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Hyperspectral Image Compression and Classification Using PCA and Deep Learning

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Abstract:-Hyperspectral imaging is a technology that uses a broad spectrum of light to study and evaluate a large volume of information in images, allowing for better data classification. These are high- dimensional data that contain voluminous information. These high-dimensional data include thousands of features in which many unrelated features might influence the quality and accuracy of data. The presence of these irrelevant data results in an increase in computational time, the density of the image, etc., Dimension reduction of Hyperspectral images is the process of removal of redundant and irrelevant data thus reducing the number of input variables used to improve the accuracy and reduce the training time of data. The idea is to implement a solution that compresses the high-dimensional data and classifies them for practical use.

Keywords: *Hyperspectral Image Compression, Deep Learning, dataset, Principal Component Analysis (PCA), Curse of Dimensionality.*

1. Introduction

Hyperspectralimages are those images that use the concept of spectroscopy to analyze how light interacts with the data in a wide range of wavelengths. Hyperspectral imaging is the process or technique used to analyze high-dimensional data using a wide range of spectral bands. These hyperspectral images are captured using high-end cameras called Hyperspectral Cameras. These hyperspectral cameras are used to measure hundreds and thousands of spectral bands for each pixel of data. The collected spectral data is used to form an image of the target, in a way that each pixel of the image includes a complete spectrum. Hyperspectral imaging provides three-dimensional data called Data-cube. Normal digital cameras are used to shoot the target in three main colours (Red, Green, and Blue) which are within the visible range of human vision. These colours are equal to the amount of information that is recorded. Whereas, the hyperspectral camera records the information in hundreds and thousands of wavelength ranges. The amount of wavelength which is recorded is fully dependent on the type of hyperspectral camera used for recording the data. Figure 1 shows the different hyperspectral cameras of different wavelengths.

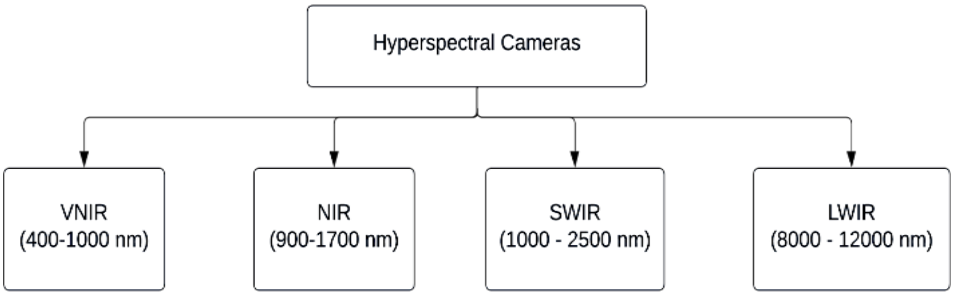

Fig 1 Different hyperspectral cameras of different wavelengths

The Data-cube is constructed based on many wavelengths and every wavelength has its information. By the combination of different wavelengths, we can process different qualities of the dataset. The hyperspectral camera measures the target in every wavelength that is located in the hyperspectral camera's spectral range to create a complete spectrum for the material. This complete spectral information is used for the analysis, detection, and identification of various materials and compounds. This high-dimensional data consists of multiple features which are sparse and correlated. The correlation and sparsity of information in high-dimensional data, affect the overall accuracy of the model and computational time of the model. To eliminate this problem, Dimensionality reduction of hyperspectral images comes into the picture.

2. Literature Survey

2.1 Dimensionality Reduction in Hyperspectral Image Classification

In this research, a brand-new penalty function for ANN pruning is proposed. The 2-norm is held constant while the I-norm of the output weight vector is minimized. When the computation converges, the neurons will become redundant. Reduce output weights to almost nil and only keep the incorrect nodes. It seems that the proposed punishment function is extreme when compared to the traditional penalties, which utilizeall of the ANN's weights

2.2 Traditional Dimensionality Reduction Techniques using Deep Learning

The primary goal of this survey article is to provide information on the various Dimensionality Reduction strategies that are employed, which describe the various techniques used to lower the dimensions to increase the algorithms' accuracy by machine learning. Consequently, it is seen and stated to choose the best strategy for lowering the dimensions, the type of dataset, and the particular requirements of Machine learning algorithms should be measured.

2.3 Fast dimensionality reduction and classification of hyperspectral images with extreme learning machines

They present a unique dimensionality reduction and classification method based on ELM in this paper, which can give numerous capabilities for using remotely sensed hyperspectral data. First and foremost, the proposed strategy can reduce the enormous volume of hyperspectral remote data and sensor data due to its high spectrum dimensionality. The suggested method specifies the compressed hyperspectral picture, offering a structure that allows for the speedy and precise usage of hyperspectral scenes by circumventing the challenges created by their high dimensionality.

2.4 A Review of Dimensionality Reduction Techniques for Efficient Computation

This study's primary goal is to explore the fundamentals of dimensionality reduction techniques. A good classification model is built using the pre-processing technique of dimensionality reduction. The first two methods to minimize dimensionality are feature extraction and feature selection.

Completed feature selection dimension reductions without transforming by choosing a feature from a subset; yet, in feature extractions. By generating a fresh collection of features from the input datasets, dimensions are reduced, and examination of a feature is a method for feature extraction and selection is described. Reduces the Machine through feature selection and extraction acquiring skills in computation time. There is a discovery of new high-dimensional data algorithms. It is possible to convert samples into low- dimensional space. Consequently, the large data set for storing will become less necessary.

2.5 Dimensionality Reduction of Hyperspectral Image Using Different Methods

In contrast to visible images, which only have three channels (Red, Green, and Blue), hyperspectral images may have hundreds or thousands of bands (or undisruptive channels), which greatly enhances the spectral details. Hence the former's capacity to perceive the unseen. As an illustration, hyperspectral photographs are used in minerals that cannot be obtained with the aid of spectral or visual pictures. However, given the broad range of numerous channels utilized in such photos, making it is quite challenging. To examine these pictures. Reduced dimensionality is important. Only pertinent data are remained with the main feature choices by put into practice until a set of predetermined requirements are met.

3. Major Concepts

3.1 Curse of Dimensionality

The term "Curse of Dimensionality" refers to the enormous growth of data dimensions and the consequent exponential rise in computer effort needed to process them. A feature of an item in machine learning might be an attribute or a characteristic that identifies it. Each attribute is a dimension, and a collection of dimensions constitutes a data point. This is an example of a feature vector that describes a data point for a machine learning algorithm (s). Increased dimensionality means more characteristics being utilized to characterize e the data when it is said to be multidimensional. For any machine learning method to operate well, an exponential increase in data points is necessary as dimensionality rises. When dealing with hyperspectral data, which has numerous dimensions, users sometimes end up over fitting their models or struggle to extract only the key features for processing and analysis because there are so many characteristics accessible. Consider an application that analyses and works with a dataset of more than 100,000 input variables as an illustration. The inability to process the vast volume of data would lead the application to fail. The term "curse of dimensionality" refers to this issue.

3.2 Dimensionality Reduction

Dimensionality reduction, which uses deep learning methods, is the idea of reducing the number of variables in the dataset while still taking important input factors into account. With the use of this technique, the likelihood of the model being over fitted is decreased, and noise, redundant data, and unnecessary information are also removed. By lowering the number of variables that must be processed in the data, dimensional reduction of high- dimensional data reduces the amount of space needed for the dataset. Additionally, it aids in enhancing data visualization and model calculation speed. This can be done using two main methods.

Selection of Features

The process of choosing features from the dataset's dimensions is what gives classification, clustering, and other machine learning tasks their mode of operation. Utilizing scoring or quantitative approaches, feature selection strategies choose which traits to preserve and which to discard. These methods employ feature selection to get rid of noisy, redundant, and irrelevant characteristics that don't really help with the categorization issue.

Extraction of Features

By choosing and/or combining existing characteristics, one may limit the amount of features that can be used to describe the data collection while still properly and thoroughly characterizing it. By doing this, one can extract the features which is mainly required for the analysis and provide better results.

3.3 Principal Component Analysis – Algorithm explained

Using the linear dimensionality reduction approach known as principle component analysis, a collection of correlated features in a high-dimensional space is turned into a sequence of uncorrelated features in a low-dimensional space. The data are transformed so that the initial component attempts to explain the most variation from the source information. The class labels are not taken into consideration in this method. The principal component analysis is the linear combination of the original features of data. The features with more variance are more important or have more explanatory power than other features. The features with more variance have more influence over its principal components. Principal component Analysis works by creating a new set of dimensions (The Principal Components of data) that are normalized linear combinations of original features of the dataset.

Outcomes of Principal Component Analysis:

1. Reduction of number of dimensions in the dataset
2. Visualization of features which explain the most variance in the data Steps in the Principal Component Analysis –Algorithm:
    a. Get the original dataset
    b. Standardization of the dataset
    c. Linear transformation of data

d. Calculation of the Covariance matrix
e. Calculation of Eigenvectors
f. Sorting of Eigenvectors by Eigen values
g. Choose N largest Eigen values
h. Projection of original data on to the Eigen vectors

4. Proposed Solution

4.1 Dataset

The Pavia University dataset is a collection of hyperspectral photographs collected over the Italian city of Pavia using the ROSIS-32 system of reflecting optics system imaging spectrometer. The image is made up of 115 spectral bands and 610 by 340 pixels. The image's 42,776 identified samples are divided into nine classes: asphalt, meadows, gravel, trees, metal sheet, bare soil, bitumen, brick, and shadow.

4.2 Phases

The phases are shown in Figure

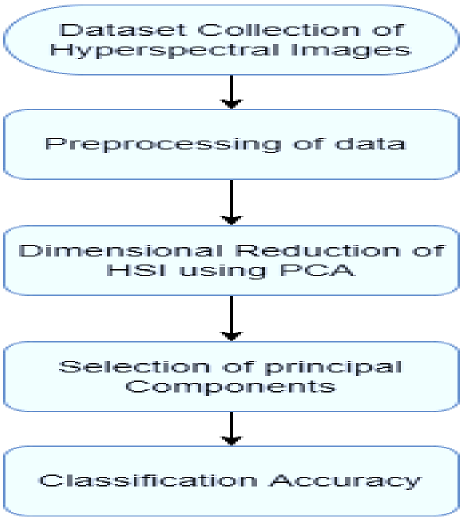

Fig 2 Phases of Hyper spectral compression and classification

4.3 Dataset Collection of Hyperspectral images:

It is the process of Collection of the original Hyperspectral data and standardization of data is done. For each value of the feature, the mean value is calculated along each feature. After which data shifting is done to standardize the data.

4.4 Preprocessing of data:

The preprocessing of the data and scaling is done to clean the data and analyze the features. Exploratory data analysis is done for visualizing the data.

4.5 Dimensionality reduction of hyper spectral images using PCA

PCA creates a new, uncorrelated vector space or co-ordinate system from multidimensional picture data. It creates a space where the biggest variance of the data is along the first axis, the second largest variance is along the second axis that is mutually orthogonal, and so on. Even lower-order PCs can occasionally have useful information. In general, it would be anticipated that the later principal components would exhibit less variation. Due to their minimal contribution to distinction, these could be disregarded, lowering the classification space's required dimensionality and enhancing classification speed. In other words, the goal of this method is to reduce the amount of original n-band data set information into less than n"newbands"or components.

4.6 Selection of Principal Components

The principal components is selected by setting a threshold of explained variance like 80% etc.., The number of components is chosen in such a way that it produces a cumulative sum of explained variance that is close to the threshold.

4.7 Improving the classification accuracy

The classification accuracy is improved by testing with dataset and with the comparison of accuracy before and after classification.

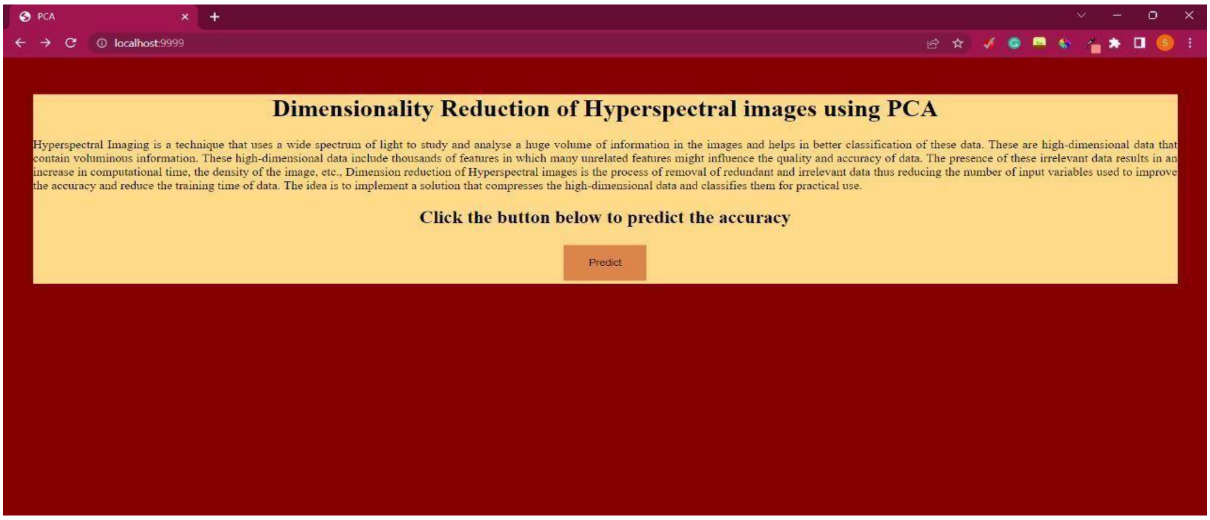

Fig 3 Accuracy Calculation

5. Conclusion

The pre-processing technique to create an effective classification model is dimensionality reduction. The first two methods to minimize dimensionality are feature extraction and feature selection. By choosing a feature from a subset without performing any changes, feature choices complete dimensions reductions; nevertheless, in feature extractions. By generating a fresh collection of features from the input datasets, dimensions are reduced. There is a presentation of an investigation into feature selection and feature extraction algorithms using Principal Component Analysis (PCA).

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