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HYPERSPECTRAL IMAGE CLASSIFICATION USING DEEP LEARING

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ABSTRACT

The traditional unsupervised loss function like mean square error(MSE)calculates the distance between the predicted value and the original input. However, it is difficult to guarantee the effectiveness of the features only by optimizing there construction error.In order to make the learned features more effective for classification tasks, we optimize the contrastive loss function to make the features fromdifferent views of the same sample consistent. This makes the features of the same classaggregate with each other, and the features of different classes are far away from eachother. Therefore, the features obtained by optimizing the contrastive loss function ofdifferent views could effectively improve the classification accuracy. We use a deepCNN as the base feature extractor.We call this proposed method deep multiview learning. Therefore, the proposed method belongs to the category of unsupervised learning, which could alleviate the lack of labeled training samples. Finally, a conventional machine learning method(e.g.,supportvectormachine)is used to complete the classification task in the learned latent space. To demonstrate the effectiveness of theproposed method, extensive experiments are carried on four widely used hyperspectraldata sets. The experimental results demonstrate that the proposed method could improvethe classificationaccuracywith smallsamples.

CHAPTER1

INTRODUCTION

1.1 GENERAL

Remotesensingisthescienceofacquiringinformationabouttheearth'ssurface without actually being in contact with it. This is done by sensing and recordingreflectedoremittedenergyandprocessing,analysing,and applyingthatinformation.Remote sensing is based on the measurement of reflected or emitted radiation from differentbodies. Objects having different surface features reflect or absorb the sun's radiation indifferent ways. The reflectance properties of an object depend on the particular material andits physical and chemical state (e.g. moisture), the surface roughness as well as thegeometriccircumstances (e.g. incidence angle of the sunlight). The mostimportant surface features arecolour, structure and surface texture. These differences make it possible to identify differentearth surface features or materials by analysing their spectral reflectance patterns or spectralsignatures. These signatures can be visualized in so called spectral reflectance curves as afunctionofwavelength.

The primary prerequisite for remote sensing is to have an energy source to lightup the target (unless the sensed energy is being radiated by the target). This energy is knownas electromagnetic radiation. All electromagneticradiation has key properties and carries oninunsurprisingroutesasindicated bythe fundamentalsofwavehypothesis.

The electromagnetic spectrem ranges from the shorter wave lengths(includinggamma X-ray) to the more extended wave lengths(includingmicrowaves and telecast radiowaves). There are few areas of the electromagnetic range which are helpful for remotesensing. Ultraviolet or UV portion of the spectrum has the shortest wavelength that can beusedforremotesensingformostpurposes.

This radiation extends beyond thevioletportion of the visible wavelengths and is thereforecalled. Some earth surface materials, essentially shakes and minerals, fluoresce or radiate certainlight whenlitupbyultravioletradiation.Electromagneticwavesutilizedasapartofremotesensingisdemonstratedin Figure.1.1.

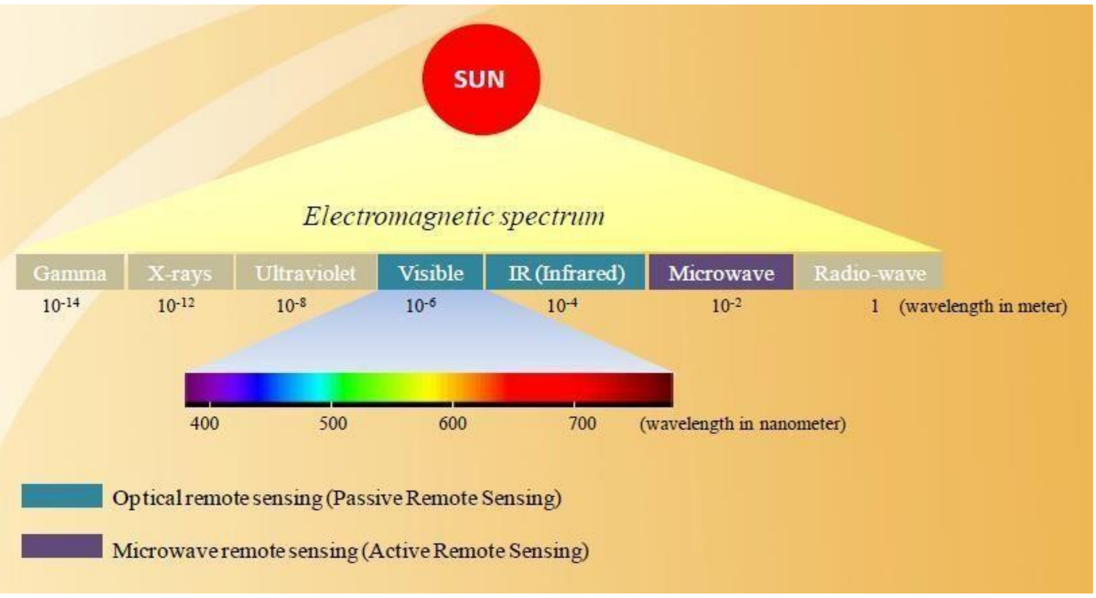


Figure1.1Electromagneticspectrum

Inremotesensing,theprocessinvolvesaninteractionbetween incidentradiation and the targets of interest. This is exemplified by the use ofimaging systemswhere the following seven elements are involved.[1] Note, however that remote sensing alsoinvolvesthesensingofemittedenergyandtheuseofnon-imagingsensors.

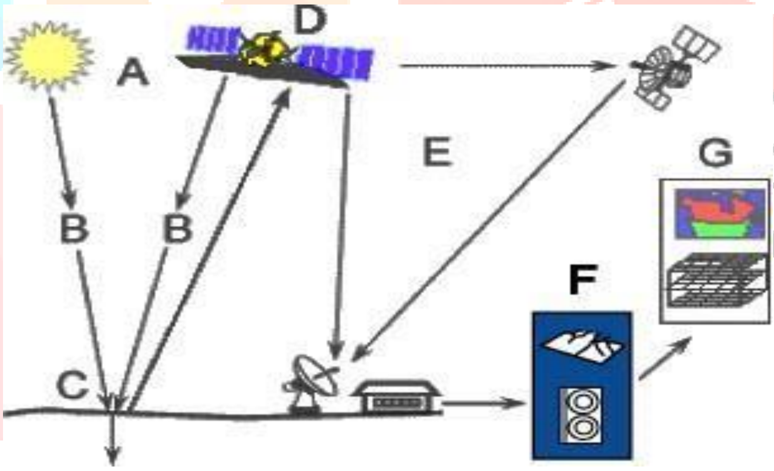


Figure1.2RemoteSensingSystem

Energy Source or Illumination (A) - the first requirement for remote sensingis to havean energy source which illuminates or provides electromagneticenergy to the target ofinterest.

Radiation and the Atmosphere (B) - as the energy travels from its source to the target,itwillcomeincontactwithandinteractwiththeatmosphereitpassesthrough.Thisinteractionmaytakeplac easecondtime asthe energytravelsfromthetargettothesensor.

Interaction with the Target (C) - once the energy makes itsway to the target throughthe atmosphere, it interacts with the target depending on the propertiesof both the target andtheradiation.

Recording of Energy by the Sensor (D) - after the energy has been scattered by, oremitted from the target,asensorisrequired to collectand record theelectromagneticradiation.

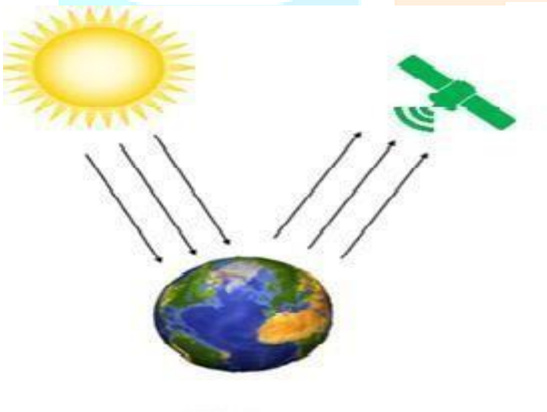
Transmission, Reception, and Processing (E) - the energy recorded by the sensorhastobetransmitted,ofteninelectronicform,toareceivingandprocessing station wherethedataareprocessedintoanimage(hardcopyand/ordigital).

Interpretation andAnalysis(F)-theprocessedimageisinterpreted,visually and/ordigitallyorelectronically,toextractinformationaboutthetargetwhichwas illuminated.

Application (G) - the final element of the remote sensing process is achieved when theinformation is able to extract from the imagery about the target in order to better understandit,revealsomenewinformation,orassistinsolvingaparticularproblem.

1.2 TypesofRemoteSensing

The sun is a source of energy or radiation, which provides a very convenientsource of energy for remote sensing. The sun's energy is either reflected, as it is for visiblewavelengths, or absorbed and then reemitted, as it is for thermal infrared wavelengths. Theremote sensing system can be classified into two types depending on the source of energy:passiveremotesensingandactiveremotesensing.



(b)

Figure1.3**a)PassiveRemoteSensing** **b)ActiveRemoteSensing**

Passive Remote Sensing: Passive sensors can only be used to detect energywhen the naturally occurring energy is available. For all reflected energy, this can only takeplace during the time when the sun is illuminating the Earth. There is no reflected energyavailablefromthesun atnight.Energythatisnaturallyemitted(suchasthermalinfrared)canbe detected day or night, as long as the amount of energy is large enough to be recorded.Examples of passive remote sensors include film photography, infrared, and radiometers.PassiveremotesensingisillustratedinFigure1.3a.

Active Remote Sensing: Active sensors, on the other hand, providetheir ownenergy source for illumination. The sensor emits radiation which isdirected toward thetarget to be investigated. The radiation reflected from thattarget is detected and measuredby the sensor. Advantages of active sensors include the ability to obtain measurementsanytime, regardless of the time of day or season. Active sensors can be used for examiningwavelengths that are not sufficiently provided by the sun, such as microwaves, or to bettercontrol the way a target is illuminated. However, active systems require the generationof afairly large amount of energy to adequately illuminate targets.[2] Examples of active sensorsare laserfluoro sensorand SyntheticAperture Radar (SAR).Active remote sensing isillustratedinFigure1.3.b

1.3 TypesofOpticalRemoteSensingSystems

Dependingonthenumberofspectral bandsusedintheimagingprocess,opticalremotesensingsystemsareclassifiedintothefollowingtypes:

(1) **Panchromatic image:** The sensor is a single channel radiation sensitivedetectorwithin awide range ofwavelengths.If the wavelength range coincide with thevisible range, then the resulting image resembles a black-and-white photograph taken fromspace. The physical quantity being measured isthe apparent brightness of the targets. Thespectralinformationor colour ofthetargetsislost

(2) **Multispectral image:** The sensor is a multichannel detector witha fewspectral bands. Each channel is sensitive to radiation within a narrow wavelength band. Theresultingimage isamultilayerimagewhichcontainsboththe brightnessandspectral(colour)informationofthetargetsbeingobserved

(3) **SuperspectralImage:**Ithasmanymorespectralchannels(typically >10)thanamultispectralsensor.Thebandshavenarrowerbandwidths,enablingthefinerspectralcharacteristics of thetargetstobecapturedbythesensor.

(4) **Hyperspectral Image:** A Hyperspectral image consists of hundred ormore contiguous spectral bands forming a three-dimensional (two spatial dimensions andonespectral dimension)imagecube.

(5) **Ultraspectral Image:** It contains thousands of spectral bands offering thecapabilitytoextendspectral imagingtoahighlevel.

1.3.1 AdvantagesofRemoteSensing

Themajoradvantagesofremotesensingare:

1. Synoptic view: Remote sensing process facilitates the study of Earth's variousfeatures in their spatial relation to each other and helps to trace the requiredfeaturesandcircumstance.
2. Accessibility:Remotesensingprocessmakesitpossibletoaccumulateinformation about the unreachable area when it is not possible doing groundsurveylike inmountainousregions.

3. Time: The information areas or foreign lands about a large area can be gatheredquickly,thetechniquessavetimeandefforts ofhumanbeings/machine.
4. Costsavings:Thecostsarerelativelysmallwhencomparedwith thebenefits,whichcanbeobtainedfrominterpretationofsatelliteimagery.
5. Coverage: With the use of high-altitude sensor platforms, it is now possible torecord extensive areas on a single image. The advent of high-flying aircraft andsatellites,singlehighqualityimagecoversthousandsof squaremiles.

1.4 LimitationsofRemoteSensing

Thedisadvantagesofremotesensingare:

- Requirescrossverificationwithground(field)surveydata
- Dataanalysisandinterpretationproblems
- Costofdatacollectionanddatapurchase.
- Possibilitiesformisclassificationorconfuseofobjects
- Potentiallimitationswiththedifferentsensors’spatial,spectralandtemporalresolutions.

1.4.1 ApplicationsofRemoteSensing

Satellite data enables our renewable and non-renewable resources tobe properlymanaged as it provides timely and detailed Earth surface information. Remote sensing findsapplicationsinthefollowingfields.

- UrbanPlanning
- Geographicinformation
- Weatherandagriculturalforecastsandassessmentofenvironmentandnaturaldisaster
- Imageprocessing
- Aerialtrafficcontrol,Interferometricsyntheticapertureradar
- LaserandRadaraltimeters
- Precisiongeo-referencing
- Ultrasound(acoustic)andradartidegauges
- Light detectionandranging
- Radiometers andphotometers
- Stereographicpairsofaerialphotographs
- Mineralogy,Biology,Defense,andEnvironmentalmeasurements

1.4.2 Hyperspectralimaging

The word “hyper” in hyperspectral means “over” as in “too many” and refers to the largenumberofmeasuredwavelengthbands.Hyperspectralimagesarespectrallyoverdetermined; they provide ample spectral information to identify and distinguish betweenspectrally similar (but unique) materials. Consequently, hyperspectral imagery provides thepotential formore accurate and detailed information extraction than is possible with other typesof remotely sensed data. A Hyperspectral Image (HSI), in general, has hundreds of spectralbands in contrast to a normal digital image which has three spectral bands (blue, red, andgreen) and thus offers a more complete part of the light spectrum forviewing and analysis.In general, hyperspectral sensors measure bands at 10 to 20 nm intervals. A regular digitalimage can be viewed as a collection of three-dimensional spectral vectors, each representingtheinformationforonepixel.Similarly,aHSIcanbeviewedasacollectionof*d*-dimensionalspectral vectors,eachrepresentingthe informationforonepixel.

Hyperspectral remote sensing images acquire many, very narrow, contiguousspectral bands throughout the visible,near–infrared,mid-infrared and thermal infraredpositions of the electromagnetic spectrum. Hyperspectral sensors typically collect 200 ormore bandsenabling the construction of an almost continuous reflectance spectrum forevery pixel in the scene. Contiguous narrow bandwidths characteristic of hyperspectral dataallows for in-depth examination of earth surface features which would otherwise be 'lost'within the relatively coarse bandwidths acquired with multispectral scanners.[3] Over thepastdecade,extensiveresearchanddevelopmenthasbeencarriedout inthefieldofhyperspectralremote sensing.With commercialairbornehyperspectralimagerssuch asCompact Airborne Spectrographic Imager (CASI) and Hymap and the launch of satellite-based sensors such as Hyperion HSI is fast moving into the mainstream of remote sensingandappliedremotesensingresearchstudies.Hyperspectralimageshavefoundmanyapplications in water resource management, agriculture, and environmental monitoring. It isimportant to remember that there is not necessarily a difference in spatial resolution betweenhyperspectralandmultispectraldata butratherintheirspectralresolutions.

Hyperspectral images typically include spectral bands representing the ultraviolet (200-400nm),visible(400-700nm),nearinfrared (700-1000 nm), and short-wave infrared (1000-4000 nm). Thus, HSI are favouredoverregularimagesforsome applicationssuchasforestry and crop analysis, mineral exploration, and surveillance. Hyperspectral image cubestructure is illustrated in Figure 1.4. Each pixel has intensity values corresponding to allspectralbandsasshowninFigure1.5.

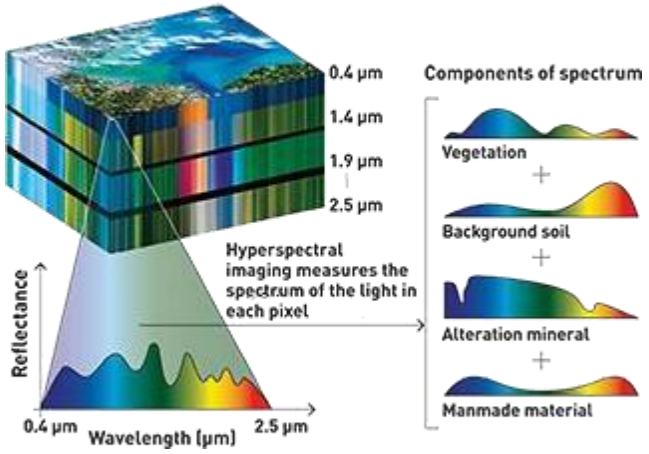


Figure1.4RepresentationofHyperspectralDataCube

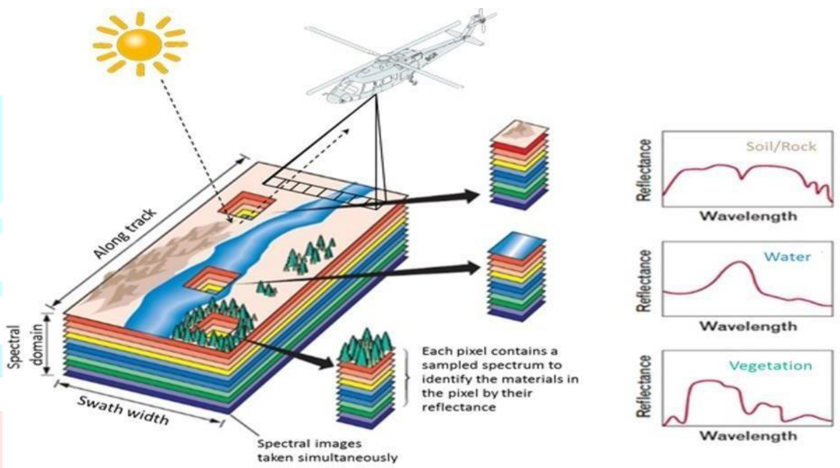


Figure 1.5 Concept of data cube generated by a Hyperspectral imager AnalyzingofHyperspectraldatabecomesadifficulttask.Importantfactorsaremakingittoocomplexsuch asatmosphericcorrections,hugesizeandlargevolumeoftheimage,curseof dimensionality,spatial/spectralsignaturesvariability,fewlabelledsamples,exploringthespatialcorrelationa mongpixelsandaddingcontextualinformationalongwithspectralinformationduringclassification.

GeneralprocessingofHyperspectraldatainvolvesthefollowingsteps:

- Datapre-processing
- Correctionsofdatabyusingatmosphericcorrection
- Dimensionalityreduction
- Pureend-memberselectionusingpixels
- Perform classification using selectedend-membersHyperspectral

imagingiscommonlyreferredtoasspectralimaging
or spectral analysis.The distinction between hyper- and multi-spectral is sometimes basedon an arbitrary "number of bands" or on the type of measurement, depending on what isappropriatetothepurpose.

Multispectralimaging dealswith severalimagesatdiscrete andsomewhatnarrow bands. Being "discrete and somewhat narrow" is whatdistinguishes multispectral inthe visible from colour photography. A multispectral sensor may have many bands coveringthespectrum from thevisibletothelongwaveinfrared.Multispectralimagesdonotproduce the "spectrum"of anobject.Landsatisan excellentexample ofmultispectralimaging.

HyperspectralImageSensors

Hyperspectralandmultispectralsensorsarebasedonthesame physicaltechnology. They both record radiance in the Visible to Near-Infrared (VNIR) and Short-Wave Infrared (SWIR) of the spectrum, VNIR spanning 400–1000 nm and SWIR 1000–2400 nm. Unlike multispectral sensors, such asLandsat-8 (11 bands), recording in a fairlylimitednumberofdiscretespectral

bands (4–20 bands), Hyperspectral sensors include a very large number of contiguous andnarrow spectral bands of 5–15 nm (Kaufmann *et al.* 2009). Airborne Hyperspectral sensorsprovide promising results for many applications as they combine a high spectral resolutionwith a high spatial resolution and are not so affected by atmospheric perturbation (Lu *et al.*2013; Wang *et al.* 2010). These platforms have played a key role in the development ofHyperspectral science and applications (Kruse *et al.* 2003; Guanter *et al.* 2012).Withtheavailabilityofemblematicsensorssuchas HyMAP,CASI,AirborneVisible/InfraRed Imaging Spectrometer (AVIRIS) , Digital Airborne Imaging Spectrometer(DAIS),ReflectiveOpticsSystemImagingSpectrometer(ROSIS),AirborneImaging SpectrometerforApplications(AISA),HyperspectralDigitalImageryCollectionExperiment (HYDICE), Multispectral Infrared Visible Imaging Spectrometer (MIVIS), etc.,HyperspectralresearchquicklyexpandedthenumberofHyperspectralapplicationsinvegetation monitoring, water resources management, geology and land cover (Govender *etal.* 2007; Van der *et al.* 2012). However, they do not allow regular and synoptic coveragesover large areas as spacebornesensors. Moreover, spaceborne sensors produce images withlower angular effects due to their much smaller field of view. Fig.1.6 illustrates the timelineof high-spatial-resolution (≤ 30 m) hyperspectral sensors. These hyperspectral sensors havebeen implemented on a number of experimental airborne platforms, including the HYDICEandtheAVIRIS.EarthObservation-1(EO-1)carriesahyperspectralsensorcalledHyperion.

Figure1.6TimelinehighlightinghyperspectralImagingSensors

Table1.1DetailsofHyperspectralSensors

Type ofSensors	**NameoftheSensors**	**No.ofbands**	**SpectralRange(µm)**
SatelliteS ensor	FTHSIonMightySatII	256	0.35 to1.05
	HyperiononEO-1	242	0.40 to2.50
ιirborneSens or	AVIRIS (AirborneVisible InfraredImaging Spectrometer)	224	0.40 to2.50
	HYDICE (Hyperspectral DigitalImageryCollection Experiment)	210	0.40 to2.50
	PROBE-1	128	0.40 to2.50
	CASI(Compact Airborne ctrographicImager)	Over228	0.40 to1.00
	HyMap	100to200	VisibletoThermal Infrared
	EPS-H(Environmental ProtectionSystem)	VIS/NIR(76) SWIR1(32) SWIR2(32) TIR (12)	VIS/NIR(0.43to1.05) SWIR1(1.50to1.80) SWIR2(2.00to2.50) TIR (8.00to12.50)
	DAIS 7915(Digital AirborneImaging Spectrometer)	VIS/NIR(32) SWIR1(8) SWIR2(32) MIR(1) TIR(6)	VIS/NIR(0.43 to1.05) SWIR1(1.50to1.80) SWIR2(2.00to2.50) MIR(3.00to5.00) TIR(8.70to12.30)
	(AISA)AirborneImaging Spectrometer for Applications	Over288	0.43-1.00

The sensors are typically measured in spectral resolution, which is the width ofeach band of the spectrum that is captured. If the scanner detects a large number of fairlynarrow frequency bands, it is possible to identify objectseven if they are only captured in ahandfulofpixels.Inthehyperspectralfieldtherearetwotypesofsystemsthattakeimages:

onaircraftandonsatellites.Mosthyperspectralsensorsaremountedonaerialplatformsthanonthesatellite.

1.5 HYPERSPECTRALIMAGECLASSIFICATION

Hyperspectral image classification is the process in which individual values(objects/ patterns/image regions/pixels) are grouped based on the similarity between thevalue and the description of the group. Hyperspectral image classification can be done byeither based on pixel information or based on the use of training samples. Based on pixelinformation, images can be classified as Per-Pixel, Sub Pixel, Per-field, Knowledge based,Contextual and multiple Classifiers. Based on the use of training samples, images can beclassifiedasSupervisedClassification,UnsupervisedClassificationandSemisupervisedClassification. Hyperspectral image classification is based on the detection of the spectralresponse pattern of land coverclasses. The majorobjective of the image classificationprocedure is to automatically categorize all pixels in the image into appropriate land coverclasses.The intent of the classification process is to categorize all pixels in an image intoone of several land coverclasses or"themes".[4] This categorized data is then used toproduce thematic maps of the land cover present in an image. One of the major problemsinHyperspectral remote sensing is a high amount of data that is available forprocessing. Dueto the huge amountof data, the processing time and classification accuracy are decreased.To deal with this huge data problem, the valuable information and more processing arerequired to increase the classification accuracy. Therefore, classification of HSI data withoutlosingimportantinformationaboutobjectsofinterestisimportant.

1.6 DEEPLEARNINGINREMOTESENSING

Deep Learning (DL) is a type of machine learning in which a model learns toperform classification tasks directly from images, text, or sound. DL is usually implementedusing a neural network architecture. The term “deep” refers to the number of layers in thenetwork—the more layers, the deeper the network. Traditional neural networks contain only2or3layers,while deepnetworkscanhavehundreds.

In recent years, DL has become emerging learning method in big data analysisand hasbeen extensively used in numerousfields, such as natural language processing(Ronan & Weston, 2008), image classification, speech enhancement, due to its exceptionalperformance comparedtootherconventionallearningalgorithms.

Recent advances in Artificial Intelligence (AI) and machine learning, especiallytheemergingfieldofdeeplearning,havechangedtheway weprocess,analyseandmanipulate geospatial sensor data. This is largely driven by the wave of excitement in deepmachine learning, as a new frontier of AI, where the most representative and discriminativefeatures are learnt end- to-end,hierarchically.[5] DL methodshave achieved huge successnot only in classical computer vision tasks, such as target detection, visual recognition, androbotics, but also in many other practical applications (Hu *et al.* 2015). They have madeconsiderable improvements beyond the state-of-the-art records in avariety of domains, andhaveattractedgreatinterestinbothacademiaandindustrialcommunities

DL offers a different outlook on feature learning and representations, where robust, abstractand invariant features are learnt end-to-end, hierarchically, from raw data (e.g. image pixels)tosemanticlabels, which isakeyadvantageincomparisonwithpreviousstate-of-the-artmethods.Manydeep learning-based methods have been proposed, including deep belief networks (DBNs) (Chen *et al.*2015),deepBoltzmannmachines(DBMs),StackedAutoencoder(SDE),anddeepconvolutional neural networks. Amongst them, the CNN model represents the most well-established method, with impressive performance and great success in the field of computervisionand pattern recognition, such as for visual recognition (Krizhevsky *et al.* 2012),imageretrievalandsceneannotation.

1.6.1DeepLearningforHSIClassification

Classification is the task of labelling pixels (or regions in an image)into one ofseveral classes. The DL methods outlined as follows use many forms of DL to learn featuresfromthe dataitself andperformclassificationatstate-of-the-artlevels.

As DLhas emerged as one of the well-known machine learning techniques,itis widely used in the field of computer vision and image processing, with applications suchas image classification (He *et al.*2014; Krizhevsky *et al*. 2012), object detection (Girshick *etal.* 2014), and super- resolution restoration (Dong *et al.* 2016). In recent past, DL is used forremotesensing image classification, and a good number of relative papers are discuss it theliterature .As a part of this survey , in this section , it is presented the pixel-wise and scenewise remote sensing image classification approaches that are based on DL, supported withcomparativeexperimentalanalyses.

HSIdataclassificationisofmajorimportancetoRSapplications,somanyoftheDL results reviewed were based on HSI classification. HSIprocessing has many challenges,including highdatadimensionalityandusuallylownumbersoftrainingsamples.Chen*et* based HSI classification framework. The input data are converted to a one- dimensional (1-D) vector and processed via a DBN with three RBM layers, andthe class labels are outputfrom a two-layer logistic regression NN. A spatial classifier using Principal ComponentAnalysis (PCA) on the spectral dimensionfollowed by 1-D flattening of a 3-D box, a three-levelDBN,andtwo-levellogisticregressionclassifier.Athirdarchitectureusescombinations of the 1-Dspectrum and the spatial classifier architecture.[6] He *et al.* (2016)developed aDBN forHSI classification thatdoes notrequire SGD training.Nonlinearlayers in the DBN allow for the nonlinear nature of HSI data and a logistic regressionclassifier is used to classify the outputs of the DBN layers. A parametric depth study showeddepth of nine layers produced the best results of depths from 1 to 15, and after a depth ofnine,noimprovementresultedby addingmore layers.

Some of the HSI DL approaches use both spectral and spatial which integratesspatial information. Small training sets are mitigated by acollaborative, representation-basedclassifierandsalt-and-peppernoiseismitigatedbyagraph-cut-basedspatialregularization. Their method is more efficient than comparable kernel-based methods, andthe collaborative representation-based classification makes their system relatively robust tosmall training sets. Yang *et al.* (2016) use a two-channel CNN to jointly learn spectral andspatial features. Transfer learning is used when the number of training samples is limited,where low-level and midlevel features are transferred from other scenes. The network has aspectral CNN and spatial CNN, and the results are combined in three fully connected layers.A softmax classifier produces the final class labels. Pan *et al.* (2017) proposed the so- calledrolling guidance filter and vertex component analysis network (R-VCANet), which alsoattempts to solve the common problem of lack of HSItraining data. The network combinesspectralandspatialinformation.The smalldetailsfrom imagery .theVCANetisacombination of vertex component rolling guidance filter is an edge-preserving filter used toremove noise and analysis, which is used to extract pure endmembers, and PCANet. Aparameteranalysis of the number of training samples, rolling times, and the number and sizeof the convolution kernels is discussed. The system performs well even when the trainingratio is only 4%. Lee & Kwon (2016) designed a contextual deep fully convolutional DLnetwork with 14 layers that jointly exploit spatial and HSI spectral features. Variable sizeconvolutional features are used to create a spectral–spatial feature map. A feature of thearchitecture is the initial layers use both [3 × 3 × B] convolutional masks to learn spatialfeatures, and [1 × 1 × B] for spectral features, where B is the number of spectral bands. Thesystemistrainedwithaverysmallnumberoftrainingsamples(200/class).

Objectiveoftheresearch

Themainobjectivesoftheresearchareto:

- Developdeeplearningtechniquesforthe analysisand classificationofremotesensingHyperspectralimages.
- Investigate the behaviorand performance,in termsofoverallaccuracy,average accuracy and kappa coefficient of the newly developed techniqueswithstandardhyperspectral data sets.
- Produce accurate classification maps that are suitable to meet thepracticalrequirementsfortheapplicationsofinterest.

Motivationoftheresarch

HSI classification plays an important role in the earth observation technologyusing data from Remote Sensing (RS), which has been extensivelyused in both military andcivilfields.However,RSimageclassificationperformancefacesmajorscientificandpractical challenges due to the characteristicsofRSdatasuchashighdimensionalityandrelativelysmall

quantities of available labelled samples.In recent years, as new DL techniques emerge,approaches to RS image classification with DL have achieved significant breakthroughs,offering novel opportunities in classification. Specifically, focus is on unsolved challengesandopportunitiesastheyrelateto (i)inadequatedatasets,(ii)human-understandablesolutionsformodellingphysicalphenomena,(iii)big data,(iv)transferlearning,(v)DL architecturesand learningalgorithms for spectral, spatial, and temporal data, (vi) non- traditional heterogeneousdata sources,(vii) betterunderstanding of DL systemstheoretically (viii)high barrierstoentry,and(ix)trainingandoptimizingtheDL.

Problemdefinition

Hyperspectral classification becomes a difficult task because of high dimensionality, fewlabelled samples, spatial variability of the spectral signature, spatial correlation among pixels andaddition of contextual information with spectral information during classification. It uses distinctfeatures like spectral ,spatial multi temporal and multi sensor information.important factors inclassification accuracy are uncertainty and error propagation chain.[6] For achieving significantimprovementinaccuracy,weakest linksinthechainneedstobeidentifiedandthentheuncertaintiesarereduced.

Based on the literature survey, it is inferred that still there is a scopefor newHyperspectralImageClassificationAlgorithmindeeplearningareato improvetheclassificationaccuracy.Thustheproblemidentifiedforthisresearchworkisimprovementin Hyperspectral Image Classification with respect to overall accuracy,average accuracyandkappacoefficient.

HyperspectralImageClassificationAlgorithmusingMultiscaleConvolutionalNeuralNetwork

In thiswork,a novel hyperspectral image classification system that usesaMultiscale Convolutional Neural Network with Gaussian Kernel (MCNN-GK) has beenhighlighted.AlthoughCNNshavesuccessfullybeenusedinremotesensingsceneclassification, the scale of the objects can changegreatly between images. When the scale ofthe image changes a lot within the dataset, it is very difficult to achieve a good classificationof remote sensing data. To solve this problem, a novel MCNN framework with Gaussianconvolution kernel function has been proposed as it is the only correct kernel function toapproximatescalespace.

In MCNN structure, three fully connected layers are added in frontof theoutput layer, which have been abandoned in many current CNN structures. The weights ofconvolution layer are initialized as Gaussian convolution kernels. The Gaussian smoothinglayer adjusts the size of the scaleby training, so that the entire learning process is carried outin a stable scale space. Different learning rates are employed in each octave in the trainingprogress and adjusted according to the change of the scales. In the training process of thetraditional CNNs, the weights in the front hidden layers are moredifficult to train than that inthe hidden layers behind it. Hence, a larger learning rate is used on the small scale fronthidden layer, and a smaller learning rate corresponding to the large scale hidden layer. Fortraining, as in CNN, the loss function is chosen as cross-entropy, and mini-batch gradientdescentisused tofindthebestparametersofthenetwork.Traininganeuralnetworkistofindthe bestparameters(weightsof the network) to minimize the lossfunction,which in aclassification task measures the compatibility between a prediction (e.g., the class scores inclassification) and the ground truth label.the experiments show that the propose methodoutperforms intermsofoverallaccuracyaverageaccuracyandkappacofficient

DATASETS

The various benchmark data sets of HSI are generally utilized for assessing the performance of theproposed methods for diverse fields ofapplication. The data set include Indian Pines, Pavia University,Pavia Center,Kennedy Space Center, Botswana, Salinas, Salinas-A and Washington images. In this work,the experimental results are exposed on three hyperspectral airborne images recorded by the AVIRISandtheROSISsensors,withdifferentcontexts(agricultural andurbanareas),differentspatialresolutions

Thesethreedatasetsaredetailedinthefollowing:

Indian Pines: It was acquired by the AVIRIS sensor in Indiana in June 1992. It isthe firstdatasetwith 20-m resolution image taken overthe Indian Pines testsite in June 1992.The image size is 145 × 145 pixels and contains 220 spectral bands. Twenty water absorptionbands have been removed (Tadjudin& Landgrebe,1999), and a 200-band image was used for theexperiments. It contains two-thirds agriculture, and one-third forest are the rnatural perennialvegetation. A ground survey of 10366 pixels, distributed in16 crop types classes, is available.[10]Thisdatasetis a classical benchmark tovalidate model accuracy and isknown to be verychallenging because of the strong mixture of the classes' signatures, since the image has beenacquiredshortlyafterthecropswereplanted.

Pavia University: The Pavia University image was collected by the Reflective OpticsSystem Imaging Spectrometer(ROSIS)senso rove rthe urban areaof the University of Pavia,Italy. It consists of 103 spectral bands with aspectral range from 430 nm to 860 nm. The imagespatial resolution is1.3m,and the total image size is610 X 340 pixels.The reference datacontainnineclassesofinterest.

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CHAPTER 3

METHODOLOGY

3.1 ClassifyHyperspectralImagesUsingDeepLearning:

Hyperspectral image classification is the process in which individual values(objects/ patterns/image regions/pixels) are grouped based on the similarity between thevalue and the description of the group. Hyperspectral image classification can be done byeither based on pixel information or based on the use of training samples. Based on pixelinformation, images can be classified as Per-Pixel, Sub Pixel, Per-field, Knowledge based,Contextual and multiple Classifiers. Based on the use of training samples, images can beclassifiedasSupervisedClassification,UnsupervisedClassificationandSemisupervisedClassification. Hyperspectral image classification is based on the detection of the spectralresponse pattern of land coverclasses. The majorobjective of the image classificationprocedure is to automatically categorize all pixels in the image into appropriate land coverclasses.The intent of the classification process is to categorize all pixels in an image intoone of several land cover classes or "themes". This categorized data is then used to producethematicmapsofthelandcoverpresentinanimage.OneofthemajorproblemsinHyperspectral remote sensing is a high amount of data that is available for processing. Dueto the huge amount of data, the processing time and classification accuracy are decreased.[7]To deal with this huge data problem, the valuable information and more processing arerequired to increase the classification accuracy. Therefore, classification of HSI data withoutlosingimportantinformationaboutobjectsofinterestisimportant.

Hyperspectralimagingmeasuresthespatialandspectralfeaturesofanobjectatdifferentwavelengths ranging from ultraviolet through long infrared, including the visible spectrum. Unlike colorimaging, which uses only three types of sensors sensitive to the red, green, and blue portions of thevisiblespectrum,hyperspectralimagescanincludedozensorhundredsofchannels.Therefore,hyperspectralimages can enablethedifferentiation ofobjectsthatappearidenticalinanRGBimage.

Load HyperspectralData Set:

ThisexampleusestheIndianPinesdataset,includedwiththeImageProcessingToolbox™Hyperspectral Imaging Library. The data set consists of a single hyperspectral image of size 145-by-145pixels with 220 color channels. The data set also contains a ground truth label image with 16 classes,suchasAlfalfa,Corn,Grass-pasture,Grass-trees,andStone-Steel-Towers.

PreprocessTrainingData:

Reducethenumberofspectralbandsto30usingthehyperpcafunction.Thisfunctionperformsprincipalcomponentanalysis(PCA)andselectsthespectralbands withthemostuniquesignatures.

SpecifyTrainingOptions:

Specifytherequirednetworkparameters.Forthisexample,trainthenetworkfor100epochswithaninitiallearningrateof 0.001,a batchsize of256,andAdamoptimization.

TraintheNetwork:

By default, the example downloads a pretrained classifier for the Indian Pines data set.[11] Thepretrained network enables you to classify the Indian Pines data set without waiting for training tocomplete.

To sum up, the successful mapping of TSS distribution in mulberries suggested that the application ofhyperspectral imaging to realize the visualization of mulberry fruits' internal quality is feasible andpromising. The PLSR and LS-SVM model based on 23 and 11 wavelengths had a good performance topredictTSSofmulberries,whichindicatedthatRFalgorithmwaseffectiveinreducingthree-dimensional data. PLSR-RF based on 23 important wavelengths provided the optimal visualizationresults. It could be revealed that PLSR was feasible to map chemical component concentration (TSS)distribution of mulberry fruits. This research provided a theoretical basis for developing the instrumentfor measuring the internal quality of fruits and made it possible to sort mulberries based on TSS spatialdistribution.

3.2 PCAFeatures

PCAisanimportantmethodforfeatureextractionandimagerepresentation.InPCA,matrixtransformationoftheimage takesplace intohighdimensionvectorsanditscovariancematrixisobtainedconsuminghigh-dimensionvectorspace. PCAisadimensionalityreductiontechniquethathasfourmainparts:featurecovariance,eigendecomposition, principal component transformation, and choosing components in terms of explainedvariance. The purpose of this blog is to share a visual demo that helped the students understand the finaltwosteps.

Principal component analysis (PCA) is a technique for reducing the dimensionality of such datasets,increasing interpretability but at the same time minimizing information loss.[8] It does so by creatingnewuncorrelatedvariablesthatsuccessivelymaximize variance.

Thefollowingrepresents6 stepsofprincipalcomponent analysis (PCA)algorithm:

- Standardize the dataset: Standardizing / normalizing the dataset is the first step one would needto take before performing PCA. The PCA calculates a new projection of the given data setrepresentingone ormorefeatures. Thenewaxesarebasedonthestandarddeviationof the value

of these features.So,afeature / variable with ahigh standard deviation will have ahigherweight for the calculation of axis than a variable / feature with a low standard deviation. If thedata is normalized / standardized, the standard deviation of all fetaures / variables get measuredon the same scale. Thus, all variables have the same weight and PCA calculates relevant axisappropriately. Note that the data is standardized / normalized after creating training / test split.Python'ssklearn.preprocessingStandardScalerclasscanbeusedforstandardizingthedataset[12].

- Construct the covariance matrix: Once the data is standardized, the next step is to create n X n-dimensionalcovariancematrix,wherenisthenumberofdimensionsinthedataset.Thecovariance matrix stores the pairwise covariances between the different features.Note that apositivecovariancebetweentwofeaturesindicatesthatthefeaturesincreaseordecreasetogether, whereas a negative covariance indicates that the features vary in opposite directions.Python'sNumpycovmethodcanbeusedtocreatecovariance matrix.
- PerformEigendecompositionofcovariancematrix:Thenextstepistodecomposethecovariance matrix into its eigenvectors and eigenvalues. The eigenvectors of the covariancematrix represent the principal components (the directions of maximum variance), whereas thecorresponding eigenvalues will define their magnitude.[8]Numpylinalg.eig or linalg.eigh can beusedfordecomposingcovariancematrixintoeigenvectorsandeigenvalues.
- Selection ofmost important Eigenvectors / Eigenvalues: Sort the eigenvalues by decreasingorder to rank the corresponding eigenvectors. Select k eigenvectors, which correspond to the klargest eigenvalues, where k is the dimensionality of the new feature subspace (). One can usedtheconceptsofexplainedvariancetoselectthekmostimportanteigenvectors.
- Projection matrix creation of important eigenvectors: Construct a projection matrix, W, from thetopkeigenvectors.
- Training /testdatasettransformation: Finally,transform the d-dimensional inputtraining andtestdatasetusingtheprojectionmatrixtoobtainthe newk-dimensionalfeaturesubspace.

HerearethestepsfollowedforperformingPCA:

- Performone-hotencodingtotransformcategorical dataset tonumericaldataset
- Performtraining/ test split ofthedataset
- Standardizethetrainingandtestdataset
- Constructcovariancematrixofthetrainingdataset
- Constructeigendecompositionofthecovariancematrix
- Selectthemostimportantfeaturesusingexplainedvariance
- Construct projectmatrix;Inthecodebelow,theprojection matrix is createdusingthefiveeigenvectors that correspond to the top five eigenvalues (largest), to capture about 75% ofthevariance inthisdataset
- Transformthetrainingdatasetintonewfeaturesubspace

3.3 DeepFeaturesClassification

CNN is a neural network that extracts input image features and another neural network classifies theimage features. The input image is used by the feature extraction network. The extracted feature signalsareutilizedbythe neuralnetworkforclassification.

Hyperspectral imaging measures the spatial and spectral features of an object at different wavelengthsranging from ultraviolet through long infrared, including the visible spectrum. Unlike color imaging,which uses only three types of sensors sensitive to the red, green, and blue portions of the visiblespectrum, hyperspectral images can include dozens or hundreds of channels. Therefore, hyperspectralimagescanenablethedifferentiationofobjectsthatappearidenticalinanRGBimage.

LoadHyperspectralDataSet

The data set consists of a single hyperspectral image of size 145-by-145 pixels with 220 color channels.The data set also contains a ground truth label image with 16 classes, such as Alfalfa, Corn, Grass-pasture,Grass-trees,andStone-Steel-Towers.

PreprocessTrainingData

Reduce the number of spectral bands to 30 using the hyperpca function. This function performs principalcomponent analysis (PCA) and selects the spectral bands with the most unique signatures. Split thehyperspectral image into patchesof size 25-by-25 pixels with 30 channels using the create ImagePatches From Hypercube helper function.[13] This function is attached to the example as a supportingfile.Thefunctionalsoreturnsasinglelabelforeachpatch,whichisthelabelofthecentralpixel.

CreateCSCNNClassificationNetwork

DefinetheCSCNNarchitecture.

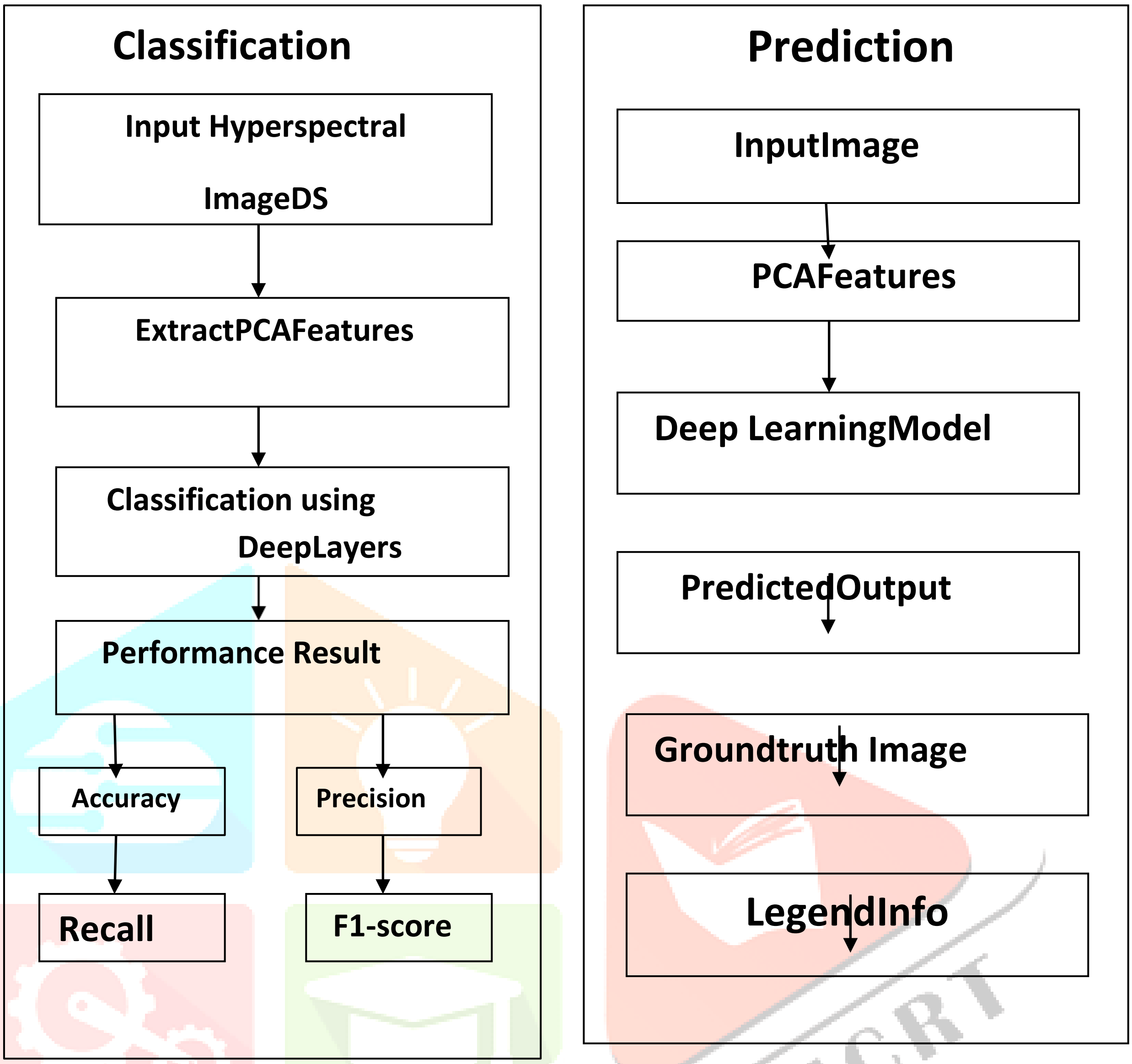
SpecifyTrainingOptions

Specifytherequirednetworkparameters.Forthisexample,trainthenetworkfor100epochswithaninitiallearningrateof 0.001,a batchsize of256,andAdamoptimization.

ClassifyHyperspectralImageUsingTrainedCSCNN

Calculatetheaccuracyoftheclassificationforthetestdataset.Here,accuracyisthefractionofthecorrectpixelclassification overalltheclasses.

3.4 ARCHITECTUREDESIGN



3.5 EXISTINGSYSTEM

The high dimensionality of hyperspectral image data and the lack of labeled samples can lead to theHughes phenomenon . Earlier in the research of hyperspectral image classification, people often focusedon spectral information, using only spectral information to achieve image classification, and developedmany classificationmethods,such as support vectormachine (SVM), random forest(RF), neuralnetworks , and Polynomial logistic regression . Dimension reduction methods such as feature extractionandfeatureselectionhavealsobeenproposed,suchasprincipalcomponentanalysis(PCA),independentcomponentanalysis(ICA),andlineardiscriminantanalysis(LDA).Theotherisanonlinear feature extraction method. For example, in 2000, the local linear embedding (LLE)algorithmpublished by Science of Roweis and Saul in Science projects local high-dimensional data points into alow-dimensionalcoordinatesystem.Theoverallinformationisobtainedbysuperimposinglocalneighborhoods,maintainingthesametopologicalrelationship,andretainingtheoverallgeometricproperties. At the same time, Tenenbaum et al. proposed (Isometric Feature Mapping, ISOMAP)analgorithm based on the classic MDS .[9] It uses geodesic distance to embed high-dimensional data intolow-dimensional coordinates. The neighborhood structure between high-dimensional spatial data pointsis still retained in low-dimensional coordinate space. Belki and Niyogi proposed a similar pull to LLE in2001. Laplacian Eigenmap(LE) , also known as Spectral Clustering

(SC); these nonlinearfeatureextractionmethodsareusedinclassificationforpracticalapplications.

It is worth noting that deep learninghas excellent capabilities in image processing. Especially in recentyears, image classification, target detection, and other fields have set off a wave of deep learning. Somedeeplearningnetworkmodelshavebeenusedinremotesensingimageprocessing,suchastheConvolutional neural network (CNN), deep belief network (DBN)and recurrent neural network (RNN).Moreover, in order to solve the problem of poor classification results due to the lack of training samples,a new tensor-based classification modelwas proposed. Experiments confirmed that this method issuperiortosupport vectormachinesanddeep learningwhenthenumberoftrainingsamplesis small.

3.6 PROPOSEDSYSTEM

The paramount challenge for HSI classification is the curse of dimensionality which is alsotermed as Hughes phenomenon. To confront with this difficulty, feature extraction methods are used toreduce the dimensionality by selecting the prominentfeatures.In unsupervised methods,the algorithmor method automatically groups pixels with similar spectral characteristics (means, standard deviations,etc.)intounique clustersaccordingtosome statisticallydeterminedcriteria.Further,unsupervisedclassification methods do not require any prior knowledge to train the data. The familiar unsupervisedmethods areprincipalcomponentanalysis(PCA)andindependentcomponentanalysis (ICA).

Principalcomponentanalysis

It is the most widely used technique for dimensionality reduction. In comparative sense, appreciablereduction in the number of variables is possible while retaining most of the information contained by theoriginal dataset. The substantial correlation between the hyperspectral bands is the basis for PCA. Theanalysis attempts to eliminate the correlation between the bands and further determines the optimumlinearcombinationoftheoriginalbandsaccountingforthevariationofpixelvaluesinanimage.

CHAPTER 4

EXPERIMENTALRESULTS

Implementation of a software package refers to the installation of the package in its realenvironmenttothefullsatisfactionoftheusersandoperatingsystem.Inshort,implementationconstitutes all activities that are required to put an already tested and completed package into operation.Thesuccessofanyinformationsystemliesinitssuccessfulimplementation.

4.1 DATASETS

The various benchmark data sets of HSI are generally utilized for assessing the performance oftheproposedmethodsfordiversefieldsofapplication.ThedatasetincludeIndianPines,PaviaUniversity, Pavia Center ,Kennedy Space Center, Botswana, Salinas, Salinas-Aand Washington images.In this work, the experimental results are exposed on three hyper spectral air borne images recorded bythe AVIRIS and the ROSIS sensors, with different contexts (agricultural and urban areas), differentspatialresolutions.

4.2 FunctionalDocumentation

Functional Documentation plays a vital role in describing thevarious functionalitiesofthe project. Basically, it considers the various forms designed for the project and explains variousfunctions associated with the form. As a matter of fact, each form is an integrated part of the project andhas its own,intendedfunctionality.Often,aformmayberelatedto otherforms intheprojecttoo.

In this section, I explain the functional documentation of the project. It considers various blocks of themodulesandtheassociatedforms.

Experiment on Indian Pines dataset : The Indian Pines dataset was gathered by AVIRIS (AirborneVisible/Infrared Imaging Spectrometer) sensor over the Indian Pines test site in North-western Indiana in1992. The Indian Pines (IP) dataset has images with 145 × 145 spatial dimension and 224 spectral bandsandthegroundtruth availableisdesignatedinto16classesofvegetation.Theexperimentswereconducted on the Indian Pinesdataset with differentnumbers of training and testing samples.Someother experiments we performed involved observing the effects of different spatial window sizes and theeffects of number of PCA components. We found 30 to be the optimal number of PCA components forthis particular dataset. It is also observed that the proposed method outperforms most of the state-of-the-artmethods.

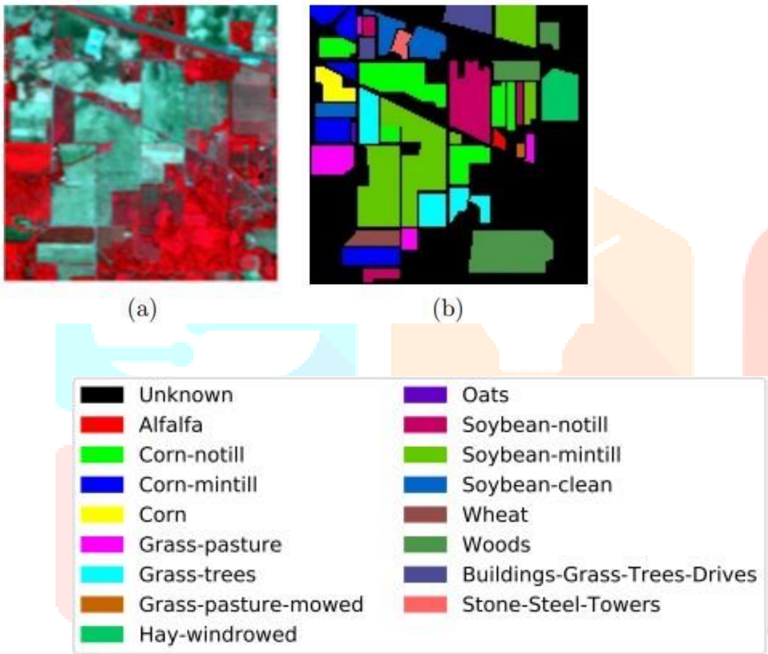


Figure4.1TheClassificationMapforIndianPines

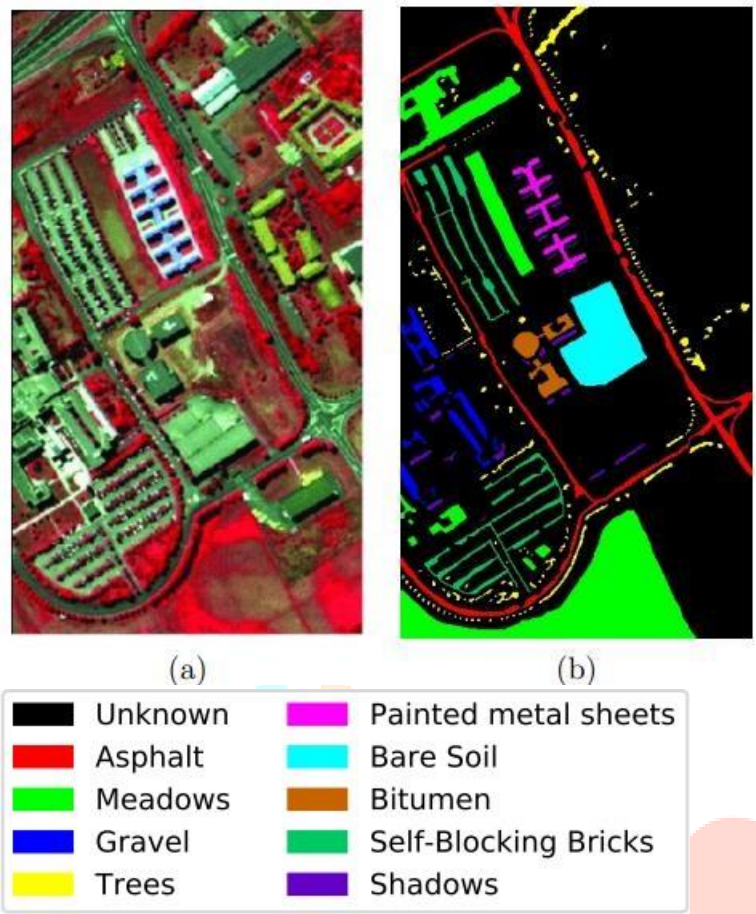


Figure4.2TheClassificationMap forPaviaUniversity

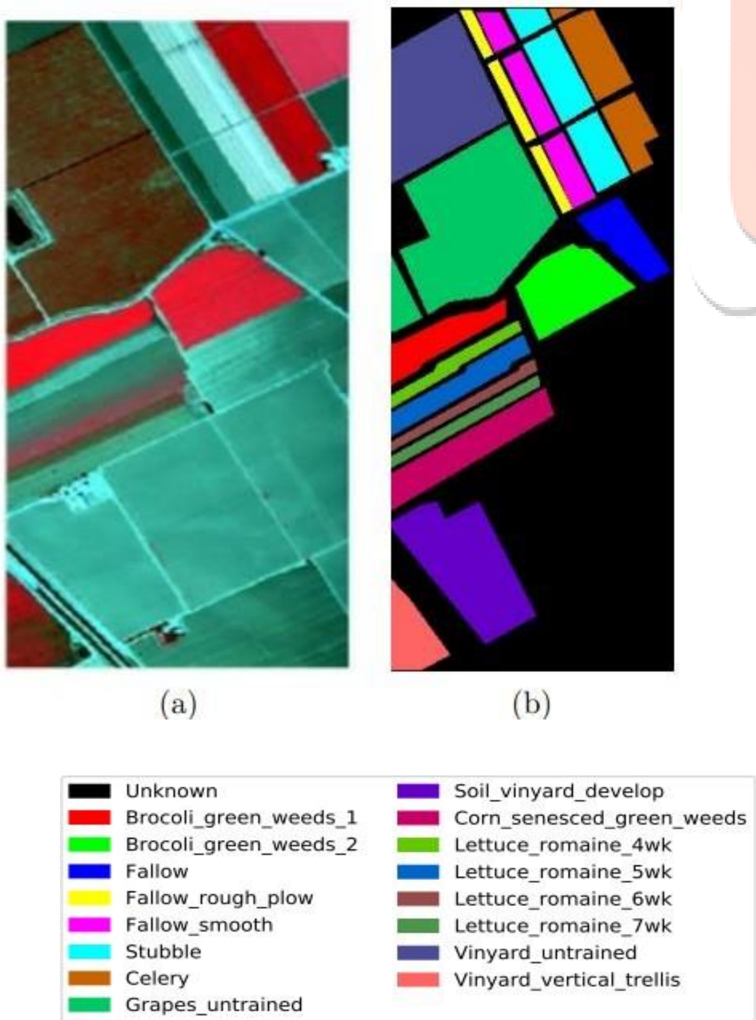


Figure4.1TheClassificationMap forSalinasScene

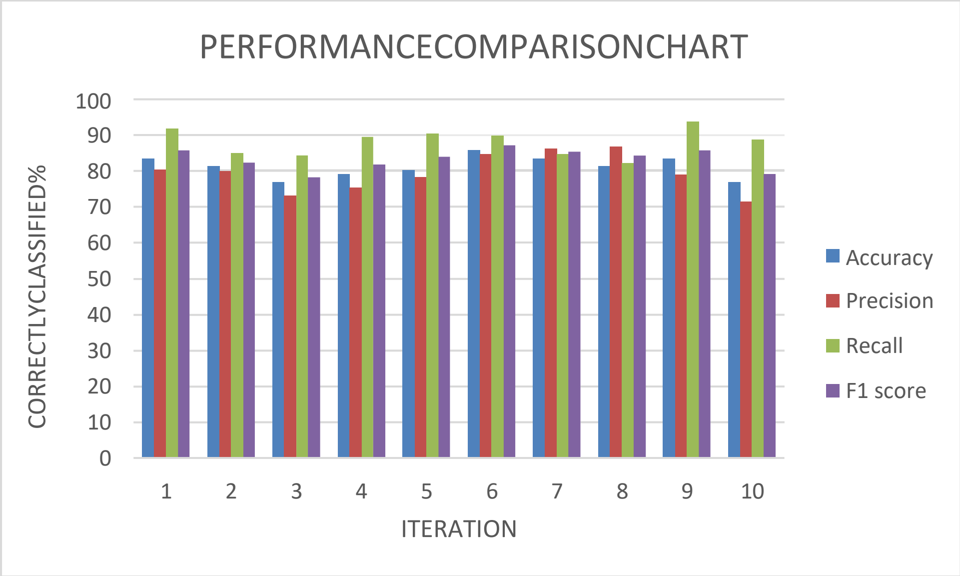


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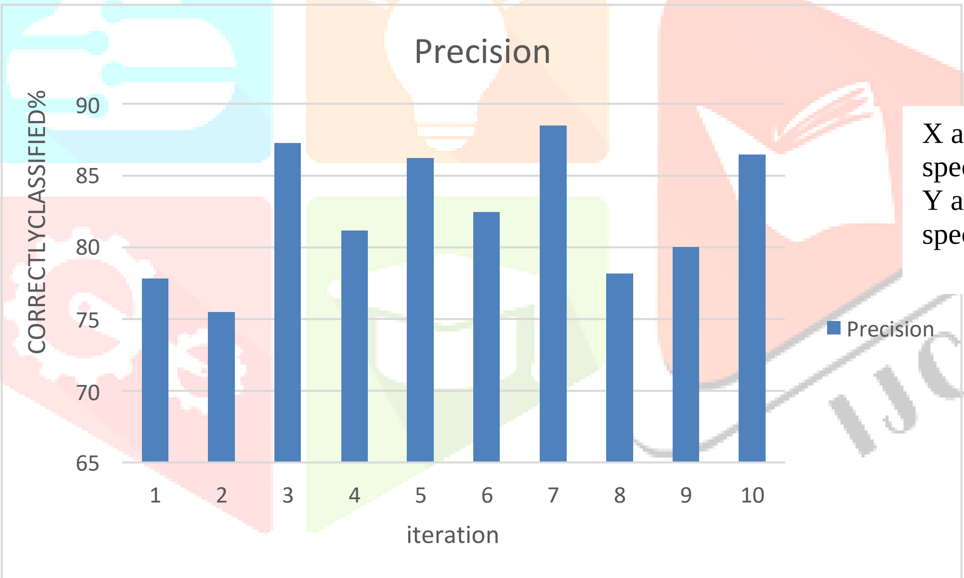
Table1.2CSCNNPERFORMANCE WITHTEMITERATION

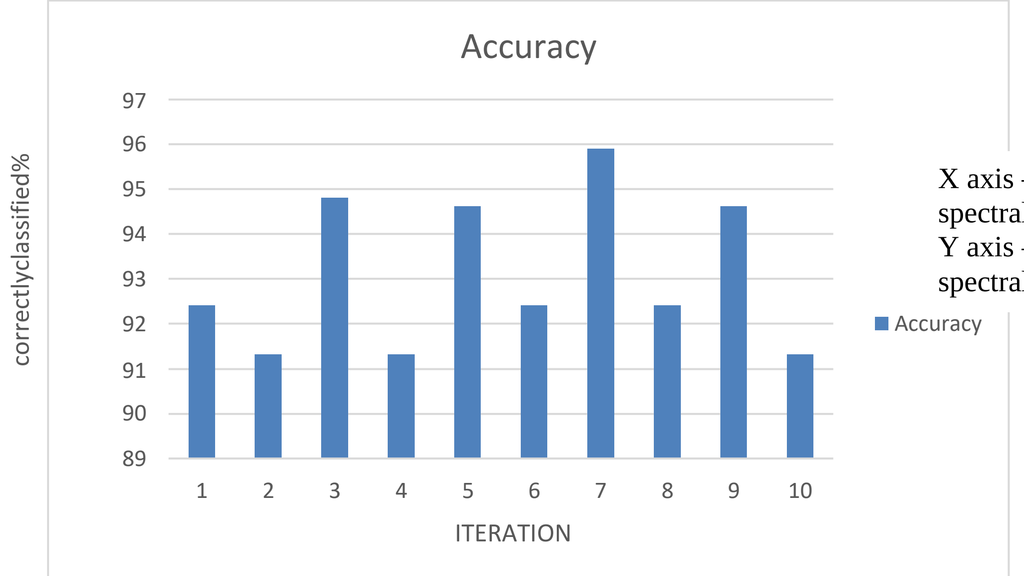
Iteration	Accuracy	Precision	Recall	F1score	TimeComplexity
1	83.52	80.36	91.84	85.71	0.8351
2	81.32	80.12	85.11	82.47	0.8131
3	76.92	73.08	84.44	78.35	0.7692
4	79.12	75.44	89.58	81.9	0.7912
5	80.22	78.33	90.38	83.93	0.8021
6	**85.71**	**84.62**	**89.8**	**87.13**	**0.8571**
7	83.52	86.27	84.62	85.44	0.8351
8	81.32	86.79	82.14	84.4	0.8131
9	83.52	78.95	93.75	85.71	0.8351
10	76.92	71.43	88.89	79.21	0.7692

The above table shows the performance of the CSCNNsuch as accuracy, precision, recall and f1-scorewith time complexity. The overall accuracy of the CSCNN is upto 85.71%,,precision of the CSCNN is84.62%,RecalloftheCSCNNis 89.8%,f1-scoreis 87.13%andtimecomplexityis0.8571 milliseconds.



X axis –hyper spectraliteration
Y axis – hyper spectralclassification

Theabovechartshowstheaccuracywisechart.Theaccuracyhasobtainedupto96%.



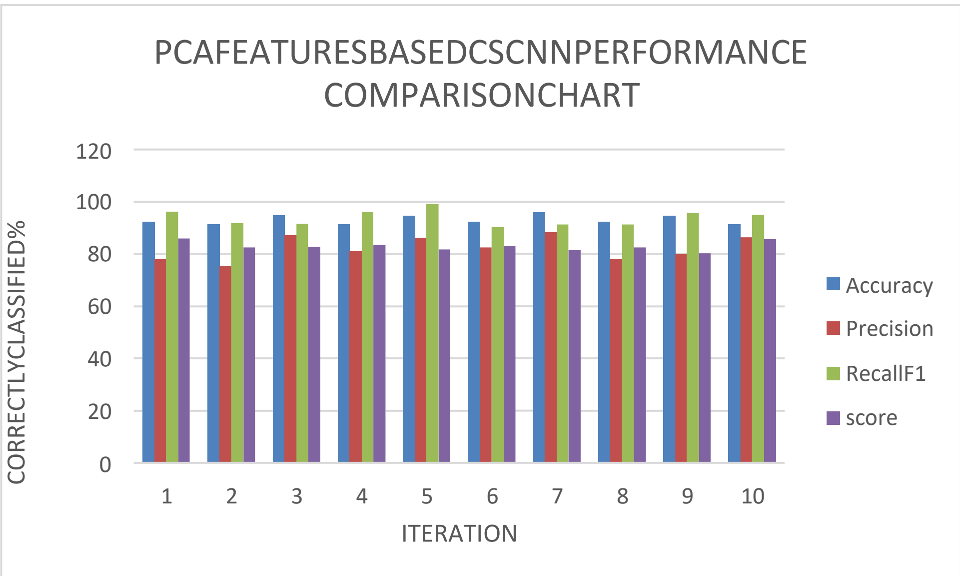
X axis –hyper spectraliteration
Y axis – hyper spectralclassification

Theabovechartshowstheprecisionwisechart.Theprecisionhasobtainedupto90%.

Table1.3CSCNNwithPCAfeatures

Iteration	Accuracy	Precision	Recall	F1score	TimeComplexity
1	92.42	77.78	96.25	85.96	0.8341
2	91.32	75.47	91.92	82.47	0.5248
3	94.81	87.27	91.57	82.88	0.8562
4	91.32	81.13	96	83.5	0.8041
5	94.62	86.21	99.29	81.67	0.8641
6	92.42	82.45	90.33	82.96	0.8421
7	95.91	88.46	91.25	81.46	0.8196
8	92.42	78.18	91.45	82.45	0.8412
9	94.62	80	95.69	80.2	0.8259
10	91.32	86.44	95	85.71	0.8031

The above table shows the performance of the PCA CSCNN such as accuracy, precision, recall and f1-score with time complexity. The overall accuracy of the PCA CSCNN is upto 95.71%,,precision of thePCA CSCNN is 84.62%, Recall of the PCA CSCNN is 99.8%, f1-score is 87.13% and time complexityis0.8571milliseconds.



The above chart depicts the performance of the PCA CSCNN such as accuracy, precision, recall and f1-scorewithtimecomplexity.

CONCLUSION

Classification and recognition of hyperspectral images are important content of hyperspectralimage processing. This paper discusses several methods of hyperspectral image classification, includingsupervised and unsupervised classification and semisupervised classification. Although the supervisedand unsupervised classification methods described in this article have their respective advantages tovarying degrees, there are limitations in the application of various methods. For example, supervisedclassificationrequiresacertainnumberofpriorconditions,andhumanfactorswillaffecttheclassification results have an impact. Therefore, based on different application requirements, combinedwith the acquisition of hyperspectral images with massive information, multiple methods need to becombined with each other in order to achieve the desired classification effect. With the development ofhyperspectralimage technology,hyperspectralimage classification hasbeenwidely used.Existingtheoriesandmethodsstillhavecertainlimitationsformorecomplicatedhyperspectralimageclassification.Therefore,researchingmoretargetedhyperspectralimageclassificationmethodswillbeanimportantresearchdirectioninthefuture.