Introduction:

Hyperspectral satellite imaging is a mature technology that captures a very detailed spectrum of light for each pixel (usually more than a hundred bands). Instead of assigning primary colors (red, green, and blue) to each pixel, HSI analyses a broad spectrum of light. To provide further detail about what is imaged, the light striking each pixel is broken down into several different spectral bands. With so much reflectance data about the underlying content, accurate HSI pixel-by-pixel classification and segmentation is possible. As a result, HSI is widely used in a variety of fields, including precision agriculture, military operations, and surveillance.

This project is focused on the development of a Deep Neural Network for landcover classification in hyperspectral images. Land-cover classification is the task of assigning to every pixel, a class label that represents the type of land-cover. The majority of current studies and research activities are focused on the creation of complex handcrafted features, which is the traditional pattern recognition model.

However, determining which characteristics are important for the problem at hand is unusual. In comparison to these methods, a deep learning-based classification method is proposed that automates the hierarchical construction of high-level features. In this project, a Convolutional Neural Network is used to encode the spectral and spatial information of pixels, and a Multi-Layer Perceptron is used to perform the classification task

Background:

Hyperspectral remote sensing is the science of acquiring digital imagery of earth materials in many narrow contiguous spectral bands. Hyperspectral sensors or imaging spectrometers measure earth materials and produce complete spectral signatures with no wavelength omission. Hyperspectral imaging is commonly used in a variety of fields, including mineralogy, surveillance, physics, astronomy, chemical imaging, and environmental monitoring.

When cultivating agriculture early detection of diseases will save plants and trees from further damage. In the last few years, convolutional neural networks (CNN) have had widespread applications in various industries. By segmenting Hyperspectral images using CNN we can yield better results and produce more accurate segmented images.

Importance of Project:

Hyperspectral imaging is an active area for research, through which new ideas can be implemented and the world can be changed. For example: Detecting diseases in the early stage can save the plants and trees from further loss, Hyperspectral sensors can assist in controlling the virus by organized methods such as fungicide applications, disease-specific chemical applications, and pesticide applications. The hyperspectral imagery is used in land cover mapping. Land cover classification is associated with the nature of land such as grassland, forest, concrete pavement sand etc.

However, there are still some issues like time-consuming, costly, limited labeled samples, and high dimensionality. This project is focused on the development of a Deep Neural Network for landcover classification in hyperspectral images. Land-cover classification is the task of assigning to every pixel, a class label that represents the type of land-cover. Convolutional

Neural Network is used to encode the spectral and spatial information of pixels, and a Multi-Layer Perceptron is used to perform classification tasks.

Project Objective:

Hyperspectral imaging is an active area for research, through which new ideas can be implemented and the world can be changed. But there are still some issues like limited labeled samples and high dimensionality. Thus, resolving the issues is the main objective of the paper.

The following are the proposed objectives of the project:

1. To gain an understanding of hyperspectral image segmentation as well as understanding its present relevance.
2. To look at deep learning and how it can be used to segment hyperspectral images.
3. To devise a framework for the HSI classification by using deep Convolutional Neural Networks.
4. To verify the advantages of various methods by testing them on challenging HIS datasets and using accuracy measures like AUC and F1 scores.

Scope:

The project's current scope is that there are few label samples available, and we should be able to use CNN to create a good classifier that can work with fewer training samples. The project's future goals are to enhance classification accuracy and investigate a fully unsupervised environment.

Problem Definition:

The main goal of this project is to use convolutional neural networks to semantically segment hyperspectral images.

Phase1:The available sample images are collected for data processing and data gathering. Both labeled and unlabeled data sets are available

Phase 2: Understanding the dataset, including all of its parameters and how the dataset's features are connected, as well as how algorithms can be used to generate predictions.

Phase 3: Splitting the Dataset into training and testing subsets. Putting the proposed CNN algorithm to work on the dataset's classification. Understanding how internal and external parameters influence a specific field.

Phase 4: Comparing the findings to other hyperspectral image segmentation systems.

Feasibility Study

The project is research-based, as shown by the following features:

1. Analyze the hyperspectral image using Principal Component Analysis(PCA).
2. Dual loss is minimized with Soft Max loss.
3. To get 1Darray, flattening is finished.
4. Acceptable labeling classification

Methodology Used:

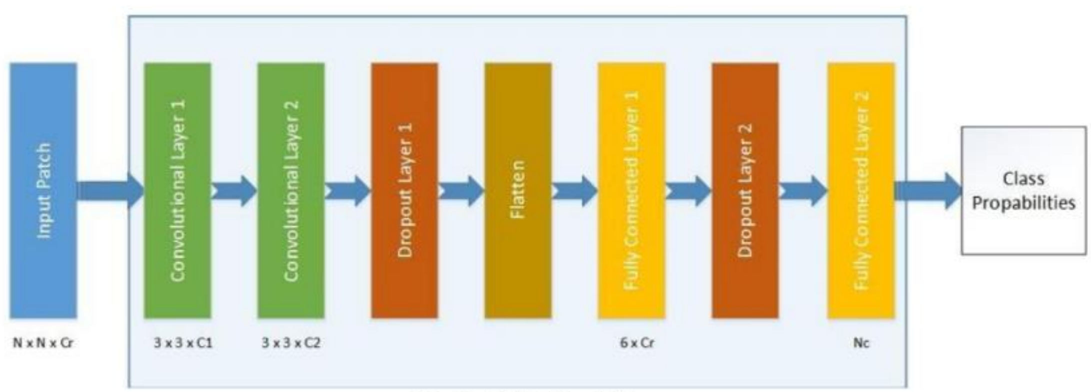

Fig2.5Methodology

In this project, exploitation of a Convolutional Neural Network is taking part, to encode pixels' spectral and spatial information and a Multi-Layer Perceptron to conduct the classification task. To remove spectral redundancy, principal component analysis (PCA) is used. The number of spectral bands is reduced. However, the spatial information is retained, making it easy to recognize any object.

Step 1: Classify image pixels according to their spectral properties. A CNN is used to create hierarchically designed high-level features that encode the spectral and spatial details of pixels. CNNs are a form of deep model that uses trainable filters and pooling operations to create a hierarchy of increasingly complex features from raw data. We must decompose the captured hyperspectral image into patches, each of which includes spectral and spatial information for a single pixel, to be consistent with the basic nature of CNNs.

Step 2: The tensor is divided into c matrices of dimensions $s \times s$ which are fed as input into a CNN, which hierarchically builds high-level features that encode spectral and spatial characteristics of pixels. Pixels in the same class have nearly identical values in each channel. Pixels belonging to different groups have different spectral properties at the same time. A dimensionality reduction technique may be used to reduce the dimensionality of the input data based on these characteristics to speed up the training and prediction processes. Randomized PCA is used to reduce dimensionality by condensing the whole image along the spectral dimension.

Step 3: Each patch is a tensor of dimensions $s \times s \times cr$ after dimensionality reduction. A convolutional layer with $C1 = 3 \times cr$ trainable filters of dimension 3×3 is the first layer of the proposed CNN. The second convolutional layer delivers a vector with C2 elements, which is fed as input to the MLP classifier.

Step 4: From a visual standpoint, we look at classification accuracy. For each dataset, pixels corresponding to annotated and unannotated regions were classified using our deep-learning approach. The results of the classification after using the developed framework are discussed. For the Indian Pines datasets, the resulting classification map is shown along with the ground truth (GT). As can be shown, the classification process results in the creation of compact areas by combining spectral and spatial information for each pixel, removing noisy scatter points.

Step 5: To identify the images, finding values like Overall Accuracy, and Average Accuracy are used in classification research.

Resources:

We will use Jupyter Notebook in this project to run deep learning models on GPU for free, using deep learning libraries such as PyTorch, TensorFlow, and Keras. We plan to use either a waterfall model or an agile approach in this situation. To begin, we'll load a hyperspectral image dataset. Then these datasets will be sorted, and patterns and associations will be found to conduct data analysis and solve problems.