MAJOR PROJECT EED497

Title: Multi-Branch Graph Neural Network for Enhanced Hyperspectral Image Classification

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ABSTRACT

Traditional Graph Convolutional Networks (GCNs) in hyperspectral image (HSI) classification are limited by fixed neighborhood receptive fields, hindering their ability to capture multi-scale spatial information. To address this, we propose a Multi-Branch Graph Neural Network (MBGNN) that uses multiple GNN branches to process superpixels at different scales, combined with a Convolutional Neural Network (CNN) for local feature extraction. This fusion network effectively captures both multi-scale spatial and local features, enhancing classification accuracy.

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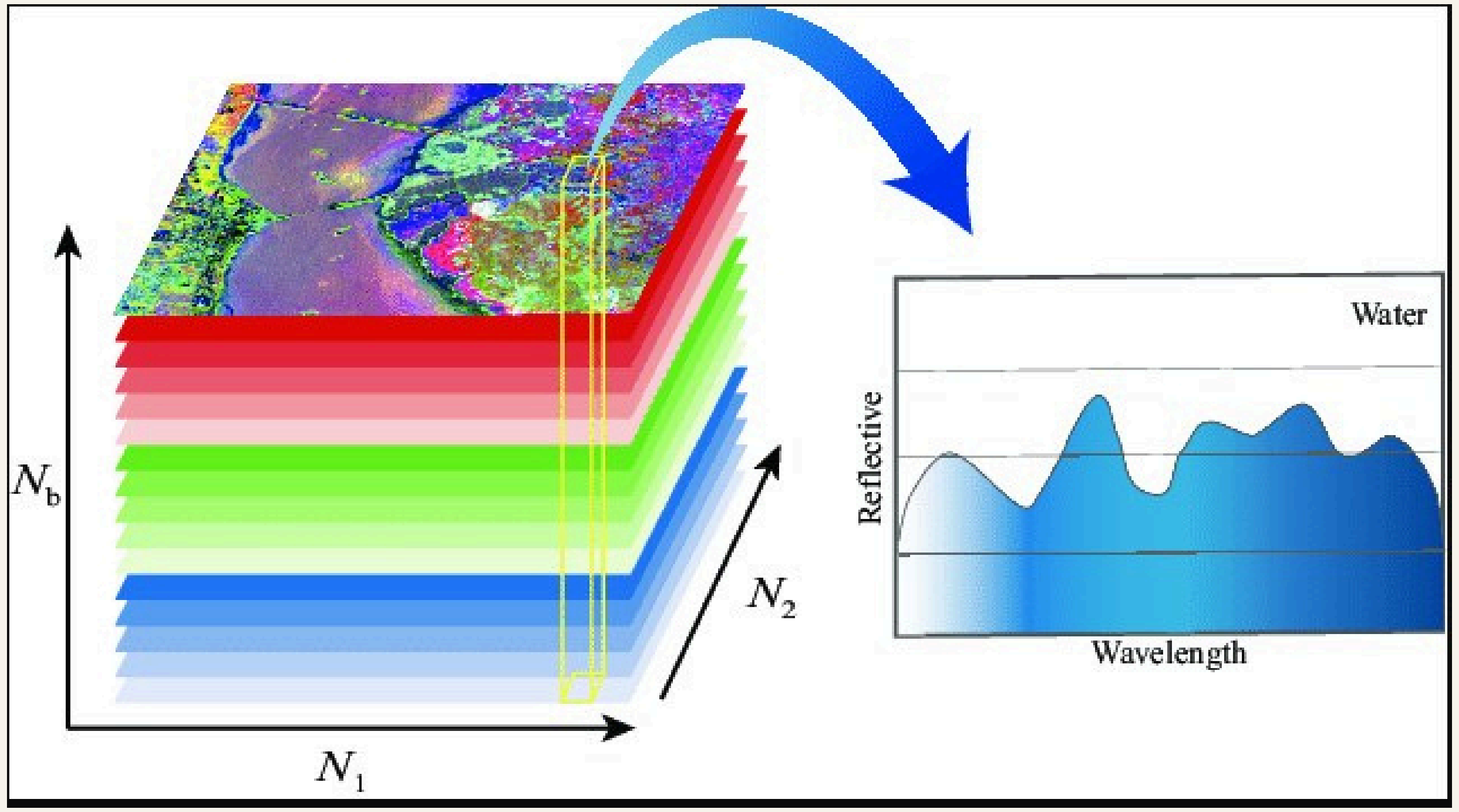
INTRODUCTION

Hyperspectral image (HSI) classification is a complex task that involves analyzing data with high spectral dimensionality and spatial variability. While traditional Graph Convolutional Networks (GCNs) have shown promise in HSI classification, they are limited by their fixed neighborhood receptive fields, which hinder their ability to capture multi-scale spatial information. To overcome this limitation, we propose a novel approach called Multi-Branch Graph Neural Network (MBGNN). This framework integrates multiple Graph Neural Network (GNN) branches to process superpixels at different scales, and combines them with a Convolutional Neural Network (CNN) for local feature extraction. By leveraging the strengths of both GNNs and CNNs, our MBGNN aims to effectively capture both multi-scale spatial and local features, leading to improved classification accuracy.

HYPERSPECTRAL IMAGES (HSI)

Hyperspectral images (HSI) capture information across many narrow, contiguous wavelength bands in the electromagnetic spectrum, ranging from visible light to infrared. Unlike traditional RGB images, which only have three color channels (red, green, and blue), hyperspectral images can have hundreds of bands, each corresponding to a specific wavelength. This enables precise identification of materials based on their spectral signatures.



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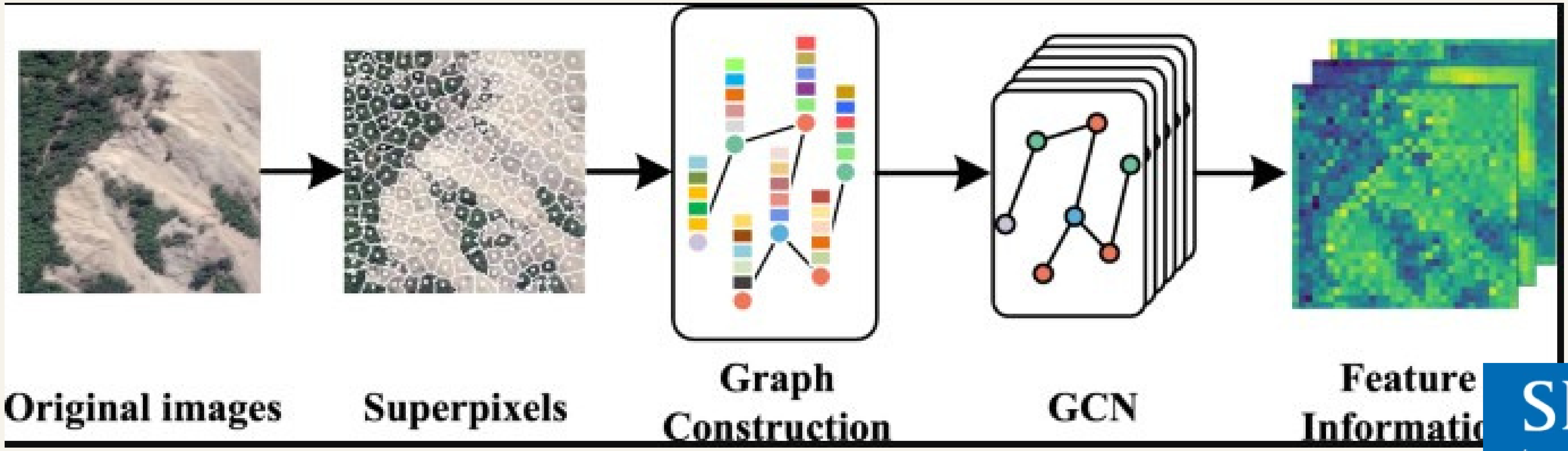
GRAPH NEURAL NETWORKS (GNNS)

Graph Neural Networks (GNNs) operate on graph-structured data, where nodes represent superpixels and edges indicate spatial relationships in hyperspectral images. They utilize message passing to update node features based on neighboring nodes, capturing spatial dependencies within irregular structures and non-Euclidean data. GNNs, especially Graph Convolutional Networks (GCNs), are applied to hyperspectral image (HSI) classification by treating each pixel as a node, with edges representing spatial or spectral relationships.



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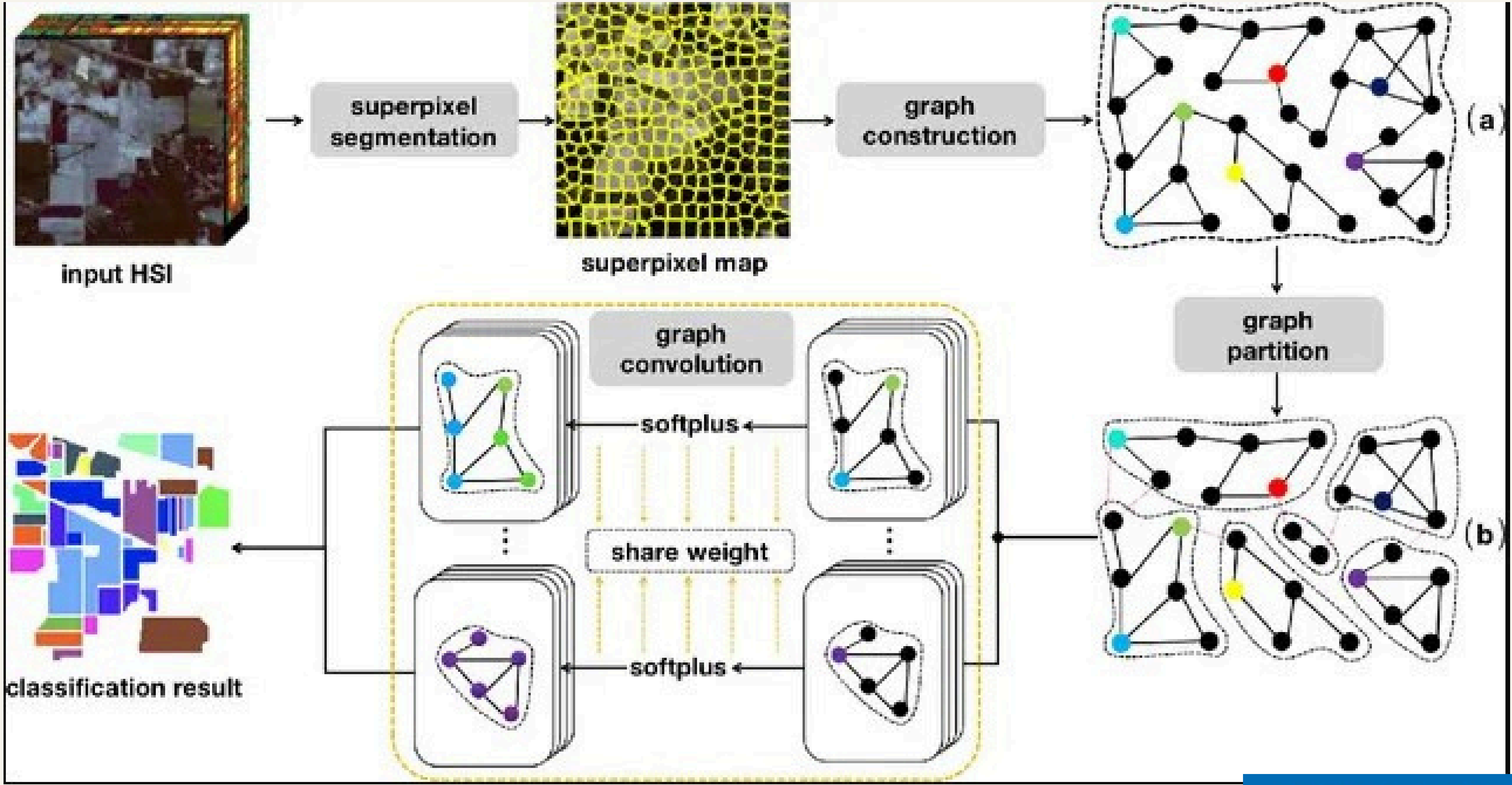
FUZZY C-MEANS (FCM) CLUSTERING

Fuzzy C-Means (FCM) is a soft clustering algorithm widely used in hyperspectral image (HSI) analysis. Unlike traditional clustering methods like K-Means, which assign each data point to a single cluster, FCM allows pixels to belong to multiple clusters with varying degrees of membership.

How It Works:

- Each pixel is assigned a membership value for every cluster, indicating the degree to which it belongs to that cluster.
- The algorithm minimizes an objective function based on the distance between data points and cluster centers, weighted by the membership values



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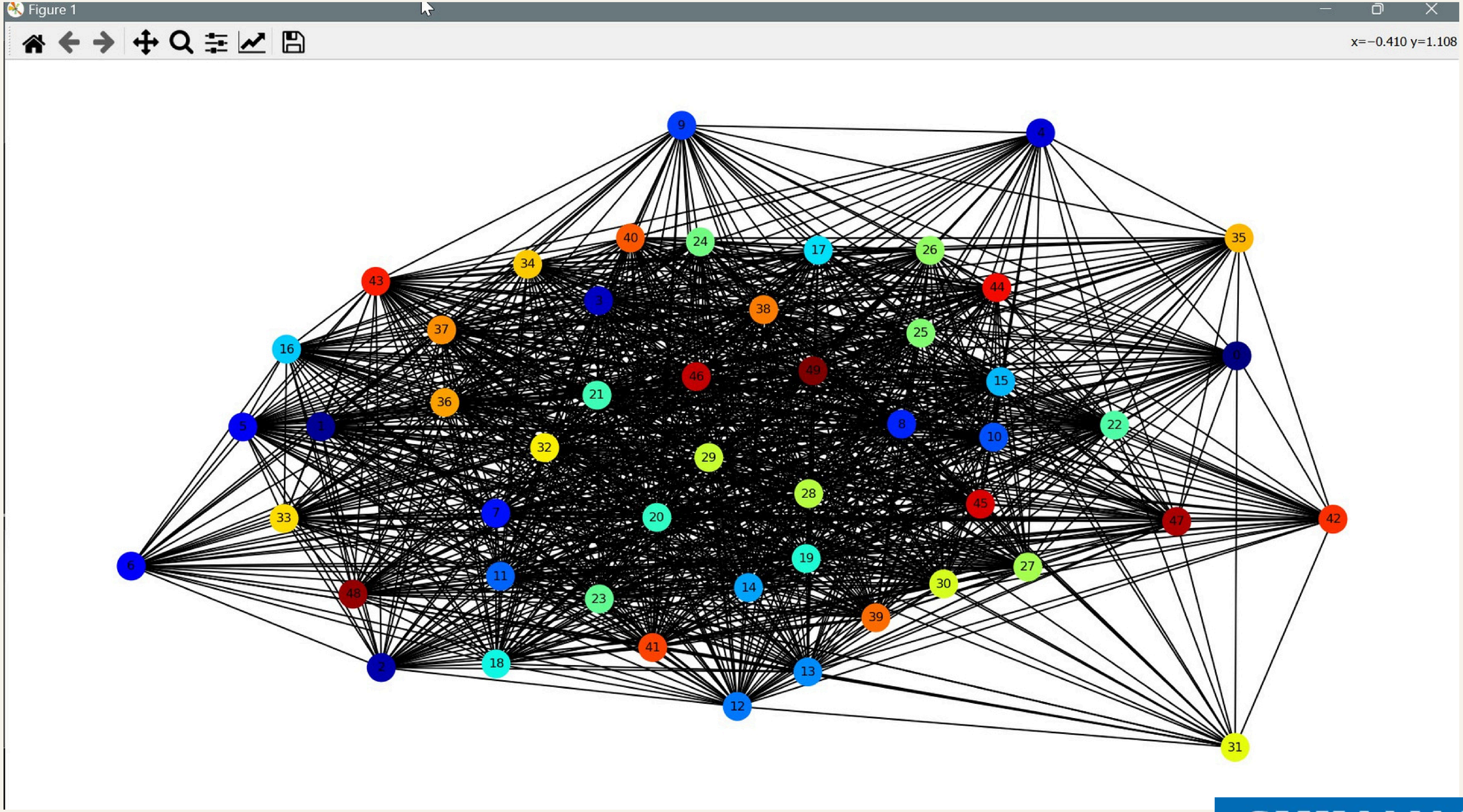
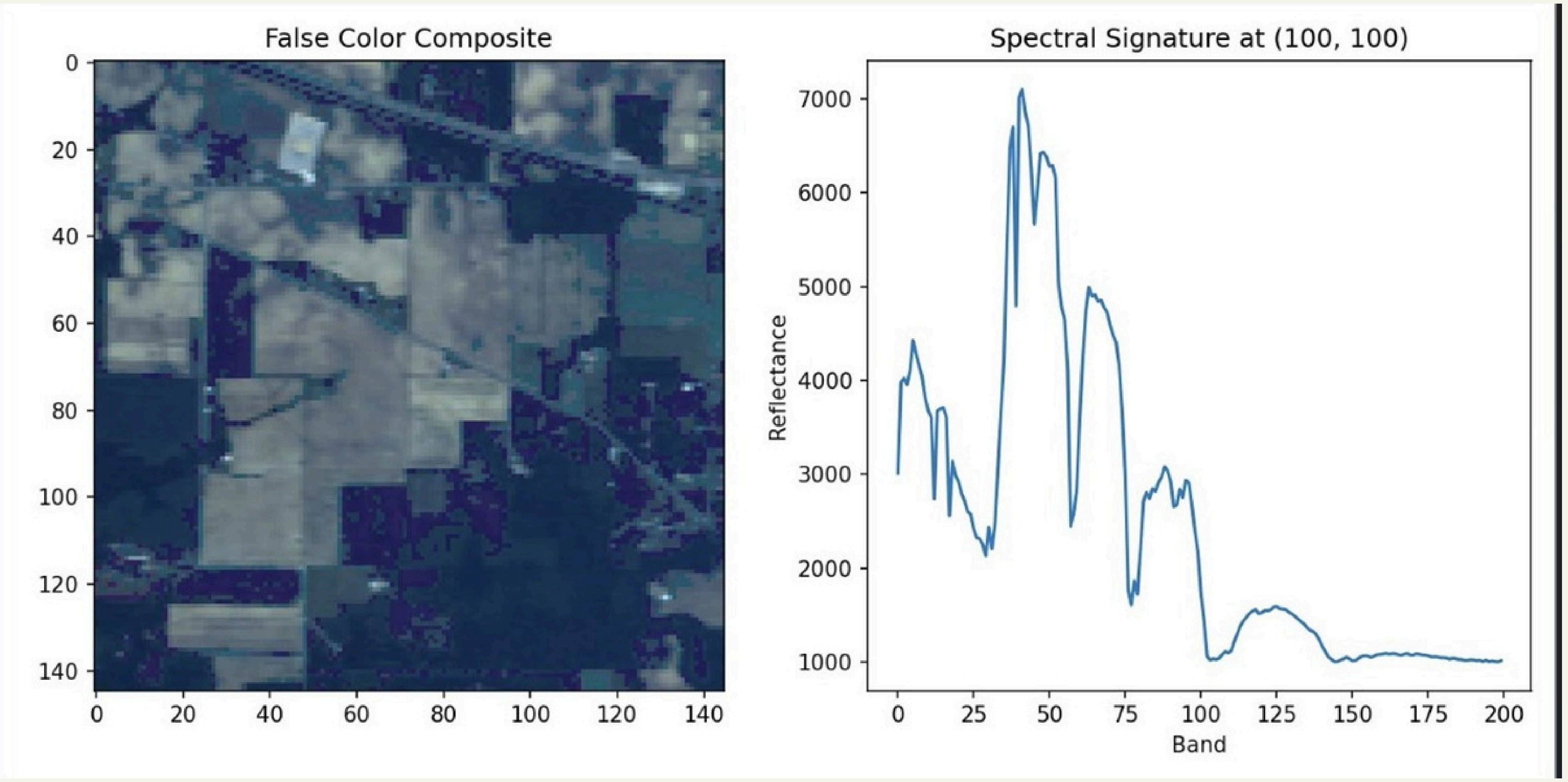
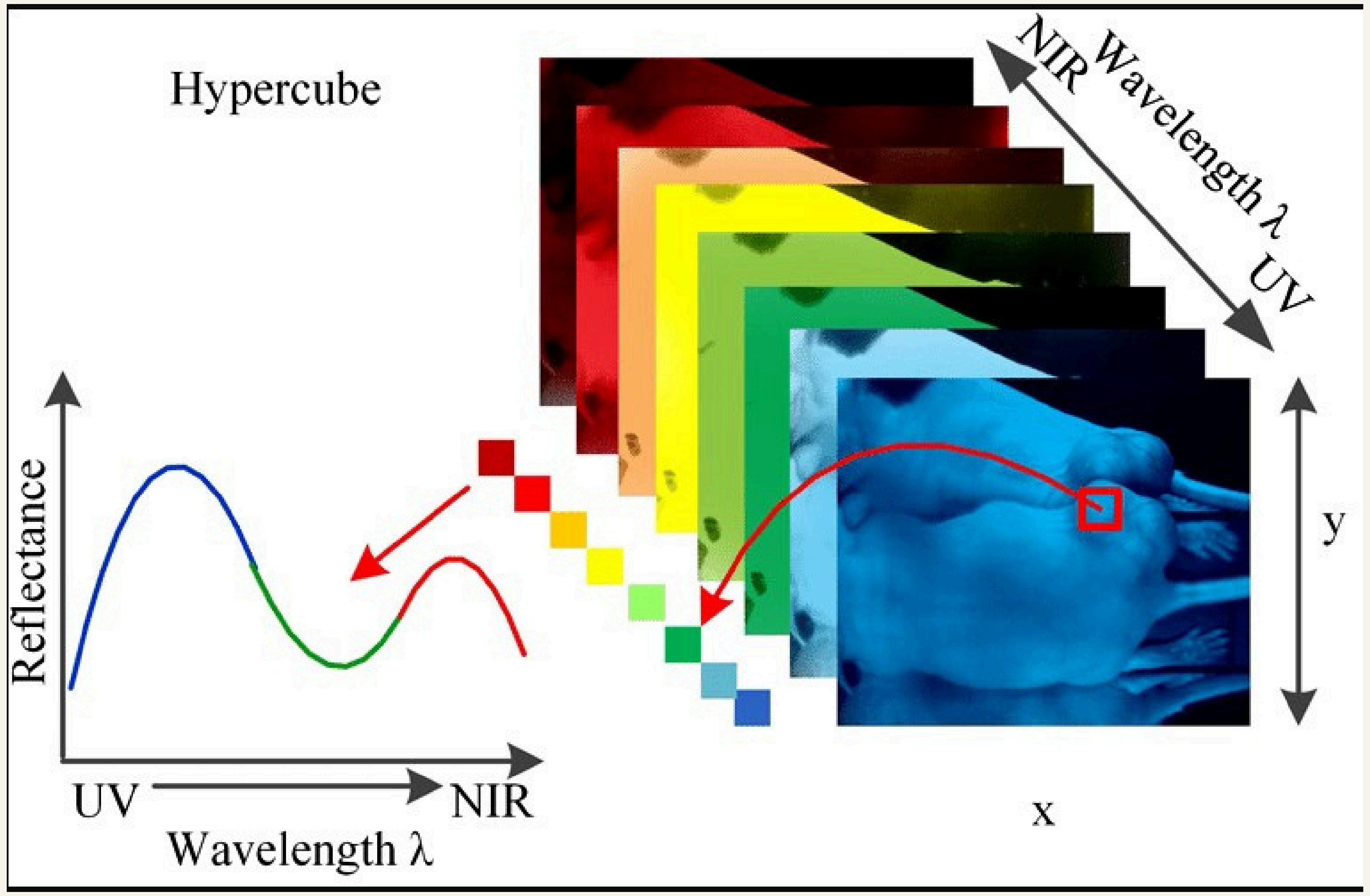


Figure 1
x=−0.410 y=1.108

RESULTS (PRE-MID)





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CONVOLUTIONAL NEURAL NETWORKS

Convolutional Neural Networks (CNNs) work on grid-structured data, processing spectral information across multiple channels in hyperspectral imaging. CNNs apply convolutional filters to extract local patterns and spectral features, excelling in image classification tasks. The primary metric for CNNs is classification accuracy, indicating their ability to accurately predict based on extracted spectral information. These local features are then used to classify pixels or regions of the image into different categories, such as land cover types, crop types, or mineral types.

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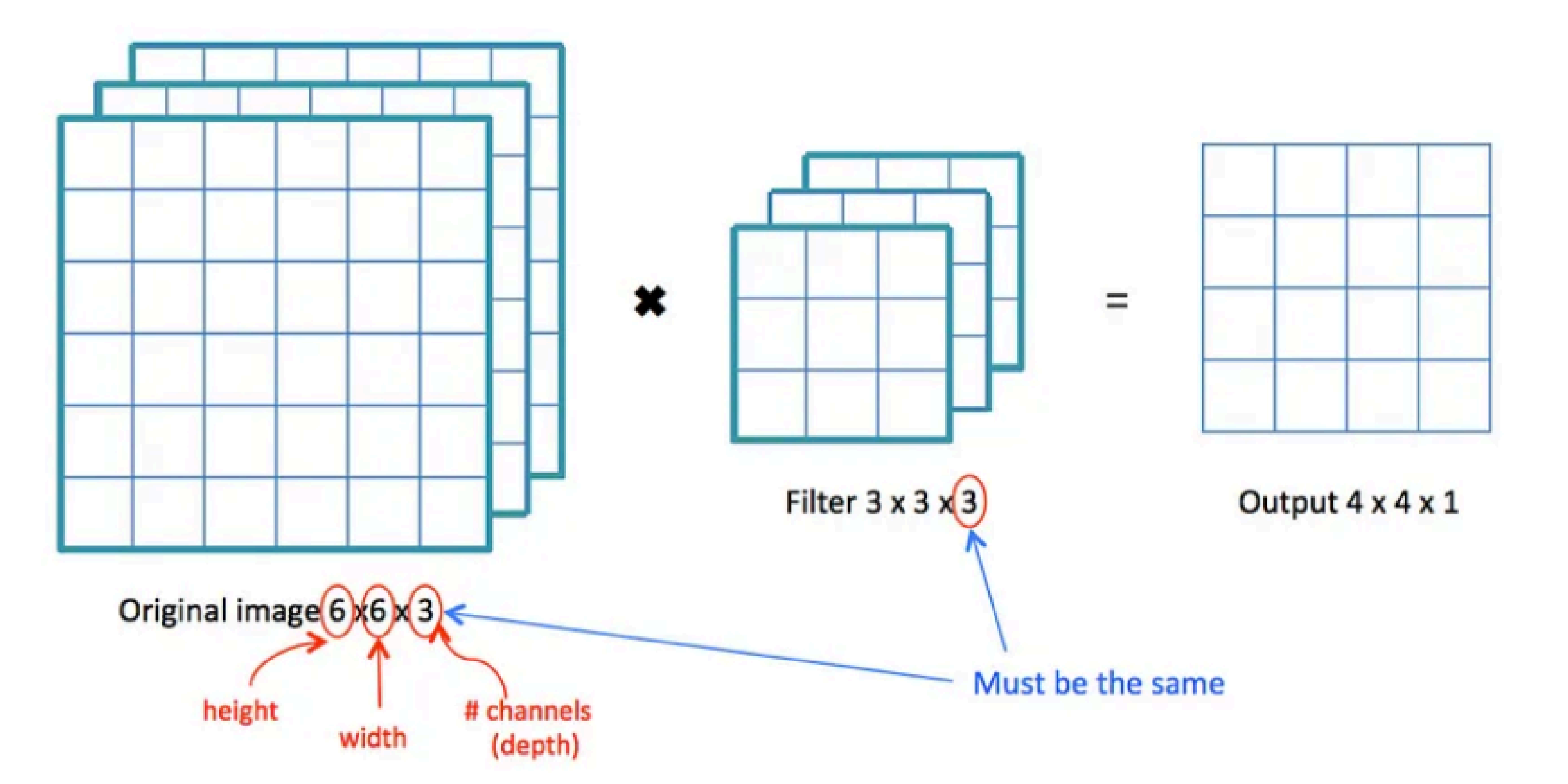
CONVOLUTIONAL

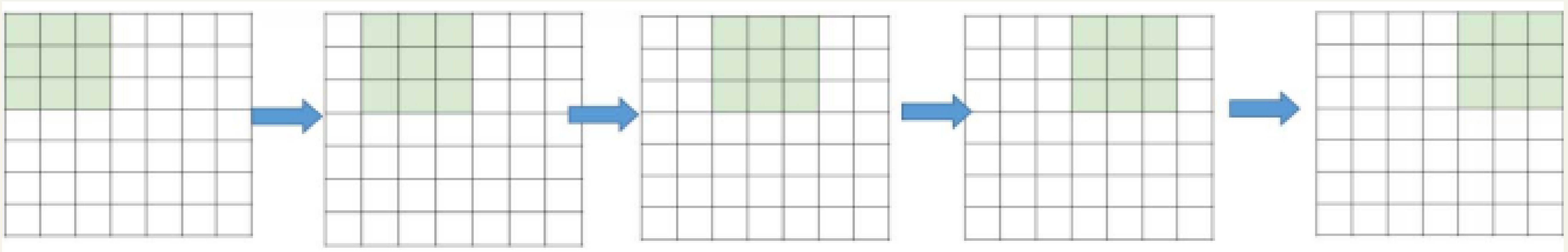
A convolution is a fundamental building block of a Convolutional Neural Network (ConvNet). Its primary purpose is to extract features from the input image. This process is crucial in enabling the network to recognize patterns and objects within the image.



$$Output\ size = \left(\frac{n + 2p - f}{s} + 1\right) x \left(\frac{n + 2p - f}{s} + 1\right)$$

STRIDE CNN

Stride is a technique used in Convolutional Neural Networks (CNNs) to control the step size by which a filter moves across the input data. It plays a crucial role in determining the spatial dimensions of the output and the number of computations required in the network. In essence, stride determines how many pixels the filter moves at a time, with a stride of 1 meaning the filter moves one pixel at a time, and a stride of 2 or more meaning it moves multiple pixels at a time.



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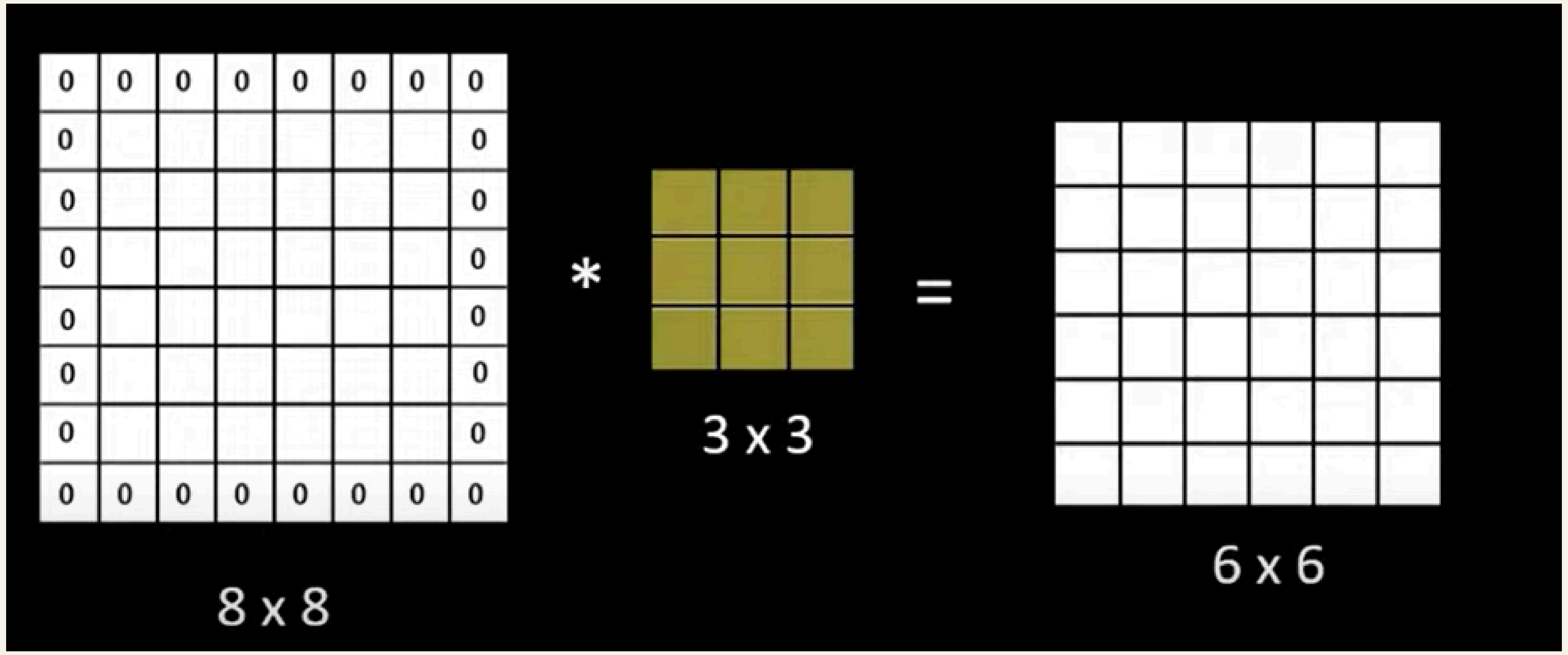
PADDING IN CNN

One major drawback of the convolution step in CNNs is the loss of information at the borders of the image, resulting in a reduced output size and potential loss of important border information. To address this issue, zero-padding is used, which involves adding layers of zeros around the border of the input image, increasing its dimensions. This allows the filter to slide across the entire image, including the borders, without losing information.



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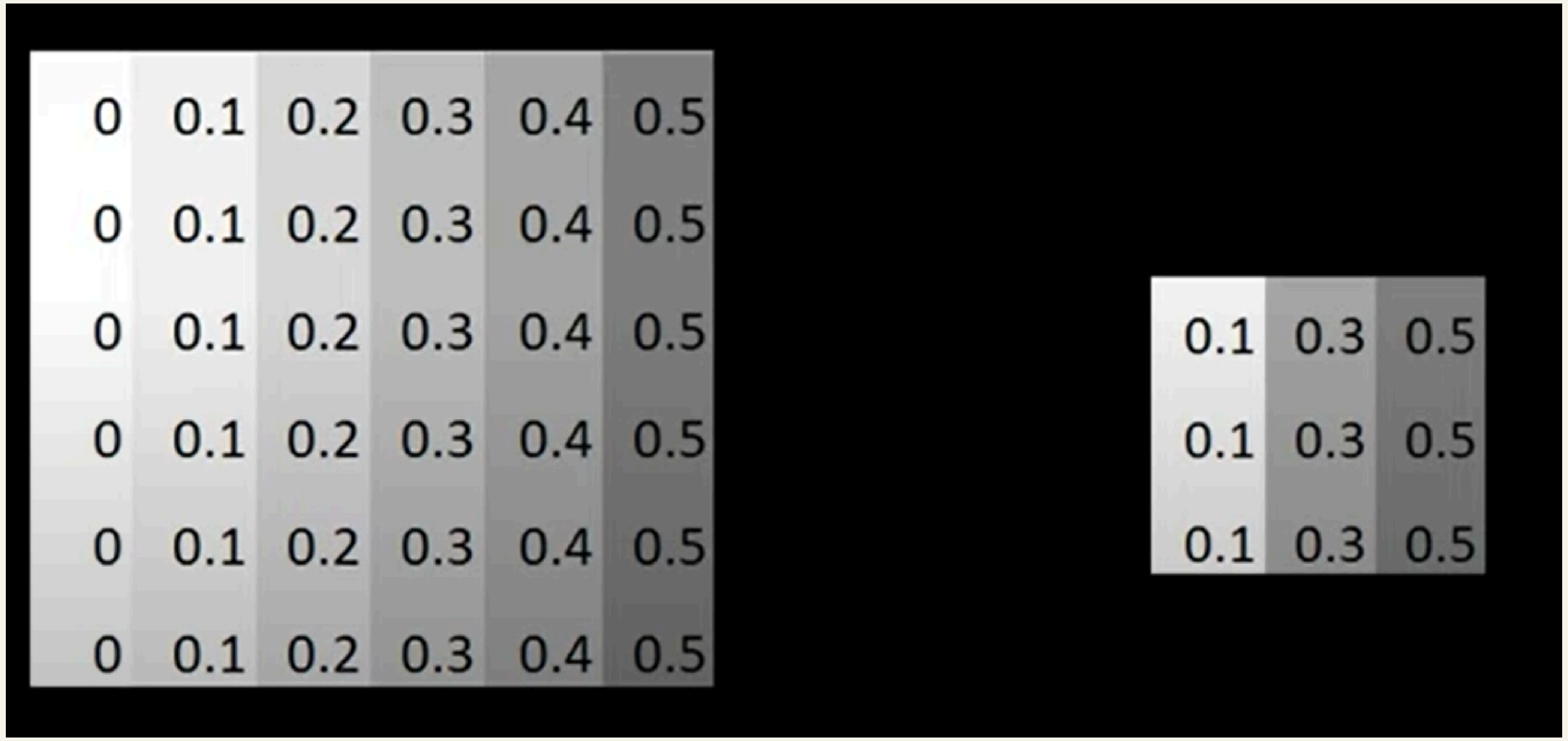
MAX POOLING IN CNN

Max pooling is a downsampling technique used in convolutional neural networks (CNNs) to reduce the spatial dimensions of an input, such as an image. It works by dividing the input into smaller regions, called spatial neighborhoods or filters, and selecting the maximum value within each region.



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RESULT OF CNN

The model achieved excellent performance in classifying hyperspectral data, with 99.45% Overall Accuracy, 99.48% Average Accuracy, and a Kappa coefficient of 0.993. The confusion matrix showed accurate predictions across all classes, with minimal misclassifications, mostly between similar classes. The results shows that fuzzy clustering preprocessing enhanced the model's ability to distinguish spectral features, making it highly reliable for hyperspectral data analysis.

```
Epoch 1/10, Loss: 0.4469894069785401
Epoch 2/10, Loss: 0.18562805011559197
Epoch 3/10, Loss: 0.13784855818334152
Epoch 4/10, Loss: 0.1095795381269867
Epoch 5/10, Loss: 0.09483250454883178
Epoch 6/10, Loss: 0.0882666865304508
Epoch 7/10, Loss: 0.08547311510338511
Epoch 8/10, Loss: 0.06795739947690049
Epoch 9/10, Loss: 0.060287980910042505
Epoch 10/10, Loss: 0.056591902147499124

Metrics:
   Overall Accuracy (OA)  Average Accuracy (AA)  Kappa Coefficient
0               0.994506               0.994786           0.992723

Confusion Matrix:
 [[ 6528     0    29     1     0     0     5    68     0]
 [    0 18626     0    20     0     3     0     0     0]
 [    0     0  2093     0     0     0     0     6     0]
 [    0     2     0  3062     0     0     0     0     0]
 [    0     0     0     0  1345     0     0     0     0]
 [    0    24     0     0     0  5005     0     0     0]
 [    2     0     0     0     0     0  1328     0     0]
 [    0     0    75     0     0     0     0  3607     0]
 [    0     0     0     0     0     0     0     0   947]]
```

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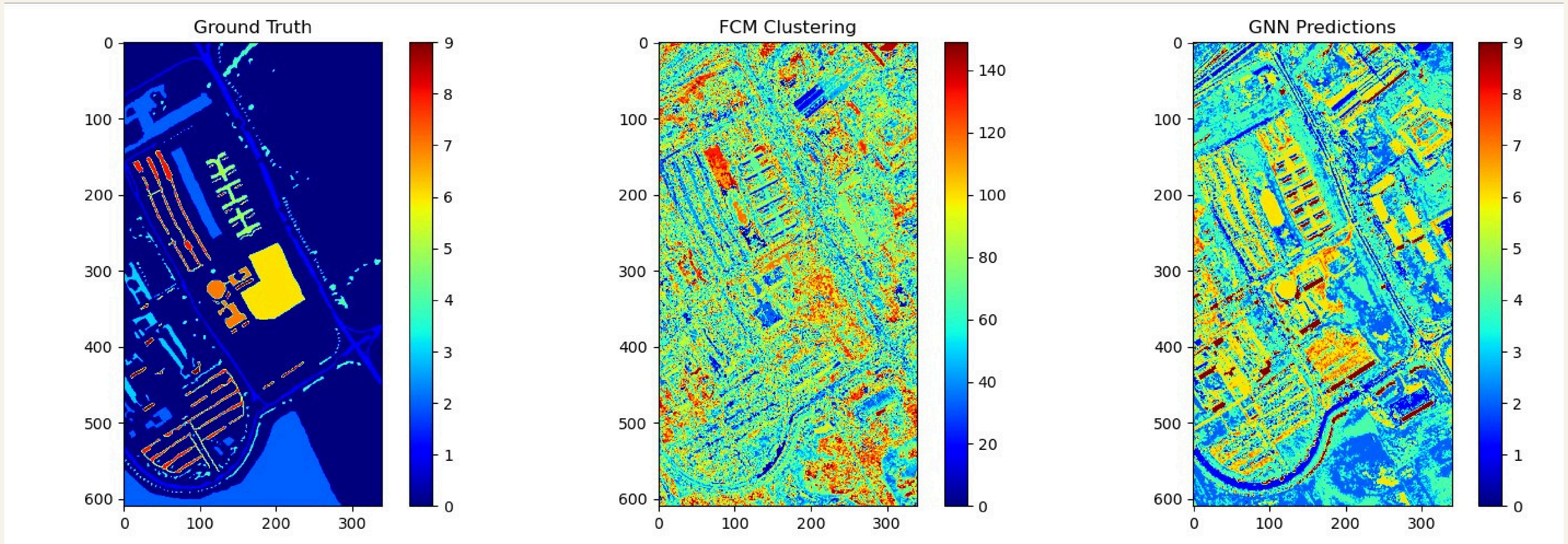
RESULTS




```
Overall Accuracy: 83.34%
Kappa Coefficient: 0.7734
Total execution time: 13.49 seconds
```

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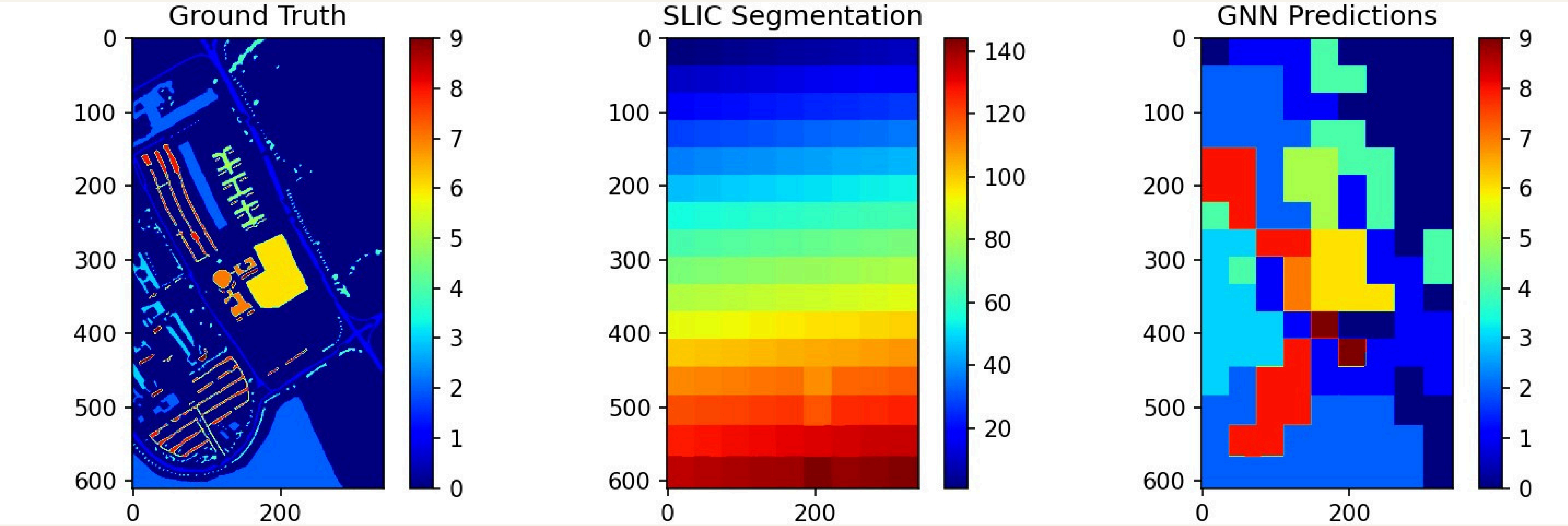
RESULTS




```
Final Results:
Overall Accuracy: 45.41%
Kappa Coefficient: 0.3202
Total execution time: 1023.96 seconds
```

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MULTI-BRANCH GRAPH NEURAL NETWORK (MBGNN)

The Multi-Branch Graph Neural Network (MBGNN) is a novel framework that leverages the strengths of both Convolutional Neural Networks (CNNs) and Graph Convolutional Networks (GCNs) to capture multi-scale spatial and local features in hyperspectral images. Our MBGNN model consists of multiple GCN branches, each processing superpixels at different scales, and a CNN module that extracts local features. The outputs from the GCN branches and CNN module are fused together to form a comprehensive feature representation, which is fed into a classification layer to produce the final prediction. By integrating CNNs and GCNs, our MBGNN model effectively captures both local and global patterns, leading to improved classification accuracy.

THANK YOU

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