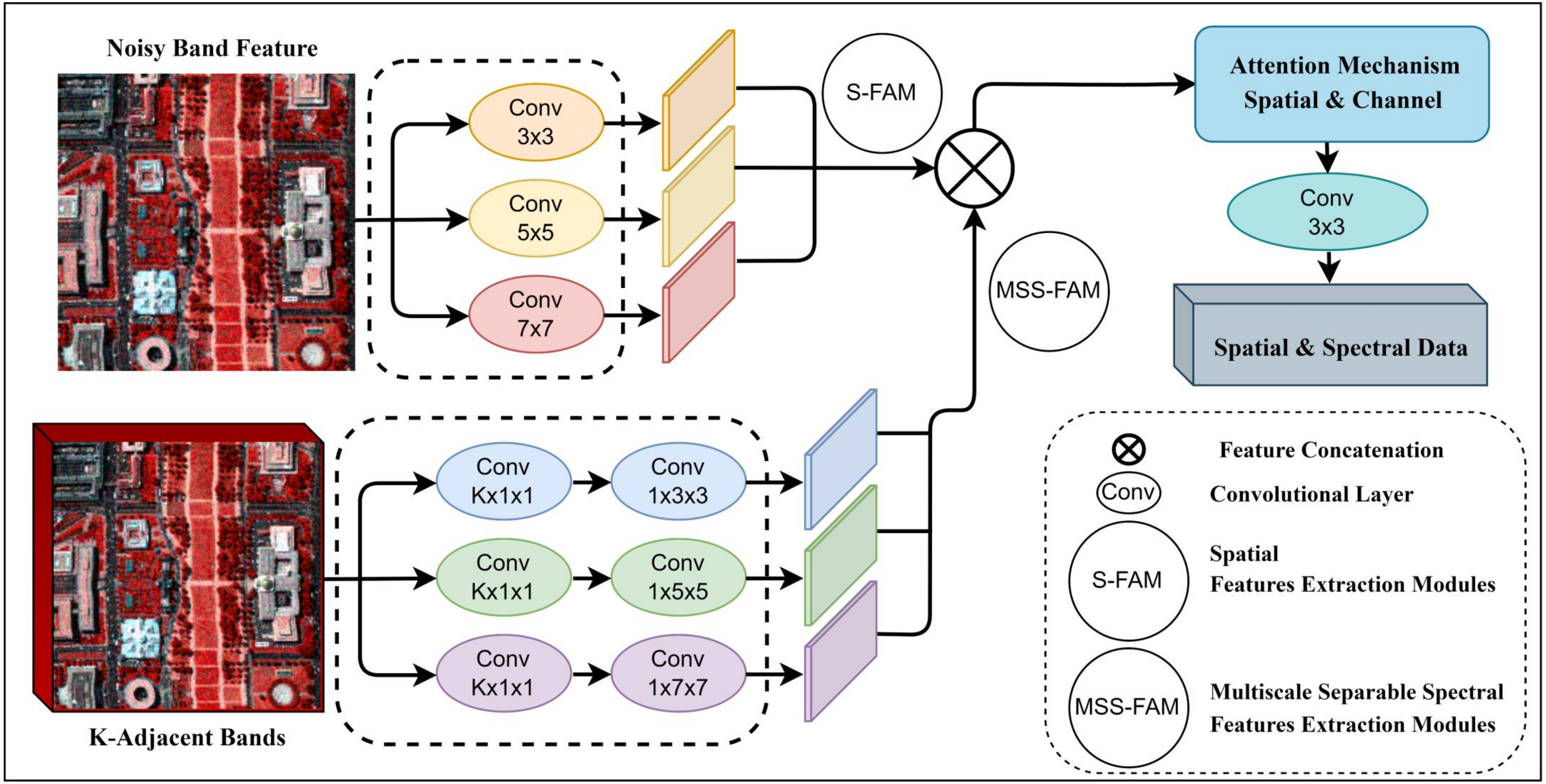
System Design (Activity Diagram) [4/4]



Decompose Frequency (Architecture) Network



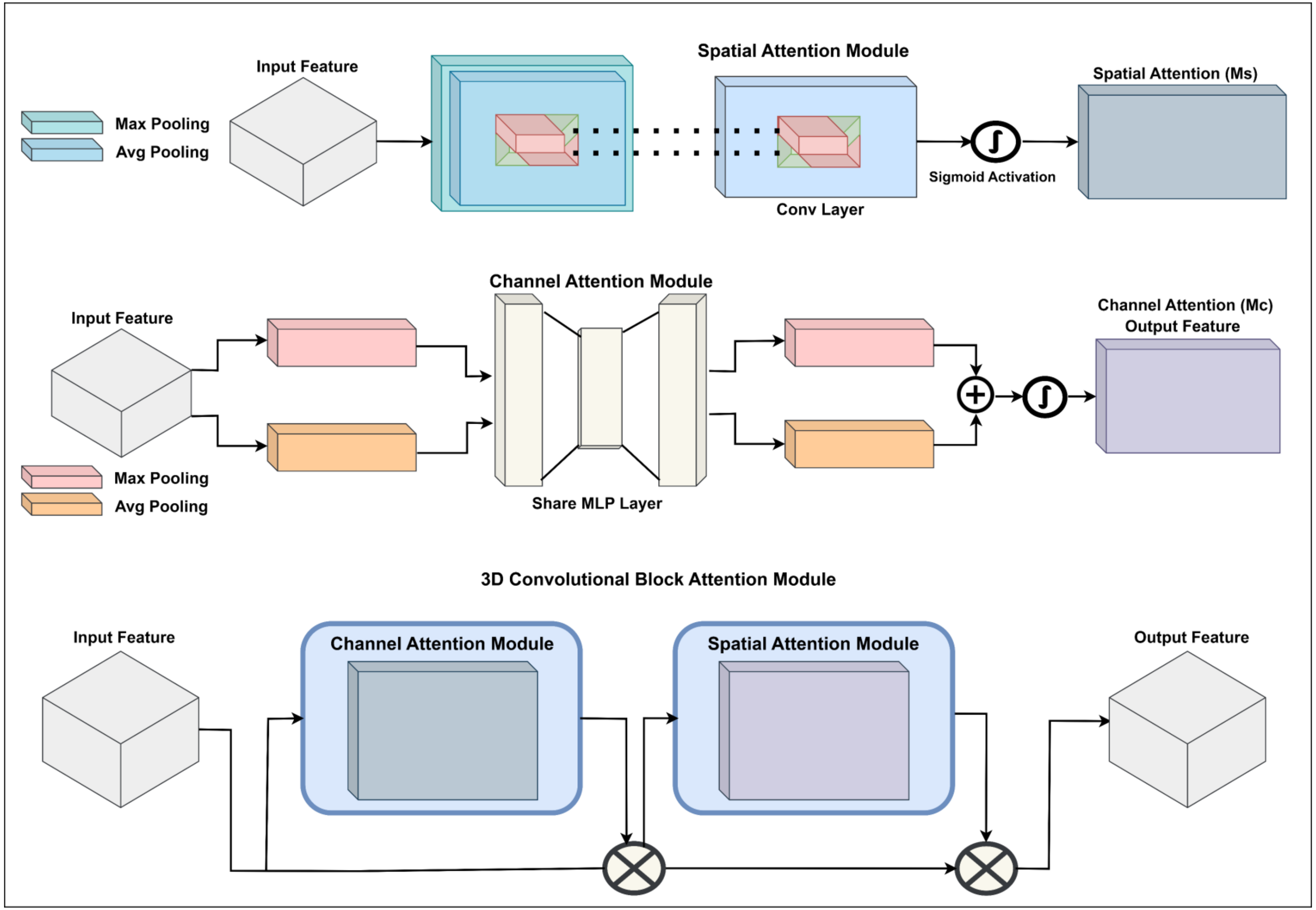
Geometrical Characteristics (Features Extraction) Modules



1: Spatial Features Extraction Module: The capture of information related to the arrangement, patterns, and relationships of objects or elements within the spatial data.

2: Multiscale Separable Spectral Features Extraction Module: Spectral features often concern the frequency domain of the data and can indicate information about images across different scales. Separable means that these features can be analyzed independently at different scales.

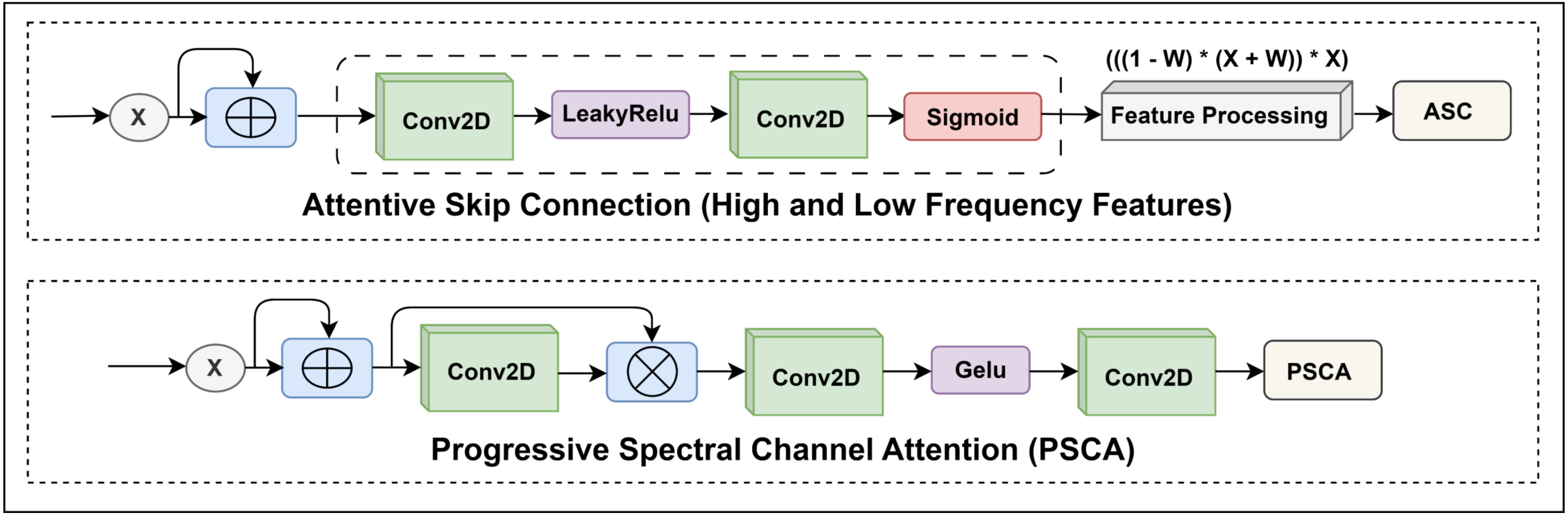
Decompose Frequency (Spatial and Spectral Attention) Modules



1: Spatial Attention Module: Enhancing the spatial features of the HSI images, which involves improving the spatial noise reduction.

2: Spectral (Channel) Attention Module: Concentrates on enhancing the spectral or channel features of the HSI images, quality and distinctiveness of the spectral bands correlation.

Decompose Frequency (ASC and PSCA) Modules



1. Attentive Skip Connection (High and Low-Frequency Features): High-frequency features typically capture fine details, while low-frequency features capture more global patterns. By incorporating both types of features, the model can make more informed and context-aware predictions or decisions.

2. Progressive Spectral Channel Attention (PSCA): The use of progressive attention suggests that the model dynamically refines its focus on specific spectral channels, potentially adapting to different frequency patterns in the input data as needed for the task at hand.

These two steps indicate that the model is designed to handle and process data with attention to both frequency features and dynamic spectral channel attention.

Quantitative Evaluation (Simulated Experiments & Comparison Models)

Comparison Models

MemNet: Incorporates a memory block composed of a recursive unit and a gate unit, designed to capture persistent memory through adaptive learning. The recursive unit learns different-level representations of the current state using various receptive fields. The gate unit then determines how much of the previous states to retain and how much of the current state to store. The authors apply MemNet **[17]** to three image restoration tasks: image denoising, super-resolution, and JPEG deblocking.

DeNet: To extract spatial information through learned filters and spectral correlation through multiple filter channels. The DeNet **[18]** offers three advantages: it preserves spectral-spatial structures, can handle various types of noise, and is adaptable to both single and multiple images with speediness in the testing phase, making it suitable for real-world applications.

Matrix Evaluation

1. Peak Signal-to-Noise Ratio (PSNR): This metric measures the quality of an image by comparing it to a reference image and calculating the ratio of the peak signal power to the noise power. Higher PSNR values indicate better image quality.

2. Spectral Angle Mapper: To compare the spectral signatures of pixels in images. It measures the angular similarity between pixel spectra, which can be useful for tasks like image classification or change detection.

3. Structural Similarity Index Measure (SSIM): It evaluates the similarity in luminance, contrast, and structure. Higher SSIM values suggest greater similarity between images in terms of their structure and appearance.

Quantitative Evaluation (Simulated Experiments & Comparison Models)

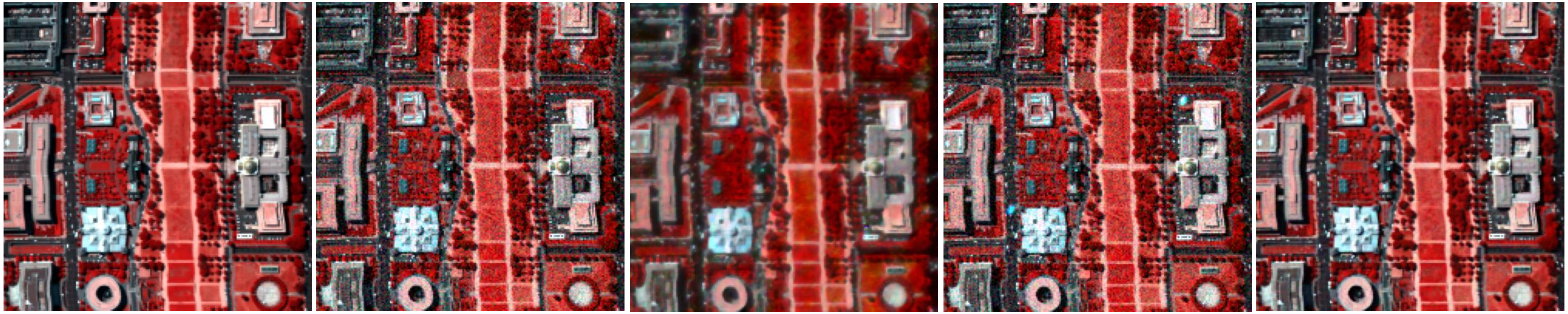
Model (Sigma-50)	PSNR	SSIM	SAM	Train Time Average %	Test Time Average %
AAFEHDN	28.9265 ± 1.5490	0.9555 ± 0.0279	0.1089 ± 0.0285	3.6936	11.5924
MemNet	19.3902 ± 6.4411	0.7737 ± 0.1128	0.2028 ± 0.1560	13.3993	14.9050
DeNet	22.5725 ± 11.6716	0.7685 ± 0.0919	0.3122 ± 0.1487	10.3661	11.3272

Model (Gaussian)	PSNR	SSIM	SAM	Train Time Average %	Test Time Average %
AAFEHDN	34.0378 ± 1.7848	0.9824 ± 0.0143	0.0748 ± 0.0226	3.8477	11.6141
MemNet	22.5151 ± 5.4515	0.8696 ± 0.1196	0.1551 ± 0.1639	13.3232	14.7361
DeNet	28.9257 ± 12.0762	0.9217 ± 0.1058	0.1724 ± 0.2174	10.2759	10.6780

Model (Random)	PSNR	SSIM	SAM	Train Time Average %	Test Time Average %
AAFEHDN	34.5645 ± 1.2742	0.9941 ± 0.0029	0.0649 ± 0.0097	3.9187	11.7451
MemNet	22.5163 ± 6.1887	0.9025 ± 0.1246	0.1598 ± 0.1719	13.4377	14.8680
DeNet	16.5397 ± 8.3215	0.9122 ± 0.0922	0.1918 ± 0.1646	10.3118	11.0173

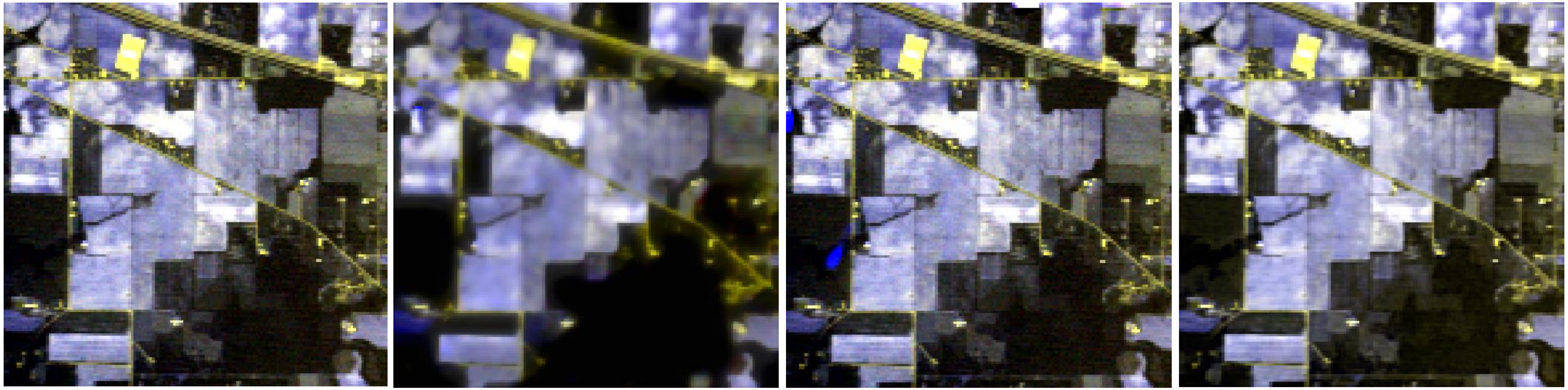
Quantitative Evaluation (Predict Images)

Simulated Experiments (Sigma-50)



Clean Noise MemNet DeNet AAFEHDN

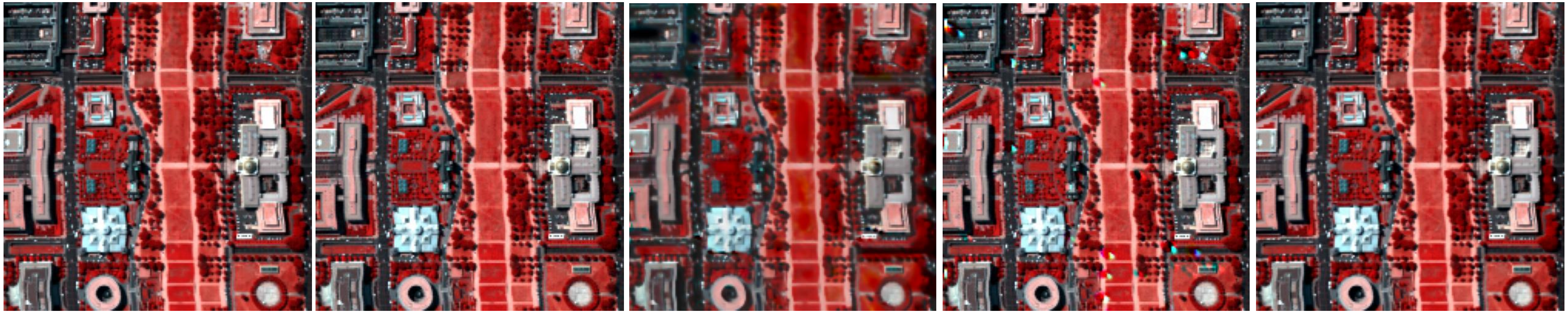
Real Experiments (Sigma-50)



Real MemNet DeNet AAFEHDN

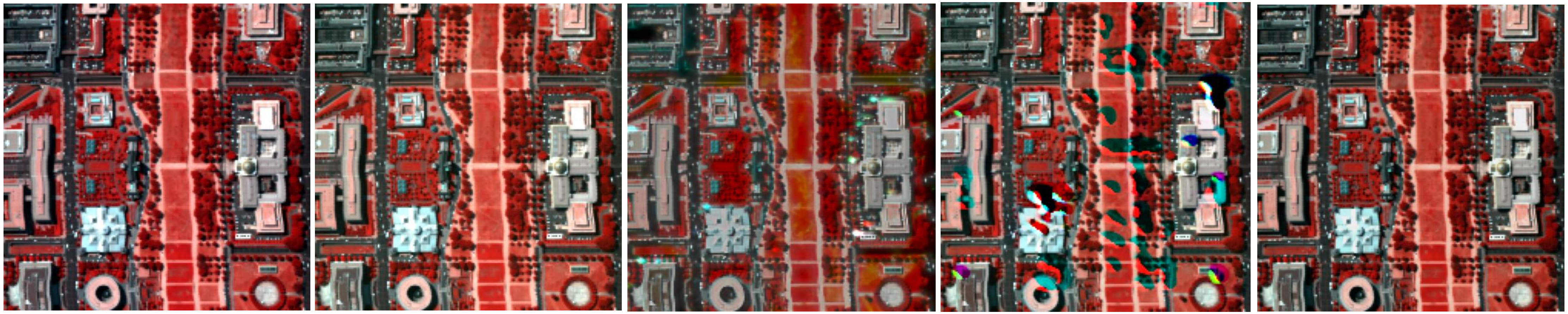
Quantitative Evaluation (Predict Images)

Simulated Experiments (Gaussian)



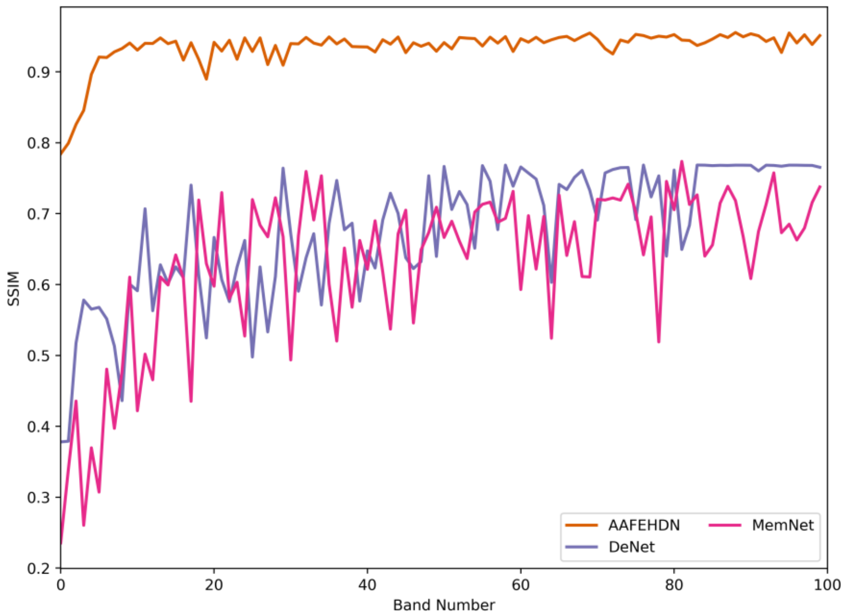
Clean Noise MemNet DeNet AAFEHDN

Simulated Experiments (Random)

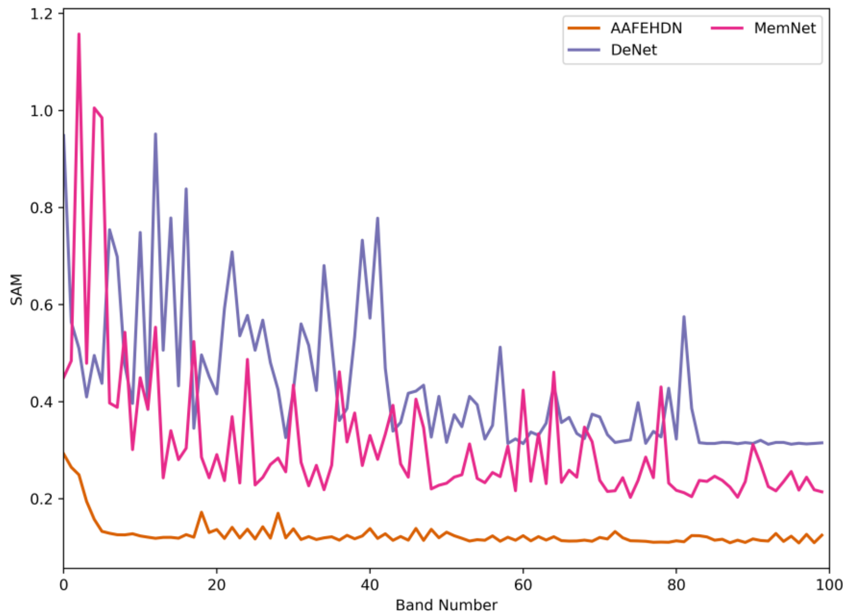


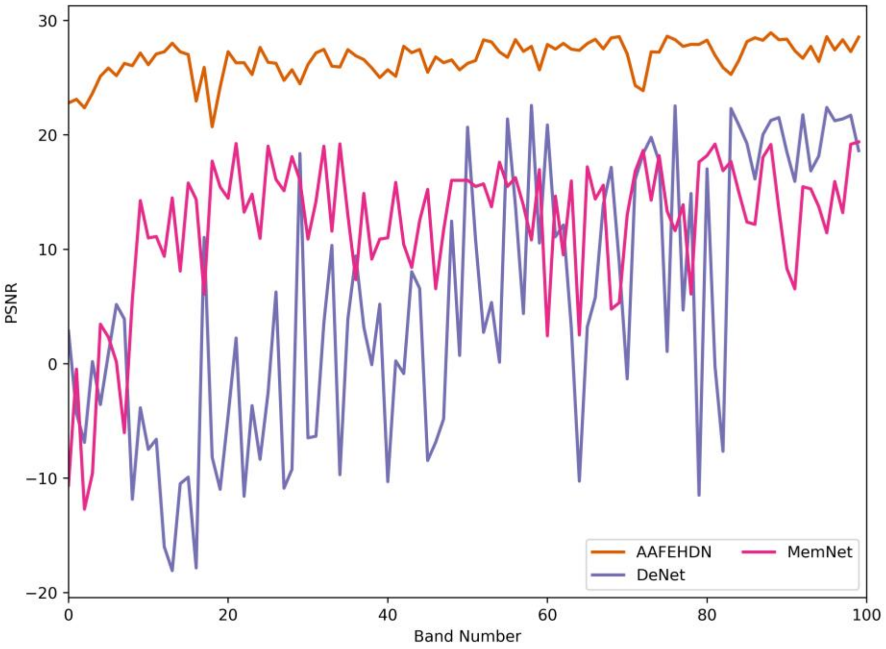
Clean Noise MemNet DeNet AAFEHDN

Quantitative Evaluation (Matrix Index Graphs)

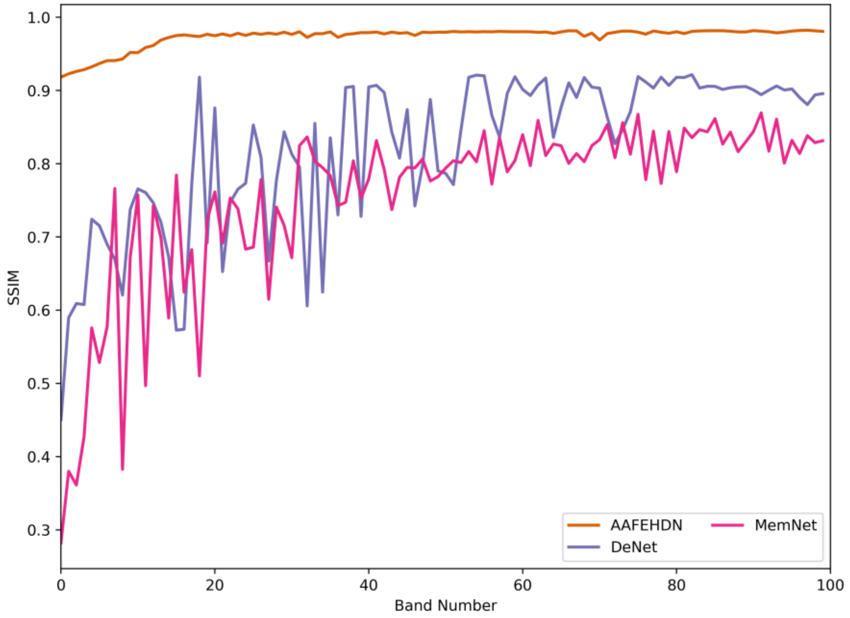


Alpha Sigma 50

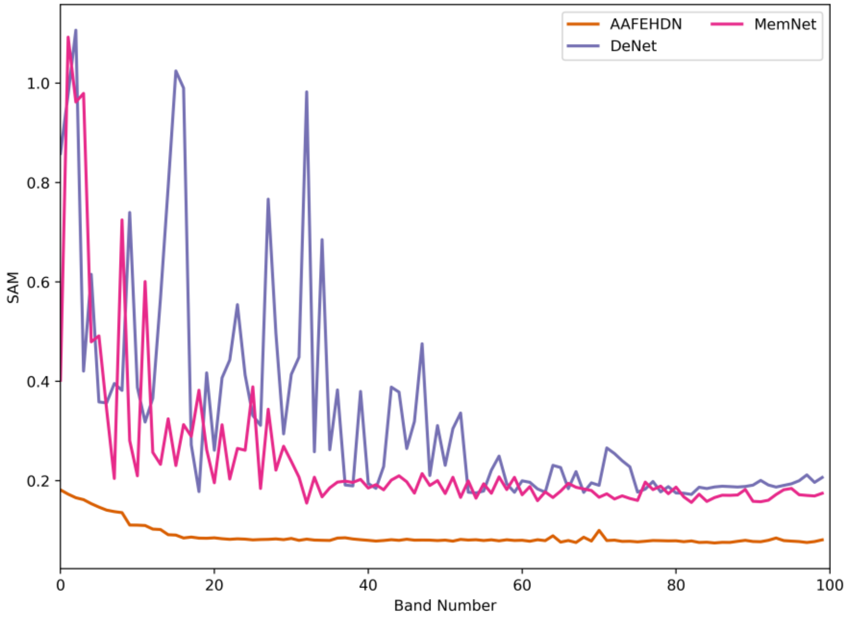


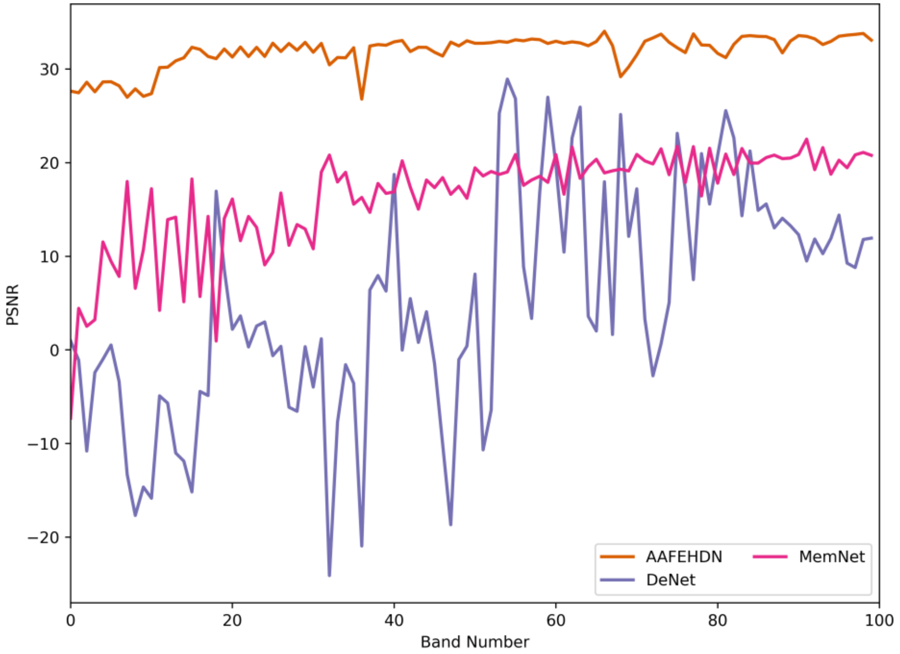


Quantitative Evaluation (Matrix Index Graphs)

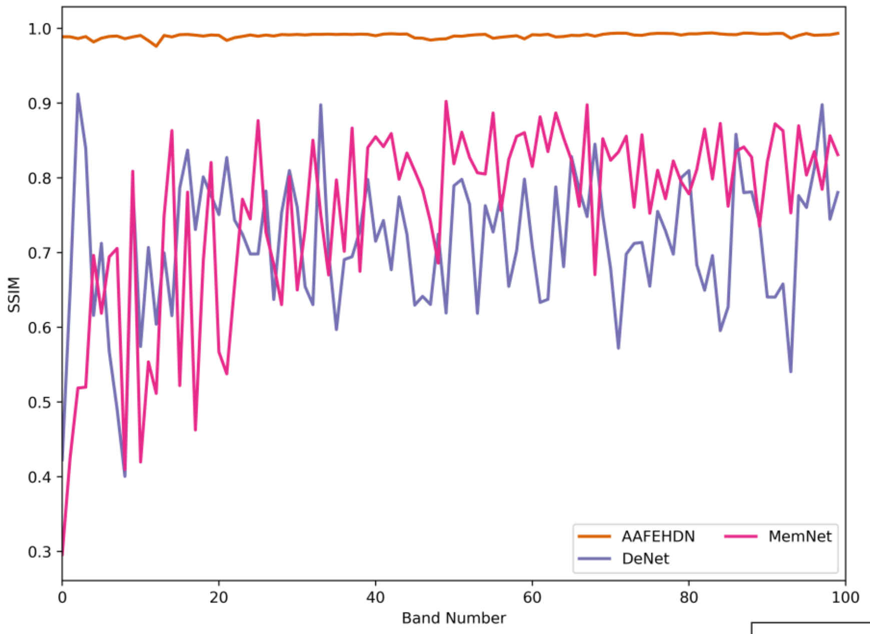


Gaussian

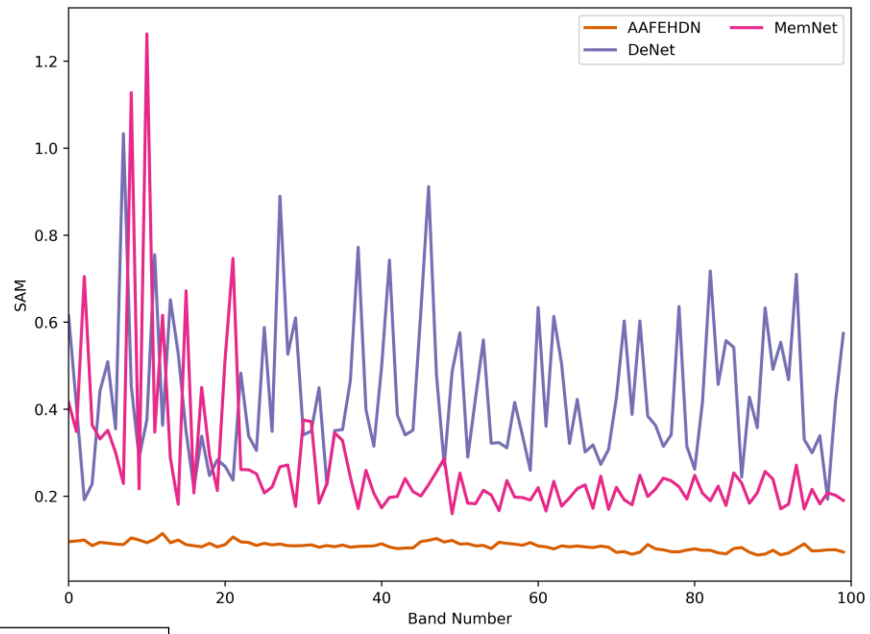


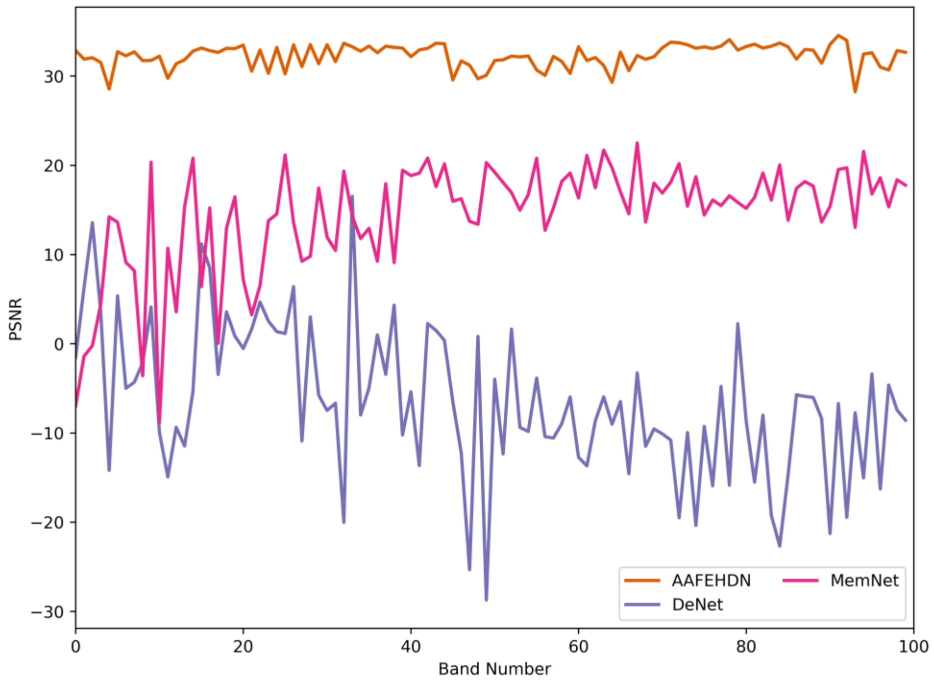


Quantitative Evaluation (Matrix Index Graphs)



Random





Data Representation

Hyperspectral Dataset

The analysis would be conducted on two widely recognized hyperspectral data sets namely Indian Pines (IP) and Washington DC Mall (WDCM).

1. **IP:** Obtained using the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) **[16]** sensor in the year 1992. Collected from the Northwestern region of Indiana. The area comprised several agricultural fields, organized geometric structures, and irregular forests. The scene covers 145 × 145 pixels with 224 spectral bands with 400 to 2500 nm wavelength and a spatial resolution of 20 meters per pixel. Due to atmospheric water absorption the four null bands and 20 other bands effect. The remaining 200 bands were employed for experimentation.

2. **WDCM:** Washington DC Mall obtained using the Spectral Information Technology Application Center of Virginia **[17]** which was responsible for its collection. The sensor pixel system in 210 bands with the 0.4 to 2.4 µm region of the visible and infrared spectrum. Bands in the 0.9 and 1.4 µm regions where the atmosphere is non-transparently dropped from the data set, leaving 191 bands. The data set contains 1208 scan lines with 307 pixels in each scan line such as a (1208-W x 307-H) shape.

Excepted Results & Industry

Excepted Results

1. Simulated Experiments: The quantitative evaluation of the denoising results.
2. Real-World Experiments: The classification accuracy of the denoising results.
3. GUI Interface: We would design the Application Interface (Website or Desktop).

Industry

1. The global hyperspectral imaging systems market [15] is projected to reach USD 35.8 billion by 2026 from USD 15.4 billion in 2021, at a CAGR (Compound Annual Growth Rate) of 18.4% during the forecast period.
2. NASA (National Aeronautics and Space Administration), IEEE (Institute of Electrical and Electronics Engineers), and etc.

Team Work

Weeks Plain

1. From 1 to 4 weeks: The working on modules of Features Extraction and Attention Mechanism.
2. From 4 to 11 weeks: The creating modules of the ASC, PSCA, and AAFEHDN Network. Conduct the Comparison Experiments with DeNet and MemNet. Generate the Test Cases of AAFEHDN.
3. From 11 to 12 weeks: The creation of Prototype (Hyperspectral Image Denoising) and Report (Documentation).
4. From 12 to 16 weeks: Build the Final Report for Evaluation.

Teamwork Participation

1. Muhammad Allah Rakha (P19-0006): Review of Research Papers and Literature, Features Extraction, Attention Mechanism, ASC, PSCA, AFFEHDN Network, Comparison Experiments, Test Cases, Prototype, and Report. PyTorch Code and Website (Streamlit) Application. Build the Final Report for Evaluation.
2. Farkhanda Saleem (P19-0004): Review of Research Papers and Literature, Features Extraction, Attention Mechanism, Test Cases, and Report. Build the Final Report for Evaluation.
3. Mina Riaz (P19-0099): Review of Research Papers and Literature, AFFEHDN Network, Comparison Experiments, Test Cases, and Report. Build the Final Report for Evaluation.

Timeline Prototype

FYP - 1 (Spring 2023)

WEEK 1	WEEK 2-3	WEEK 4-8	WEEK 8-12	WEEK 12-16	WEEK 1-16
Project Proposal	Project Defence	Research Papers Review	Problem-solving strategies and Project Outlines	First Prototype of our project.	Documentation

FYP - 2 (Fall 2023)

WEEK 1-2	WEEK 2-6	WEEK 6-9	WEEK 9-12	WEEK 12-16	WEEK 1-16
Build the structure and functionality of components	Development of core components and GUI interface	Testing and Validation	Research finalize	Write-up research/report	Documentation

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The End

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