Land Classification Based on Hyper Spectral Images using Deep Learning Techniques

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Abstract

The study of chemical and physical properties of a remote sensing data is done by one of the form called as Hyper Spectral image. The Hyper Spectral image (HSI) is a captured data with consistent materials in a nonlinear relation form. Each HSI has specific wavelength with spectral reflectance in a matching entries on vector with high dimensional pixels. Although classification of HIS performance is good based on spectral-spatial but they depend heavily on hand craft or based on shallow descriptors. The ability of representing features in the form of custom made is not sufficient to label the dissimilarity among the classes of altered or same. Extracting the features is measured as essential technique in HSI classification. To extract the features Deep Learning method is used due to classifying the 2D and 3D dimensions and to extract certain shapes in an image etc., can do clearly. And compared what outcomes will come by applying deep learning to the data using Big Data.

Keywords: *Hyperspectral image, Deep Learning, Big data, feature extraction, PCA.*

I. INTRODUCTION

In remote sensing Hyper Spectral image [9] is a gather of electromagnetic spectrum with range of observable infrared wavelength which is most important technique. HIS holds the narrow spectral bands in hundreds of bands are collected from the surface of earth and from the area. HSI has dimensional vector pixel is high and recordsrelate to the spectral reflectance in a definite wavelength. The distinctive spectral dissimilarity is the main advantage which is extensively used in numerous fields.

The major challenge in hyperspectral images are dimensionality because it has highly dimension [1]. The dimensionality of spectral is equivalent to the whole sum of bands, with a piece of band is representing a dimension, and it is large extending in hundreds. When the sum of dimensions is linearly enlarged, the size of feature space rises exponentially. Hence huge volume of data is vital for modelling in the space [5]. Though, the troubles in gathering and outlays connected with the analysis of physical and chemical materials properties, ground truth data is very unusual in hyperspectral datasets. These disastrous combinations of high dimensionality and inadequate ground truth data leads to over fit and consume low generalization performance. This problem has been mentioned as Hughes or dimensionality phenomenon. The classical methodology for this difficultly is called as reduction of dimensionality [3] which is executed as feature extraction that alter the spectral to an inferior dimension illustration or band selection [6] that will choose a subset of most important bands for analysis. To reduce dimensionality hypothesis is used for extracting features in hyper spectral bands over samples which vary gradually in spectrum reflectance at most wavelengths to represent spectral data. Like hypothesis is used for band selection to effect different material properties to manifest in few bands also titled as spectral features, for analysis complete spectrum is not needed. At present, it has been prevalent to use spatial data along with spectral information during analysis the difficultly in high dimensionality [4, 2]. In high resolution hyper spectral image neighbouring pixels are highly dependent because the land cover is bigger in scope of the pixel and occurrence of a material in one part of the image controls the probability of another material being extant in another part of the image. For analysing spatial and spectral images are jointly estimated to group the pixel and construct the independent modelling with one another over distinct pixel that requires less ground truth data for accuracy of same level.

Hyperspectral image classification [13] was primarily done with some of former information to acquire spatial and spectral data for classification. Mathematical morphology is mainly used to extract characteristics present in the image as patch based sparse representation as spatial features. For classifying the training samples of spatial and spectral data of an HSI machine learning method called conventional is used. This method requires the powerful information of HSI to process the extraction of features is niggling is important to fail the features are important.

Hyper Spectral image falls under big data because it has enormous sum of bands are taken continuously using sensor spectrometer. Here after big data is used for collecting and analysing an enormous volume of tangible produced data competently and efficiently but it has excessive volume of complex data arising invasion of confidentiality. Big data scrutiny will get exact customised and active analysis. Big Data may initiate from (a) derived hyper Spectral image for products with high-frequency (b)IoT and network monitors ground data that is collected from multi-sensor (c) experiment on fields using multiple instruments datasets are collected by large-scale (d) earth system models are simulate the data by large scale and (e) crowd sourced information from societal media and civilian science.

Presently Deep learning is becoming more eye-catching in dissimilar fields like image classification and image monitoring etc. Neural Network is the most collective network for frame work. The ultimate benefit of this features are extracted from the concealed layer in the network deprived of too much pre-processing of the data. The kernel sharing is used to extract the dispersed feature expression in the entire window and get more intellectual and more expensive features over manifold pooling and full connection processing at dissimilar levels. To be motivated to acquire the good results.

II. PROPOSED METHODOLOGIES

About datasets

Salinas

Salinas's valley (SA) is an AVIRIS sensor with 224 bands and it is considered as extraordinary spatial resolution with pixels of 3.7 meter. The covered range has samples of 217 and lines 12. Unwanted absorption bands of water are20 within224 [154-167] and [108-112] are available at sensor radiance data and contain 16 classes in ground truth.

Indian Pines

Indian pines (IP)is an AVIRIS sensor with 224 bands and it is situated in north western Indiana which consists 143 pixel and reflectance bands of spectral has 224 with 0.4 to 2.5 meters range wavelength. This extract covers two third of cultivation and one third forestry and other natural persistent plants. The extract is taken at June which has some crops. The designed ground truth has classes of 16 which are not reciprocally limited.

University of Pavia

This extract attained by the ROSIS sensor in a flight campaign on Pavia which is in northern Italy. This has spectral bands of 103 for Pavia University (PU) and it has pixels of 610*610. The geometric analysis has length of 1.3Meters. The image has ground truth distinguish the classes of 9 each.

HSI analysis

The HSI is the mixture of spectral and detection if image techniques. Where image has dozens of bands in narrow and are scattered for apiece of spatial pixel for constant spectral. The information is formatted visually and described in 3D data block as illustrated in figure 1(a). Where the 2D is represented in a planar pixel data with coordinate axes x, y and 3D is a wavelength data coordinate axis. The pixel with band spectrum is labelled in a category for training samples.

The HSI contains the spectral information with correlation between pixel neighborhoods with high. The pixel contains the 4 neighbour, 8 neighbour, single pixels which needed to classify as illustrated in figure 1(b).

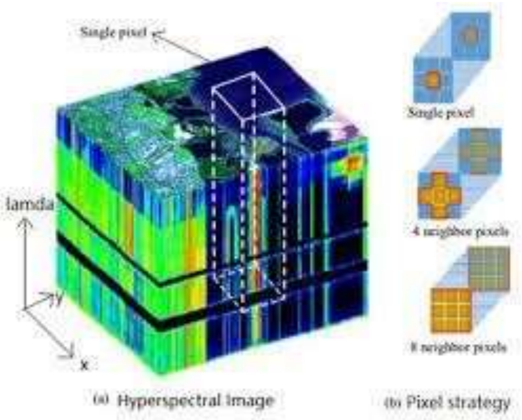

Fig 1. Pixel strategy of Hyperspectralimage

There are several methods have been developed to classify the HSI which uses spatial, spectral information to join the data of both types. This containsclustering techniques of unsupervised. This classification often preferred due to classification [8] accuracy is high. These methods may affect the limited training models because they require a bulky sample to get a good result. The following techniques are used to classify the methods are as explained below

Deep Learning Method

The performance of brain is an artificial intelligence which replicates the human brain working process and makes the patterns used in the decision taking to fretful algorithms and structure using machine learning are used and its subfield is called Deep Learning [12]. Deep learning is changed day by day with digital era and it cause an explosion of knowledge in all procedures and form the region of the planet.

However, the information is in unstructured form which is so huge and it might take spans for human to understand it and extract applicable data. Which results are in incredible to unravelling the information is increased by adapting AI systems for automated support.

Big data

Big data [10] is a monotonous process in event of hyperspectral image in the below comparison as described. Let input samples be A and F(A) is function mapping among spaces as A is an input vector and B is the output.

$$B = F(A)$$

This big data analysis commonly familiarizes the parallel state that is $A= A_1, A_2, A_3, \ldots\ldots, A_N$. which means sharing a usual models A to N which are small data models are assigned to handle big data for better results.

Mongodb

Mongodb is used for storage and regaining huge files like image, files like audio, video etc. it is one of the kind of storing data files but it stores using Mongodb. Gridfs is used to store the data because it has the ability of storing the 16 MB and more than its size. It distributes file into chinks and store every data in a single document with size has 255 KB of each file approximately.

Analysis of principal Component

The dimensionality reduction is computed by PCA [11] which is an appreciable reduction variable is likely to recollecting most of the data enclosed in original dataset. The considerable relationship among the hyperspectral bands is the source for PCA. The analysis tries to remove the relationship among the bands and advance determines the optimum linear grouping of the original bands accounting for the dissimilarity of pixel values in an image.

The calculation of PCA is based on the eigen values which is a corrosion of matrix covariance in HSI bands. The hyper spectral information is organized with pixels along with its size and the bands in numbered. $X_i = X_1, X_2 \ldots X_N$, where number of hyperspectral bands is denoted as N. The calculation of pixel vectors is represented as

$$m = 1m \sum_{i=1}^{m} X_1 X_2 \ldots \ldots . . X_N ITE1$$

Where Hyper Spectral image pixel vector is represented as M= p *q here "p" represents rows and "q" represents columns. The calculation of the matrix covariance is follows as

$$C = 1MI \sum_{I=1}^{M} X_1 = m\, X_I - MTE2$$

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The matrix covariance can be represented as

C=ADA TE3

Matrix diagonal is collection of eigen values $\lambda_1 \ldots\ldots \lambda_N$ and it is denoted as D, matrix orthogonal are represented as C and A are the consistent eigen vectors in columns. The linear alternation of y_i= at X_i, i=1,2, …M is modified to attain the vectors pixel that are transformation of bands using PCA from novel image. The rows of first K in the matrix AT are selected and the rows are in eigen vectors parallel to the eigen values set in a descending order. The row K is selected to multiply the pixel vector X_i to crop the bands with PCA composed of the information enclosed in the hyperspectral bands.

In hyperspectral data features are encloses the sensors with great spectral resolution which cannot defined by the another order type.

CNN

Convolution Neural Networks (CNN) [7]has established admirable performance on numerous pictorial tasks with the classification of shared 2 D dimensional image. In this CNN network [14] contains the input units in INPUT layer, output units in OUTPUT layer, and numerous unseen units in layers F4, M3 and C2. Assuming X_I is the i^{th} layer of input and the $(l-1)^{th}$layer is the output, then we calculate X_{I+1} as

$$X_{I+1} = f_i(u_i)$$

Wherever

$$u_i = WT_I X_I + b_i$$

and $WT_i$is a matrix weight acted on data of input in i^{th} layer, and it is preservative bias of i^{th} layer vector is the beginning role of i^{th} layer. F_i in our intended architecture, we pick the hyperbolic tangent function tanh(u) as the initiation function in C1 layer and F3 layer. max(u) used for M_2 layer as maximum function. Meanwhile the suggested CNN is a multiclass classifier, and the output F3layer is fed n_5 to tactic softmax function which yields a dispersal over the n_5 class labels, and the softmax regression model is well-defined as

$$Y = \frac{1}{\sum_{k=1}^{n_5} e^{WT_I X_I + b_i}} \left[e^{WT_I X_I + b_i} + e^{WT_I X_I + b_i} + \cdots \ldots \ldots \ldots \ldots + e^{WT_I X_I + b_i} \right]$$

The output vector Y= X_{L+1} is the output layer represents the probability of the classes in existing iteration.

III. EXPERIMENTAL RESULTS

Firstly, to extract the classification Hyper Spectral Image (HSI) python programme language is used because it is a common persistence of interpreted, object oriented, interactive and high level programme platform. Then data set is loaded for analysing or to extract features. Here three publically available HSI datasets are taken. Initial step is to train the values for testing then arrange the sample to reshape for that principal component analysis is taken. Then shape margin is assigned, for classify the image is partitioned into cubes and cube values are written and trained them into specified window shape after that Keras package tools are applied because it is deep learning algorithm method which is informal and firm prototyping (because it is customer friendly, modularity, extensibility) and provisions both recurrent and convolution network or combination of both. Then find the dense, reshape, dropout, Batch Normalization, flatten, conv2D, conv3D and spatial for that output shape is calculated and compiled the model to organise the Hierarchical Data Format (HDF5) because it is a binary file format considered to store huge volume of mathematical data and calculate each Epoch to improve the accuracy of the image to reshape and predict the classification image is as shown in figure 2. And compared the data sets accuracies is shown in table 1.

Here used HSI dataset corrected and ground truth for analysing in python due to reduced data but while using the big data original dataset of HSI is used for analysis because it has fully available data. To do that Mongo dB is used for storing the data and it is stored in the form of chunks because it is designed to sort the storage and is pretty handy to store image files through many altered servers in a technique that all servers can use. Then it is loaded into python and applied all the previous application for the classification of the image as illustrated in figure 2 and compared the three datasets accuracies as shown in table 1.

Here used Kappa Coefficient (Kappa), Average Accuracy (AA),Overall accuracy (OA), to analyse,

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performance of HSI classification. OA refers as total number of classified samples, tested samples. AA refers as classification accuracies in class wise and Kappa refers as measure of statically metric that provides the information about the ground truth map and classification map. In terms of Kappa, AA and OA for dissimilar datasets outperforms are compared and maintained minimum standard. Here output is built on the hierarchical demonstration of spectral and spatial. The Salinas dataset has two classes like Grapes untrained and vinyard untrained which has alike textures over most spectral bands due to this it has amplified redundancy in the spectral bands due to that it has more outperformance than other dataset like Indian pines, university of Pavia.

By comparing both type of analysis it concluded that both got the same output prediction and accuracies for all the three dataset but got different accuracies are analysed.

Table 1. Accuracy comparison of datasets of both analysis

Data sets	Test Accuracy (aprx.)	Kappa Accuracy (aprx.)	Overall Accuracy (aprx.)
SA	99.99	99.9	99.9
IP	98.63	98.71	98.75
PU	99.2	99.64	99.7

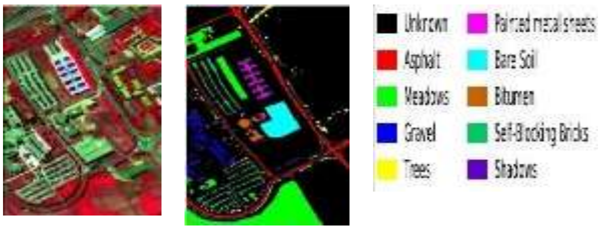

Fig 2. TheHyperspectral classification image for both analysisa) Input image b) classified image c) Classification types

IV. CONCLUSION

The hyperspectral image classification is crucial for analyse the sensed data to find the behaviour of the special characteristics in HSI data.Deep Learning method is used for classifying the hyperspectral image because it modernizes the image analysis and demonstrated asainfluential tool for handling the remote sense data. For effective power of spectral information and spatial contextual presented in HSI data cube is used to extract the features and for that CNN method is used because it is more operative for analysis. Each cubes dense, dropout layer, CONV3D, CONV2D are calculated to find detailed layers of the image to remove unwanted data and analyse the features. And here concluded that by using big data we can analyse the original image because it has more band and by using the data directly to analyse uses corrected and ground truth data. By applying method, the output shape file is calculated and complied the model with the hierarchical Data Format to analyse the image and give the output with feature extractions of the HSI image.The kappa accuracy, overall accuracy, average accuracy is taken in consideration for the performance applied for three datasets. And by comparing the data sets performances Salinas dataset has the best performance accuracy due to spectral bands has more textures. In further work, this method is applied to any hyperspectral image because by using big data analytics we can store any large data for analysis.

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