APPLICATION OF MACHINE LEARNING TECHNIQUES FOR HYPERSPECTRAL IMAGE DIMENSIONALITY: A REVIEW

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ABSTRACT:

Dimensionality reduction for hyperspectral imagery plays a major role in different scientific and technical applications. The large and increasing number of remote sensing data is now readily available online with the rapid advancement of hyperspectral imaging technology. Machine learning provides the potential to efficiently classify spatial images efficiently. The major issue of this survey: The hyperspectral imagery enables the identification of multiple urban-related features on the surface of the earth, such as building, highway (road), tree, other natural and man-made structures. Since manual road detection and satellite imagery extraction is time-consuming and costly, data time and cost-effective solution with limited user interaction will emerge with automated road detection and building extraction techniques. Therefore, the need to concentrate on a deep survey for improving machine learning techniques for dimensionality reduction and automated building footprint and road extraction using hyperspectral imagery. The main purpose of this survey is to identify the state-of-the-art and trends of hyperspectral imaging theories, methodologies, techniques and applications for dimensional reduction. A different type of machine learning algorithm is partly included such as artificial neural networks, Self-Organizing Maps, Support Vector Machine (SVM), DT, etc. including an overview of the concept of deep learning. These algorithms can handle high dimensionality data map classes with complex features and comparison studies with different methods. Finally, it proposes to look for the dimensionality reduction of hyperspectral imagery, automated building footprint extraction, automated road detection and smart city enhancement using machine learning and deep learning techniques.

KEYWORDS: Hyperspectral Image Analysis; Machine Learning Algorithms; Hyperspectral Applications; Image classification.

I. INTRODUCTION

Remote hyperspectral detection also referred as to spectroscopy, it reflects a full use of field-vegetation, resources and land use/terror monitoring by scientists and researchers. While this information has been available since 1983 in various fields of engineering and science, it is primarily used by many complicated factors. For many years' scientists, in particular, physicists have used spectroscopy for the identification of material composition. In the field of analytical chemistry, many techniques used for reflectance spectrum analysis have been developed. Identify the characteristics of the individual absorption by using solid/liquid chemical gassing bonds. Technological progress made it possible to extend image spectroscopy to satellite applications outside laboratory conditions in order to concentrate their applicants globally [1]. Hyperspectral was used synonymously with the spectrometer for imagery in some books. Not all the spectral bands can be used in the electromagnetic spectrum for remote sensing purposes. The consuming bands appear to be isolated where remote sensing is possible by atmospheric windows or areas. In these atmospheric windows, hyperspectral images are measurements. The remote sensing technology combines the imaging and spectroscopy of the hyperspectral in one system, which produces large groups of data requiring complex handling procedures. In general, data set hyperspectral consist of around 100 to 200 spectral bands which, in contrast to the multi-spectral data sets, possess only five to ten bands with relatively large bandwidths that are relatively small. The Hymap or hyperspectral mapper used for airborne and visible / IRS imagery (AVIRIS) is an example of a hyperspectral device. NASA first used in the early 1980s.

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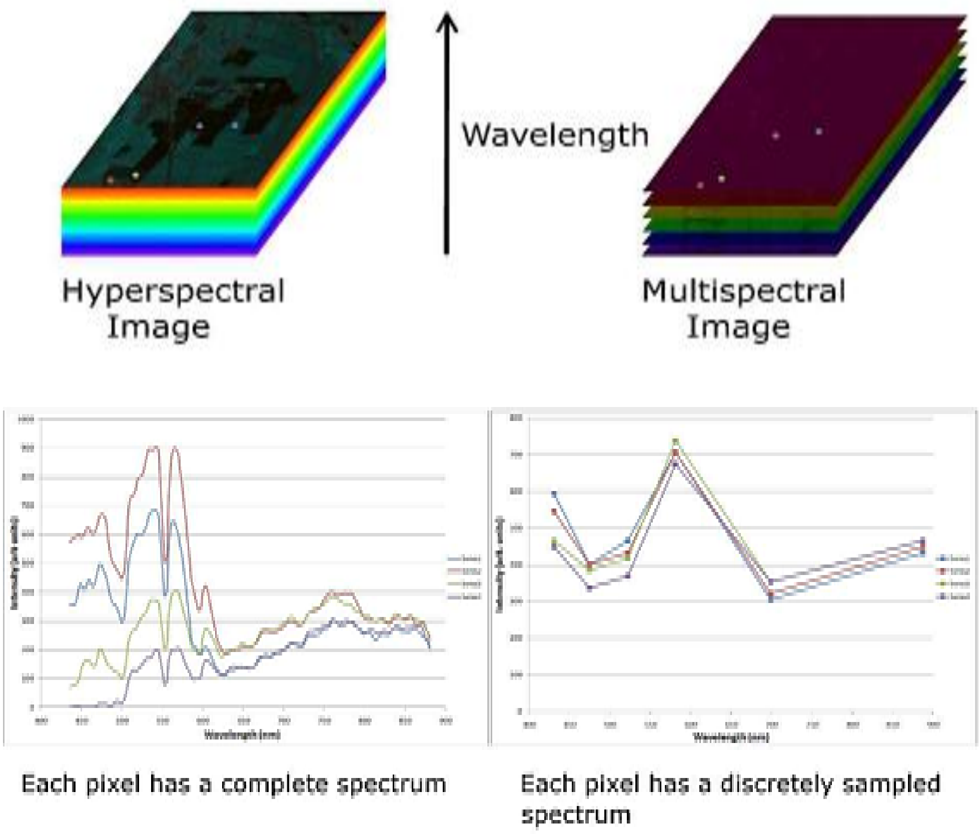
Fig 1: Multispectral Vs Hyperspectral Remote Sensing



3D imagery can be viewed as spatial information; data cube collected in X, Y level, where the information collected is presented in the Z direction in different bands, hyperspectral imagery in 3D space can be viewed. This enables us to see the hyperspectral images in two ways; first, the characteristics of a specific pixel/position point in a Z-direction based on the spatial patterns of an X-Y axis.

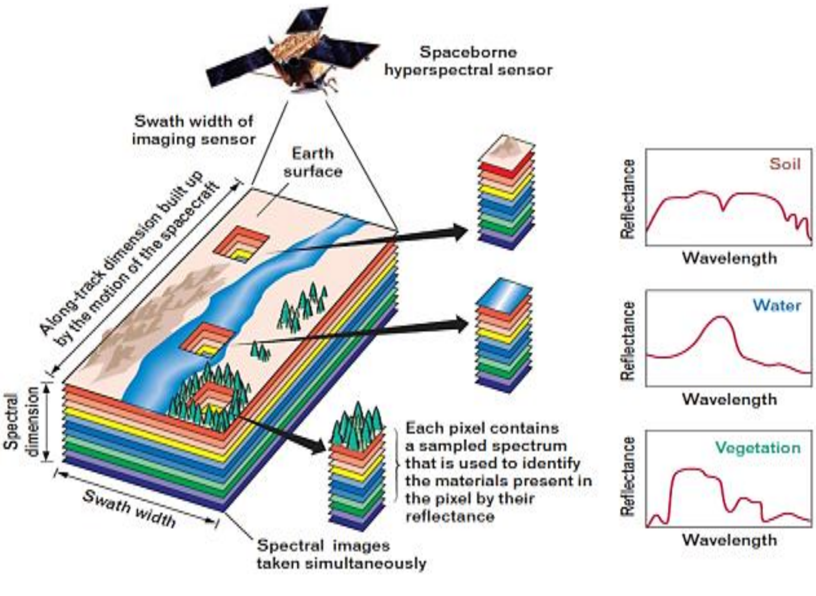


Fig 2: Concept of an Imaging Spectrometer

Hyperspectral remote sensor system records hundreds of relatively small bandwidth spectral bands (5 to 10nm) together with these details; it is greatly improved that unique tends have been detected and identified on the ground and atmosphere. It makes it possible to analyze land cover by far more specific. The emissivity levels of each band can be combined to form a spectral reflectance curve. Hyperspectral data may produce higher accuracy of the classification and a more detailed taxonomy. But it is also a unique challenge to classify hyperspectral data [2].

A. Dimensionality reduction

Dimensionality reduction (DR) methods keep hyperspectral image interpretation thoroughly studied and appropriate Commonly, a set of the preprocessing method, dimensional reduction processes is sufficient to overcome very high-dimensional data to the availability of the low-dimensional distance, where the information search can be made in a larger efficient and strong way. Two main classifications, such as transformation-based dimensionality reduction (TDR) and band selection-based dimensionality reduction (SDR) can be reviewed in the article discussed. The original data into a compressed space takes into account basic elements which are the first process. The main classical approaches include the main Folded- PCA, Principal Components Analysis (PCA), Independent Component Analysis (IPA), Orthogonal Subspace Projections (OSP), Minimum Noise Fraction (MNF), The applications for hyperspectral image (HIS) were fully united.

B. Feature Selection

The selection of feature is a significant step in analyzing the high-spectral image needed for a small number of examples compared to numerous characteristics which cause the harsh phenomenon. We can divide three categories of feature selection algorithms such as filtration, wrapper, and embedded techniques, in a variety of highly correlated and immaterial features [4].

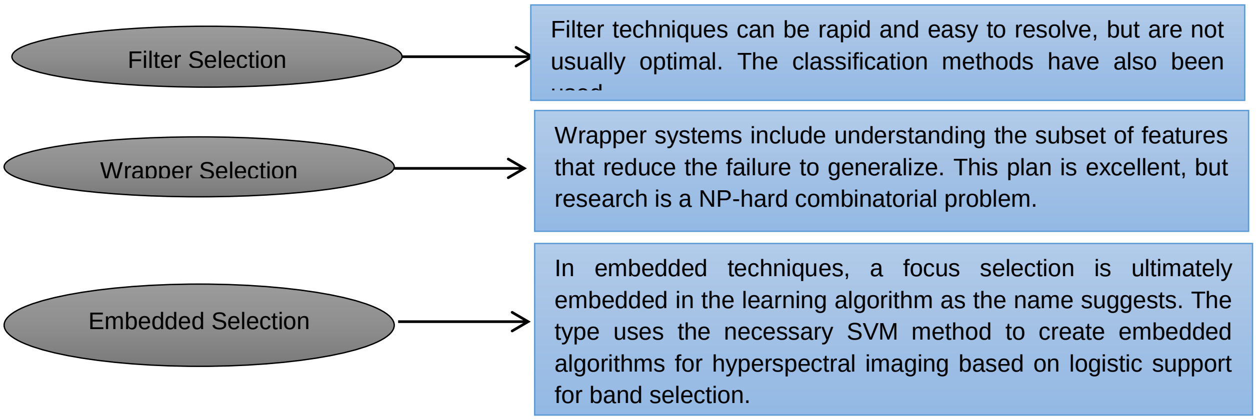


Fig 3: Feature Selection Algorithm

C. Feature Extraction

Feature extraction has primarily been investigated by a data mapping technique that establishes a subspace of suitable dimensionality M from the actual dimensionality space N ($M \leq N$) the characteristic extraction can be linear or non-linear. Must be designed the feature extraction algorithm in order to keep interesting data on a certain issue such as de-noise or compression and classification. For example, the classification of the hyperspectral image is better because the separation of the processing class is more efficient. In feature extraction, a main component process technology has been commonly used [5].

D. Principal Component Analysis (PCA)

The standard main principal components analysis is used to decrease dimensionality. The method of dimension reduction was usually implemented by the PCA. The PCAs converts the presented attribute space (here: the hyperspectral bands have all spanned feature space) to different feature space crossed by linear meta-features. The PCA showing the variability of the data displayed, including a specific dimension. The greatest variation is, therefore, the meta-functions of the various related data are processed In the case of a PCA-based feature ranking, the sorting-meta, the sorting meta-feature of the data variability, a subset of the PCA collection characteristic, apply a set of several important meta-features, containing 99.9% of the data variance, and suppose no significant decrease is achieved in imports. It is also assumed that the number of important data is not significantly reduced [6].

E. Methods for Road Extraction: General Classification

A review of state-of-the-art automated road extraction has been submitted. This research can used to collaborate on this subject as a detailed summary. A number of methods and suggestions have been considered, including a comment on a number of them [7].

Due to the various kinds of literature, proposals already in existence, classification of studies and different techniques for automated and semi-automatic methods of road extraction and related work are very difficult. In order to achieve this, it can choose the main factors. The preset target, the removal method and the type of sensor used are the following factors. Schematically in table1: is presented the proposed classification of road mining methods

and works. Obviously, in order to deal with this structure at the same time. Next, classification shall be drawn up in accordance with the predefined target and classification by extraction method. Classification by sensor type is not specifically established because it is contained implicitly in the other two categories.

Table 1: General Classification of road extraction methods and works

According to the preset objective:
• Road extraction, general methods
• Road network reconstruction methods
• Segmentation general methods
• Vectorization methods
• Optimization methods
  ○ Neural networks
  ○ Genetic algorithms
  ○ Other optimization methods
• Evaluation methods
• Other objectives
	Low and medium level techniques have been used according to the extraction method.
	• Road tracking methods
	• Morphology and filtrate
	• Dynamic programming and snakes
	• Segmentation and classification
	• Multi-scale and multi-resolution
	• Stereoscopic analysis
	• Multi-temporal analysis
	• Other techniques

According to the type of sensor utilized • Another type of sensor • Monochromatic imagery • Infrared band • Color imagery (RGB) • Multi-and hyperspectral imagery (HYDICE) • Synthetic aperture radar imagery (SAR)	**Mid and high methods** Knowledge representation and fuzzy modeling ○ Logic systems ○ Rules-based systems ○ Blackboard systems ○ Frames based systems ○ Semantic networks ○ Fuzzy logic-based systems Other methods of spatial reasoning

A various earth remote sensing problems that can be used to address health information receive data to a hyperspectral imaging spectrometer. The hyperspectral imagery requires preparing the classifications for many applications which perform two basic objects 1) identify also analyze each component substance to every pixel within each image; 2) minimize that information amount dimensionality, out a loss about censorious data, so which can be executed systematically including confirmed on a human investigator. The small list of applications involves geological study, wetlands mapping, plant and mineral recognition, also wealth opinion, environmental mapping, global change research, bathymetry, and crop analysis. The general aim in each from some applications implies essentially for every classification about every pixel within that image also decreases in the input amount to the manageable size. The demerits are covered the high-resolution aerial images and, are extremely complex in context. So need to reduce the **time-consuming and costly** and improvising the classification accuracy using hyperspectral imagery [56].

Approached orthogonal subspace projection (OSP) operator, This executive exists an optimal, interference destruction method into each shortest intersection though. An operator can be enlarged on k signs about a concern, thus decreasing some dimensionality like k moreover analyzing specific hyperspectral image concurrently. This method implies connected into both spectrally simple because, well-being, combined pixels [8].

Presented a method is the Hierarchical Multi-classification framework in the difficult classification issues involving a moderately large number of classes? A problem with land cover classification with hyperspectral data is illustrated in the proposed method: A 12-class AVIRIS subset with 180 bands. The classification precisions extracted were superior to most of the other methods for hyperspectral classification of this problem. In addition, the class hierarchies that have been automatically found conformed well to the opinions of human domain experts, showing that such a modular approach is able to automatically discover domain knowledge using the data [9]. Present new lossless compression methods that have been presented by combining and comparing existing methods with AVIRIS images. The methods cover the self-organizing map (SOM), the primary analyzing of components (PCA) and the transformation of three-dimensional waves combined with traditional lossless coding techniques [10].

Strongly addressed pattern recognition algorithms focused on object hyperspectral imaging. The layout of structures is complicated by the existence of multiple levels, such as retina/spectrum, artifacts, materials, and classification [11]. Presented to useful feature extract in the hyperspectral classification images through a new extraction feature method on the basis of matching pursuit (MP). The corresponding pursuit method uses an avaricious strategy in order to find the hyperspectral information sequentially and optimally from a strongly redundant dictionary of wavelet packaging [12]. The suggested technique for dimension reduction and classification of hyperspectral remote sensor images based on an ant colony algorithm. As regards the correlation between bands, the hyperspectral data area in high dimensions is divided into multiple colony algorithms into low dimensions (ACA). The main component analysis is then used to extract characteristics in the subspace, whereas the classification of the hyperspectral picture is done by the high probability classification [13].

Present a comparison of various techniques of aerial image and laser data automated building detection at various spatial resolutions. Five methods for two fields of study, using both pixel and object-level features, but with strong requirements for all methods to use the same set of training [14]. Provide for the automatic extraction of high-resolution remotely sensed imagery of the new morphological building index (MBI). The MBI is basically concerned with establishing a link between building explicit (e.g., contrast, luminosity, and size) and morphological operator properties (e.g., reconstructing, granulomere and orientation). The Building is extracted by the MBI feature image threshold. Consequently, for refining the binary building map the shape features, such as area and length ratio are used [15]. Presented the Eigen map modularity reduction algorithm, based on the approach for modularity maximization in clusters, then modularity was compared with the well-known Laplacian maps as a preprocessing step in the classification of hyperspectral images [16]. The reported technique for recognition of an urban pattern in medium and very high-resolution of multi-spectral satellite images used this performance evaluation structure; in addition, machine learning algorithms are part of contemporary object-based image research. The four analysis algorithms are K-Nearest, Normal Bayes, Support Vector Machines, and Random Tree [17].

Suggested remote image classification method through the use of sparse deep learning created by hierarchical structures comes with deep features. Although the deep features can be large, they are located in subspaces or in sub-manifolds dependent on the class [18]. Introduced building recognition; it is addressed by a binary classification task on the basis of profound learning functions. The deep attributes measured can account for the inbuilt discrimination in the buildings of the influential CNN, Alex network and also by incorporating spectral information during the training process [19]. Presented a Spectral-Spatial Classification Framework (SSFC) that is for spectral and spatial feature mining, jointly utilizes dimensional reduction and profound learning techniques respectively. In this context, a balanced local discriminate embedding algorithm is given for spectral extraction from high-dimensional hyperspectral data sets [20]. Presented a spatially discriminatory deep faith updated (SDBN) network, using spatial information effectiveness for the HIS classification within spectral identical contiguous pixels. The approach proposed divides HSI into adaptive spatially similar boundary adjustment regions, following a similar function, whereby object-level extraction is carried out with a deep belief network fusion approach (DBN), which includes contextual and spectral information spatially segmented as part of an effective spectral system's DBN framework [21]. Proposed an unsupervised technique for hyperspectral image band selection that takes in order to reduce data dimensions, spectral and spatial information are taken into account. This method takes advantage of the concepts of superpixels and chuckles to identify the spectral channels best suited for classification in the discriminating classes of land over [22]. Submitted a 3DCNN classification approach based upon parameter optimization and in conjunction with transfers and virtual samples is proposed to solve insufficient samples and improve the classification of HSIs. First, the 3D-CNN parameters can be adjusted by the variable principle. Second, initial weights can be converted from another well-trained 3D-CNN with source data from the parameter optimized bottom 3D-CNN layers of the specific data [23]. Recommended the problem of data classification for hyperspectral imagery with a large data set size. Dimensionality reduction and deep learning techniques were used to reduce the computational burden and improve classification accuracy. The most reliable measures for the reduction of dimensionality and also the proposed neural network shall be analyzed with precision success [24]. Using image processing to described deep learning methods and as well as features extracted from video, text, audio, and images. The method of deep learning is very advanced to predict the accuracy of the high classification [54]. Presented a classification framework multi-class video-based. The support vector machine (SVM) by integrating Principal Components Analysis (PCA) to accomplish classification tasks. PCA integrated feature reduction dimensionality to reduce the classification complexity of multi-class SVM [55].

II. HYPERSPECTRAL IMAGE ANALYSIS

The hyperspectral sensors allow the identification and discrimination of different earth surface characteristics, they suffer from disadvantages. Some include increased data volume, poor noise-to-noise ratios, and atmospheric interference. Hyperspectral image analysis, therefore, uses physical and biophysical models to absorb light at specific wavelengths than other statistical techniques. Light is absorbed by air gasses and aerosols at special wavelengths. Atmospheric diminution in the form of dispersion (add to the sensor area of perspective an outside radiance source) and absorption (radiance denial). As a result, a hyperspectral sensor cannot compare the radiance recorded with the imaging generated at other times/locations. The techniques used in hyperspectral image analysis are derived from spectroscopy, which refers to the various absorption or pattern of reflection of context at a different wavelength of the particular material molecular composition. This image must be subject to appropriate techniques of atmospheric correction in order to compare each pixel's reflection signature against the spectrum of known material; in laboratories and in 'library' storage areas known materials spectral information like soils, minerals, type of vegetation's, etc. The reference spectrum is compared to the spectral reflectance obtained by different. To identify every absorption characteristic by choosing the spectral band at the bottom of the two bands in each hand. The image data are ranging from this method for noise. Overlapping absorption features are also difficult to handle.

This approach has helped with a rise in computer systems to compare whole spectral signatures and no single absorption characteristics in a signature. Another method is the rationing of the spectrum; divide each reflective value by the corresponding range value in the range. The drawback of this technique is that the mean image spectrum light is no longer or smaller than the average reference light spectrum as seen on a topographic shaded route. Spectral angle mapping (SAM) has been another technique frequently used. This method considers a measured reflection multidimensional spectrum vector. It allows the spectral bands to be equal to the number of dimensions. Although the total luminance increases/decreases, this approach has the advantage to increase/decrease the vector length its angular orientation remains constant. In order to compare the two spectrums, the multidimensional vector must be specified for each spectrum and the angle between the two spectrums must be determined. Even one spectrum is brighter than the other, a corner value that is less than which the result will be a match (between the library reference and the spectrum of the pixel image). The areas of hyperspectral dimensional vector sensors with 300 bands are hard to view that. There are different ways of processing hyperspectral imagery. Although the whole topic in this module can never be covered, two techniques are addressed below.

- Derivative Analysis
- Atmospheric Correction

Derivative Analysis

Regards to a two-dimensional function with pixel value (DN number) associated with each row (r) and column (c), a digital image may be represented in such a way that the pixel value is represented = f (r, c) but for all possible

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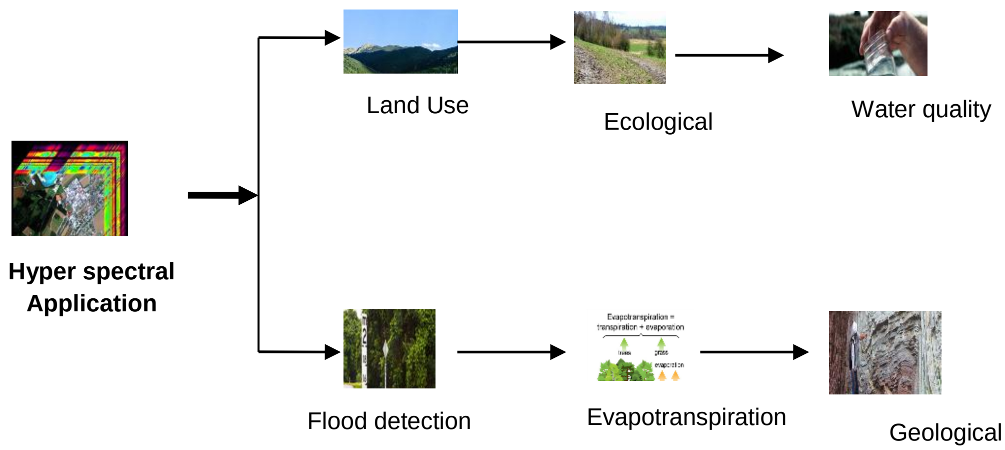
values of r and c, this function is not continuous and therefore non-differentiable in nature. The technique of variations is therefore adopted in order to assess at a specific stage the rate of change. Assume the spectral reflection curve of a target is collected by a hyperspectral sensor. Let Yi and Yj denote the neighboring, separate reflectance of the curve at wavelengths Xi and Xj to allow the expression to indicate its first difference value. The first difference in range along the x-axis basically results in a similar rate of change in function y, and the second distinction can also be seen, showing how fast the path changes with a distance along the x-axis. In the single-dimensional and two-dimensional spectrum, the first and second calculate differences provide an approach to derivatives of a un-specifiable function. In a derivative study, it is possible to estimate the position and magnitude of the absorption bands in the pixel spectrum. Derivative methods aim to intensify the noise when the information is present. Hyperspectral data, therefore, range from simple methods of filtering, more complex methods for wavelets to various modes of removing noise [25].

Atmospheric Correction

As previously mentioned, the atmosphere influenced distant sensors through the two main dispersion and absorption stages. More marked are the impacts of water vapor with reduced ozone, carbon dioxide ect., the principal phase of the analysis is the conversion of information into values that allow comparison with lab libraries or field information between individual spectra. The data are this lab configuration allows the initial wavelengths to be calibrated. The atmospheric narrow ranges of 0.69, 0.71 and 0.76m. It can be used for example to calibrate wavelengths invisible and close-infrared electromagnetic spectrum regions. The estimate of an average spectrum for an entire image spectrometer data set is another method for the calculation of internal average relative reflectance. This can be used to separate each spectrum by the average spectrum in the data set. It should be noted all these techniques tend to generate images and spectrums that possess similar characteristics to reflect.

III. APPLICATIONS OF HYPERSPECTRAL



A. Land use applications

Generally, the processing of digital images (for example, controlled and unattended classification) is used in remote sensing images. The possibility of land use classification is increasing the availability of enhanced spatial and spectral resolution hyperspectral information. This data collected in specific spectral bands complement existing information from typical remote sensed images. The vegetation mapping should be mentioned especially because, in its different stages of growth, it has unique spectral signatures of a variable species. The hyperspectral imagery ensures improved classification due to the improvement in quality in the reference spectrum.

B. Ecological applications

A vegetation indicator derived from hyperspectral sensors is more sensitive and better than that obtained from optical images. For many applications, knowledge of the vegetation reflection spectrum is crucial. The biophysical factor which affects the spectrum of activity vegetation is leaf chemistry which is accountable for leaf spectrum absorption features in the visible waveband. Various vegetation has different curves of spectrum reflection characterized by vegetation indices. These indicators are primary relations that do not measure the steepness of the spectral reflecting curve in the red infrared area. With the help of hyperspectral sensor data, this steep increase in the reflection curve can be characterized by a single wavelength.

C. Water quality

Implicit use of the hyperspectral image was the classification of lake trophic status, the classification of algal blooms and the estimation of complete ammonia levels for monitoring changes in wetland most open water marine habitats have water quality. The content of chlorophyll is usually assessed with a remote sensor image which can then it will be used to track the content of algal and, hence, the water quality. The hyperspectral image improves chlorophyll and algal sensing in the small adjacent ranges.

D. Flood detection

Although the sensing remote satellite allowed in inundated areas to be monitored during floods or any other natural disaster, it was impossible to detect floods almost in real-time. In order to provide information about natural disasters such as flooding in real-time, sufficient space and temporal resolutions need prompt information on water conditions. This is possible with the use of sensors like Hyperion on the EO-1 satellite. Many USGS and NASA studies have been performing early warning systems for satellite-based precipitation observations, topography, soil humidity, evapotranspiration. In research on the development of a flood wave in a synthetic river channel, it can be used hydraulic information obtained through remotely controlled images. There's also a research project to calculate river leakage with microwave, satellite sensors in order to enhance altering systems.

E. Evapotranspiration (ET)

The different applications including irrigation, reservoir loss study, runoff prediction, climatic science, ect., information regarding Evapotranspiration is essential. Although it cannot be measured directly, hyperspectral sensors provide a way of estimating energy balance components for ET mapping spatially. AVHRR and MODIS data are typically used in the estimation of the evaporative fraction, which is an ET ratio with the radiant energy available. Further details could be found in the study of hyperspectral objects that can encourage the quality of spectral information by detecting the earth's surface properties. The analysis of large volumes of hyperspectral images is currently underway. This is important, as mentioned previously, in different applications such as aerosol verification, gas plumes, etc.

F. Geological applications

The remote sensing of hyperspectral is very likely to identify not only, but also to particular chemical and geometrical land patterns, which can be connected to the identities of precious mineral /oil deposits [26].

IV. MACHINE LEARNING CLASSIFICATION FOR HYPERSPECTRAL ANALYSIS

Classification is the method used to identify actual-world objects/land cover in remotely sensed images. Consider a multi-spectral image that has m bands. If the pixel is simplest, its features are expressed as a vector, where the vector elements represent the pixel's spectral features, these m bands are captured. Using certain indices or with prior can be determined by the number of classes. The pixels are classified in water bodies, forests, grasslands, agriculture, metropolitan areas, and other landforms. Classification identifies each pixel's land cover based on its spectral reflection value (or digit number). The method also consists of labeling a numeric value on a classification rule or a decision-making rule for each class entity. In this respect, the clustering method includes an exploratory process aiming to assess and attribution of the pixels to these groups of various soils covering classes in a region. The classification of images can be different. The two main types of classification are supervised and unsupervised. These two pixels labeling techniques can also be used to segment an image with similar attributes into regions. The spectral data currently in the bands can be used to define features/models. In other words, a pattern is identified in an image that is associated with each pixel position. Methods of pattern recognition in multiple engineering and scientific fields were commonly employed.

Supervised Classification

The location of types of land cover should be known a priori in a supervised classification technique. Training sites are known as areas in every land cover type. In order to produce multivariate statistical parameters for each of the locations, spectral features of pixel images within each land-covering type can be used. Since these techniques of controlled classification are based on statistical ideas, they are also referred to as a per-point and per-pixel grade. The generation of a scatter plot was the first technique utilized to visualize the distribution of spectral values measured against two features (for example, water body and farmland). Two different kinds of land use will be shown during a visual inspection. This illuminates two basic classification thoughts. The first thing which represents the selected features is using Euclidean space. Secondly to use the club's measurement or the approximation of pairs of points as a rule for the decision to classify the pixels as a water body and agricultural land Intuitive and easy in nature visual interpretation. The eye and brain recognize together the presence of two clusters or areas with a tight distribution of points in between them with a relatively empty zone. The supervised classifiers require the number of classes in advance and the prior knowledge of certain statistical features of each class [42].

Unsupervised Classification

Unsupervised classification needs minimal original input from the analyst compared to the supervised classification method. In multi-spectral feature space, the nature, grouping of spectral information present in pixels emerged. Unsupervised classification allows the computer to select the mean and covariance class matrices, which are further utilized for classification, instead of allowing the user to collect the training data. The system is left entirely to the automatic process of classification, so the name is not controlled. The client selects the number of clusters to be created. After classification, the analyst will assign these spectral groups to the valuable knowledge categories. In order for the clusters, they can be labeled as containing useful information or meaningless, the analyst should understand clearly the spectral characteristics of the terrain. For identifying the spectral classes created by an unsupervised classifier, the analysis relies on whatever reference information (surface truth) about the classified surface. For this reason, sometimes the term exploratory is used instead of unsupervised classification. In recent years, numerous clustering algorithms have been developed which different terms of clustering reliability and classification rules. All these algorithms require a certain type of iterative estimates to achieve optimal decisions for the information set [43].

In this section to examine the new techniques of hyperspectral image analysis and machine learning. In every section, techniques are discussed and using a specific type of machine learning algorithm.

Gaussian Models

Gaussian multivariate models for land cover classification and target detection from the basis for the most classic algorithms. The hyperspectral land cover classification algorithm is the Gaussian higher probability classificatory or only higher probability classification, which is the quadratic discriminatory method. In hyperspectral anomaly and goal detection, Gaussian models have also been widely used. Also, in more advanced algorithms Gaussian models can be found as components. Gaussian models are used to perform both active and transfer learning. This method used Gaussian distributions to model the class probabilities of the data. The database tasks defined above the probabilities of the class were used to iteratively remove examples from the training set which belonged to the source dataset and add examples from the training set.

Linear Regression

Linear regression is a commonly used technique of hyperspectral analytical information used for physical parameters estimation and unmixing. Linear regression is a controlled process that learns from the modeling of the output factors a linear connection as a weighted sum of the internet variables plus a constant of real input factors. The majority of research has reversal step by step. Most studies use step-by-step reversal. When used for linear unmixing, the reflection of observable spectrums is modeled on each band as a weighted sum of reflectivity of the end members of the band, with constant weights for all bands and the corresponding weights.

Logistic Regression

Logistic regression is a hierarchical method used mainly to characterize the soil cover of remote sensing. The distribution of class probability is modeled as the weighted sum of the input function 'logistical function. Logistic regression was used mainly for pixel-specific classification and is the building block of more advanced algorithms that use ensemble, random fields, and deep learning.

Gaussian Mixture Models

The mixture design represents the probability of data density and a weighted sum with a few Gaussian densities with different means and standard variations. The information is generally used for modeling non-Gaussian information in a few clusters in Gaussian. For modeling class probability in the highest possible classification, if the Gaussian properties do not display the image spectrum, the Gaussian model mixture is an excellent choice. The hyperspectral data were also clustered using the Gaussian mixture model. Gaussian model of the mixture, followed by connected component analysis into a homogeneous area segment of the hyperspectral image.

Clustering

Clustering is the grouping into homogeneous groups of unlabeled data. Unsupervised land cover classification of hyperspectral images was mainly applied to clustering algorithms. Band selection, semi-supervised classification, reduction in dimensionality and non-mixing were also used. K-means, ISODATA, meaning shift, dispersion of affinity, graph-based clustering and mixture of processes by Dirichlet is commonly used.

Affinity distribution is a method of clustering that utilizes the signal which goes between information points and does not involve a previous knowledge of the set of clusters. It is mainly used to group bands into an image and pick for each cluster a specified band. Graph-based clustering methods depict the graphic structure of information with node data centers and their resemblance with the edge and graphing cluster issue.

Normal Bayes (NB)

Normal Bayes (NB) is a simple prevention method, which allows the feature area in every other class to appear naturally. These indicate that the whole purpose of the distribution of information is considered as a Gaussian mixture with a separate class section. For all classes based on selection, training, the NB methods are utilized to measure Co-variation and mean vectors for prediction.

K-Nearest Neighbors (KNN)

K Classification methods for nearest neighbors (KNN) are classifications for every unlabeled case: K-nearest neighbors are split by training in the multidimensional function examples and are class methods that are designated in a particular neighborhood for the majority of a specific class. The nearest K neighbors are on the list to determine the distance to be examined between the un-labeling example, vectors and the set of training instances provided to the classificatory. The nearest neighbors are listed; the forecasts are based on the most or weighted lengths.

Random Trees (DT)

Furthermore, Random Tree (RT) was also offered as random forest and launched by Leo Breiman and Adele Cutler as a combined decision-making tree (DT). The DT manages a simple choice chain based on the effect of regular searches on the distribution of class labels. DT branches have made a number of decisions in which experiments are carried out on the tree nodes and class name leaves.

Support Vector Machine (SVM)

In a classification of the support vector machine, which discovers the theory of mathematical learning, Vladimir Vapnik has individually introduced it. For example, the standard pixel classification process is a pixel classification by using conventional classifiers, generally accepted, for example, Random Forest (RT) or Support Vector Machine (SVM) [12]. The SVM is a supervised learning technique based on the analytic theory. A good generalization and handling of non-linear grading kernels benefit SVM over other approaches to machine learning. A kernel function is used for designing non-linear splitting classes to provide an outstanding dimension of the original space where classes are not linearly divided by the original linear space [17].

Deep Learning

Deep learning techniques are based on information that produces an abstract and valuable representation through the hierarchy of non-linear transformations. Increasing the development of graphical processing units (GPUs), the availability of large-scale data sets and innovations in the field of deep network training such as dropping out, correcting linear units, residual learning, batch normalization, and thick connections have resulted in cutting-edge machine learning, voice recognition, and machine learning achievements. Furthermore, researchers in the remote sensing industry have developed numerous methods of high-quality, remote sensing data analysis based on the learning. The focus is currently on the classification task on land cover, but we can also expect profound training for further tasks in the future. A common, visionary architecture of deep learning is CNN (Convolution Neural Network). Inspired by the visual mammal scheme, these neural networks have a variety of convolution layers, non-linear layers, and layer bodies to learn low to high-level tasks. Each hidden layer unit in the convolution layers is connected to the local receiver filed around the entry via share weight (pixels in the neighborhood for images) rather than fully connected to the input. Layer with non-linearity does not perform the activation of the input. In the pooling layers, answers to input translation invariance are the max operations are summarized at several input sites.

V. RECENT ADVANCES OF HYPERSPECTRAL IMAGERY

Year's	Author's	Methods/Algorithms	Advantages
2019	Hong Huang, Zhengying Li and Yinsong Pan [27].	Manifold discriminant analysis (MFMDA), multi-feature classification.	The proposed MFMDA technique can enhance classification efficiency considerably and lead to smoother classification maps, respectively 95.43%, 97.19%, and 96.60%, as compared to some state-of-the-art techniques and less training samples.
2019	Lan Zhang, Hongjun Su and Jingwei Shen [28].	Super-pixel Segmentation, Kernel Principal Component Analysis (KPCA).	In most cases, the proposed method performs better than SuperPCA (by performing PCA on each Superpixel) based on single-scale segmentation or multi-scale segmentation.
2019	Weijia Li, Conghui He, Jiarui Fang, Juepeng Zheng, Haohuan Fu and Le Yu [29].	Deep Learning, U-Net-based Semantic Segmentation method.	The experimental results show that our proposed method increases the overall F1 score by 1.1%, 6.1%, and 12.5% compared to the top three approaches in the Space Net building detection competition.
2019	K. Dijkstra, J. van de Loosdrecht,L. R. B. Schomaker, M. A. Wiering [30].	Convolutional neural networks and end-to-end trainable method	All tests were carried out with a 4 × 4 image mosaic, but it can easily modify our similarity to integrate larger sensor mosaics. The method generates an image cube hyperspectral 16 times the current cube spatial resolution while maintaining a 0.85 median structure similarity (SSIM) index (compared to a 0.55 SSIM when using bilinear interpolation).
2019	K. S. Charmisha, V. Sowmya, and K.P. Soman [31].	Vectorized convolution neural networks (VCNNs)	The experiment results show that although there is a reduction in dimensions, a VCNN can achieve nearly the same accuracy in classification as that of raw hyperspectral image data.
2019	Tao Li, Jiabing Leng, Lingyan Kong, Song Guo, Gang Bai1 & Kai Wang [32].	Deep cube Convolutional neural network model	The number of well-designed studies tests the DCNR system absolutely. The results show that the high classification of the CNN cube with neighboring pixel spectral-spatial information can be achieved and that RF outperforms other models like RF (Random forest) and SVM indicating the DNCR model's performance.

2019	Ugur Ergul and Gokhan Bilgin [33].	Multiple kernel learning, Composite kernels.	The results show MCK-ELM's advantage in terms of accuracy as compared with others. It is also an effective solution because complex optimization tasks are not needed. Unlike classical CK methods, it is longer necessary to manually arrange the spectral and spatial parts.
2019	Utsav B. Gewali, Sildomar T. Monteiro and Eli Saber [34].	Machine learning techniques.	It provides the two-way map of the tasks of the analytical image and the various types of algorithms that can be used.
2019	Yang Zhao, Yuan Yuan, and Qi Wang [35].	Spectral clustering techniques, Unsupervised Hyperspectral image classification.	The suggested enhanced algorithm offers an effective solution for the classification of large-scale Hyperspectral images where the traditional spectral cluster is unable to handle.
2019	Bei Fang, Ying Li, Haokui Zhang, and Jonathan Cheung-Wai Chan [36].	Novel dense conventional network	It uses dilated convolutions to learn features at various scales rather than traditional scaling operations.
2019	J.T. McCoy and L. Auret [37].	Machine learning techniques	Interesting methods, challenges, and opportunities were identified as the three main categories of application identification (database modeling, fault detection and diagnosis, and machine vision).
2019	Philipp Schuegraf and Ksenia Bittner [38].	Fully conventional network	Presented an End-to-End U-shaped neural network, efficiently combined for binary building mask generation, that combines depth and specimen in two parallel networks.
2019	Qixia Man and Pinliang Dong [39].	Multi-resolution object-based classifier, Support vector machine classifier.	The SVM and object-based classifiers decision fusion outcomes, enhance the general classification precision by 5.00% (from 87.30% to 92.30%).
2019	Murinto, Nur Rochmah Dyah Puji Astuti, Murein Miksa Mardhia [40].	Particle swarm optimization, Fractional order Darwinian Particle swarm optimization.	A hyperspectral image dataset from 103 Aviris India Pines bands is used for this experiment. The experiments show that the FODPSO approach is better than the PSO and DPSO with respect to average processing time and optimum fitness value.
2019	Annalisa Appice and Donato Malerba [41].	Spectral-Spatial Classification	It takes account of the spatial addiction of spectral bands, addresses the dimensionality curse and deals with the spectral variability. In order to obtain an informative spectral-spatial joint representation, local spatial regularization of spectral information is used.

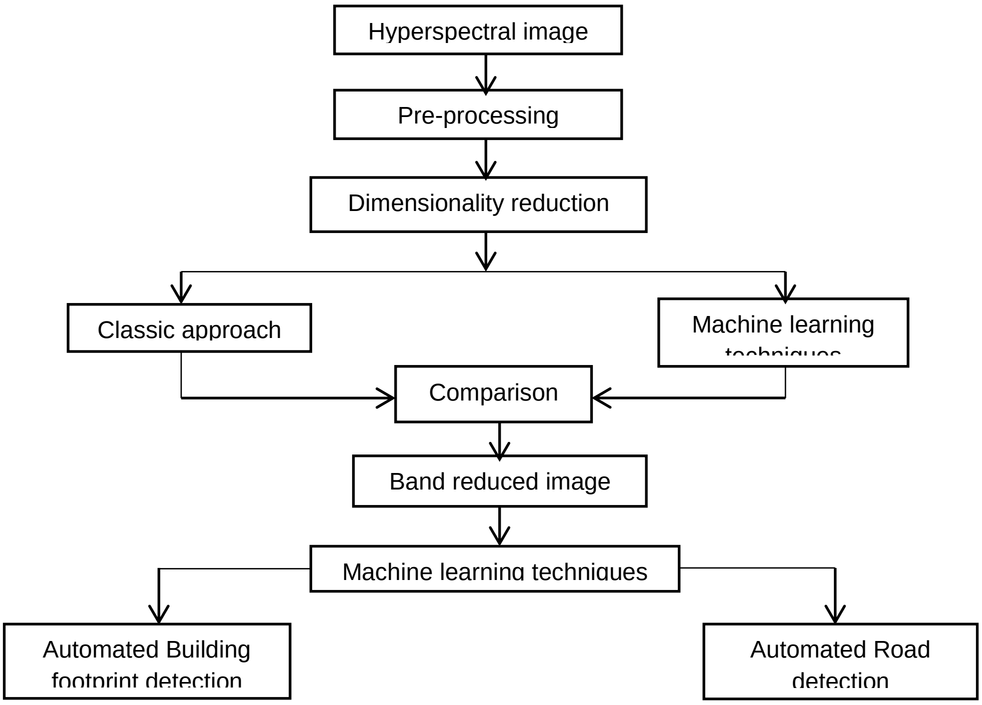
Table 2: Advantages of hyperspectral imagery

VI. PROPOSED FLOW OF RESEARCH & DISCUSSION

To make the satellite image processing more efficient, fully automated analysis methods are more important and crucial. Most of the time, when remote sensing satellite records data of the earth's surface, it actually records multi-spectral or hyperspectral data. Each of the records would have many variables/features. We need to reduce the number of variables/features in order to view the information more meaningfully. Principal Component Analysis is a statistical method for the extraction of features. Machine learning enables the ability to classify spatial imagery effectively and usefully. Machine learning involves multiple algorithms along with Artificial Neural Networks, Support Vector Machine, Self-Organizing Maps, and DT. Such algorithms are capable of managing large-scale data and mapping properties of different components. Machine learning has become a major priority in remote sensing Literature over the last few years. Artificial Intelligence - Machine learning concentrates on automatic data extraction using computational and mathematical mechanisms. In figure 5 the ML-based approach for several earth sciences applications was also significantly improved. The main challenge for these regarding apply Machine Learning methods is data models. The main objectives of this research are, Dimensionality Reduction of Hyperspectral Imagery with Machine learning techniques, Automated Building Footprint Detection from Hyperspectral Imagery by Artificial Neural Networks, Automated Road Detection from Hyperspectral Imagery using Support Vector Machine/Relevance Vector machine and Exploring the possibilities of applying Deep learning in geospatial data in smart city development.

The flow of research shows the overall proposed framework for building footprint and road detection. It consists of various phases, such as data collection, pre-processing portion, dimensionality reduction, and classification. The first phase is designed for pre-processing hyperspectral data. Generally pre-processing precedes data analysis. The second phase is the dimensionality reduction using machine learning techniques. The results of machine learning methods are compared with a classical approach. After reducing bands to require no bands, the hyperspectral image is used for automated building footprint extraction using advanced machine learning techniques which extracts the boundary of the building. This result would be used for smart city development and reconstructing the building. The fourth phase: the dimensional reduced hyperspectral image is used for automated road detection. For doing this, machine learning algorithms will be proposed for road detection.

Fig 5: Proposing Flow of Research



A. Building Extraction (BE)

Building footprint (boundary) provides primary information about a building structure since a footprint shows the exact position and the potential shape of a building. Different data sources are would be used for building footprint extraction includes such are aerial images, interferometry synthetic aperture radar (InSAR), recent high-resolution satellite imagery, and light detection and ranging (LiDAR). The study focuses on the extraction of a building footprint using a hyperspectral image. Automatic building footprint extraction from remote sensing information is a requirement for many applications of GIS (Geographic Information System) applications, such as urban planning and disaster management. A building footprint is digital from the actual building boundary.

B. Road Detection (RD)

Detecting the road network without remote sensing data is time and cost consuming. So, this research proposes a novel technique to detect the road network from hyperspectral images. Roads are the backbone and vital of transport, supplying human civilization with many distinct supports. For traffic management, city planning, road track tracking, navigation, and map updates, work into path extraction of great importance. Even though, different remote sensing data available, mainly this research is concentrating on the hyperspectral image. Because the need to be extracted after dimensionality reduction.

VII. ANALYSIS STUDY OF HYPERSPECTRAL IMAGERY

References	Spatial Resolution	Spectral bands	Spectral Range	Pixels	Place / Area	Data types	Classes	Data center
Wenzhi zhao and Shihong Du(2016)	1.3m (per pixel)	115	0.43-0.86 µm	1096×715	Peri urban	Hyperspectral digital imagery	Water, meadow, brick, Bare soil, asphalt, bitumen, Title, shadow.	Pavia Center
	1.3m (per Pixel)	103	_	_	Dense urban		Asphalt, meadows, gravel, trees, metal sheets, bare soil, bricks, shadows	University of Pavia
Daniel et.al (2016) [45].	20m (per pixel)	224	0.4-2.5 µm	_	Jasper Ridge	HIS	Soil, forest, Grass, chaparral, lake.	NASA’s
Akrem et.al (2017) [46].	20m/pixel	220	375-2500 nm	145×145	Northwest Indiana	HSI	Corn min-till, corn, soya beans, no-till, soya bean min-till,	Indian Pines
	1.3m/pixel	115	430-860nm	610×340	Urban	HSI	Tree, asphalt, bitumen, gravel, metal sheets, shadow, brick, etc...	University of Pavia
Tian Tian et.al (2018) [47].	0.631m/pixel	3	_	500×500 (each pixel)	_	VHR	Roads, a dark roof, lawn area, baare4 soil, bright roof, trees, water, bright roofs, bare groum’s	Quick bird datasets
Qishuo Gaoet.al (2018) [44].	20m	220	0.2-2.4µm	145×145	Northwest Indiana	HIS	The corn no-till, corn min-till, corn, soya beans, no-till, soya bean min-till,	Pavia data set
	1.3m	103	_	610×610	North Italy	HIS	Asphalt, meadows, gravel, trees, metal sheets, bare oil, bricks, shadows.	Saline data set
Yanni Donget.al (2018) [48].	20m /pixel	224	370-2510 nm	200×200	Northern New country	HIS	Mean target spectrum, roof, bare soil, road, airstrips, shadow, grass.	AVIRIS San Diego airport dataset
	3.5m	224	370-2510 nm	100×100	San Diego, CA, USA (Airport area)	HIS	Mean target spectrum, grass, road 1, road 2, bare soil, parking lot.	HYDICE urban data set
Gizem Ortac and Giyasettin Ozcan (2018) [24].	20m	224	0.4-2.5µm	145×145	Northeast of Indian	HSI	The corn no-till, Soya bean no-till, alfalfa, soya bean min-till, Soya bean–clean, grass-pastures, woods, building-grass-trees-drivers,	Indian pines hyperspectral data
M.E Paolettiet.al (2018) [49].	10nm	224	400-2500 nm	145×145	Northeast of Indian	HSI	The corn, no-till, corn min-till, corn, soya beans, no-till, soya bean min-till, alfalfa, grass/pastures, grass/pastures,	AVIRIS Indian dataset

References	Spatial Resolution	Spectral bands	Spectral Range	Pixels	Place / Area	Data types	Classes	Data center
Seyyid Ahmed and Mohammed Ouali (2018) [50].	1.3m/pixel	115	0.43-0.86	640×340	Italy	HIS	Asphalt Meadoues, gravel, trees, painted, metal sheets, bare soil, bitumen, selt-blocking, bricks, shadows	Pavia university dataset.
	_	220	0.4-2.5μm	145×145	Indiana (agricultural area)	HSI	Alfalfa Corn- on till, corn- min-till, corn, grass/ pasture, grass/tree.	Indian Pines dataset.
Chen yang et.al (2018) [22].	20m	220	_	145×145	Northwest Indiana	HSI	Alfalfa Corn-on till, corn- min-till, corn, grass- pasture, grass-trees, grass-pasture, mowed, hay-windrowed, oat.	Indian Pines scene
Shuato Li et.al (2018) [51].		115	0.43-0.86 μm	610×340	Urban area	HSI	Asphalt Meadows, gravel, trees, painted, metal, sheets, base, soil, bitumen, self-blocking, bricks, shadows.	University of Pavia data
Juan Mario Haut et.al (2018) [52].	1.3m/pixel	103	0.43-0.86 μm	610×340	Northern Italy	HSI	Alfalfa Corn-on till, corn- min-till, corn, grass- pasture, grass-trees, grass- pasture, mowed, hay-windrowed, oat, soybean-no till, soybean – min-till,	Indian Pines
Yanhui Guo et.al (2018) [53].	_	220	0.4-2.5μm	145×145	Northwestern Indiana	HIS	Alfalfa Corn – n, corn – n, wrn, grass-m, grass-t, grass- p-m, hay- w, oats, soybean – n, soybean – m.	Indian pines
	_	103	0.43-0.86 μm	610×340	Urban area	HIS	Asphalt Meadows, gravel, trees, pm-sheets, bare soil, bitumen, s-b-bricks, shadouer.	Pavia university
	3.7m	220	_	512×217	California	HSI	Broccoli-gw-1, broccoli–g-k1-2, fallow, fallow-r-p, fallow, smooth, stubble, celery, grapes- untrained, soil- v-d,	Saline data set
K.S.Charmisha et.al (2019) [31].	20m	220	0.4-2.2μm	145×145	_	HSI	Corn-no till, corn-min till, corn, grass-pasture, grass-trees, grass- pasture, mowed,	Indian Pines
Hong Huang et.al (2019) [27].	20m	200	_	145×145	Northwestern Indiana	HSI	Alfalfa(46), corn-no till (1428), corn-min till (830), corn(237), grass/pasture (483), grass/ trees (730).	Indian Pines
Annalisa Appice and Donato Malerba (2019) [41].	1.3m	103	0.43-0.86 μm	610×340	Urban area	HSI	Asphalt, meadows, Gravel, trees, Painted metal sheets, bare soil, bitumen, self-blocking bricks, shadows.	Pavia University
Lan Zhang, Hongjun Su, and	20m	220	0.4-25μm	145×145	_	HIS	Asphalt, corn-no till, corn-min, corn, grass	Indian Pines

References	Spatial Resolution	Spectral bands	Spectral Range	Pixels	Place / Area	Data types	Classes	Data center
Jingwei Shen (2019) [28].							or pasture, grass or trees, oats, wheat, woods.	
Qixia Man and Pinliang Dong (2019) [39].	4.8 nm, 2.5m	144	_	_	_	HIS	Grass, grass-synthetic, road, soil, railway, parking-lot, tennis-court, water, trees, building, highway.	LiDAR data

Table 3: Analysis study of hyperspectral imagery VIII. Conclusion

In various scientific and technological applications, the reduction of dimension for hyperspectral imagery plays a major role. The Principal Component Analysis (PCA) is a numerical method of feature extraction. Machine learning provides the potential to efficiently classify spatial images efficiently. The main purpose of this review is to identify the state-of-the-art and trends of hyperspectral imaging theories, methodologies, techniques and applications for dimensional reduction. An overview of the concept of deep learning is provided in different types of algorithms, such as artificial neural networks and support vector machine (SVM), etc. these algorithms may handle complex characteristics of high dimensional data map classes. Finally, it proposes to look for the dimensionality reduction of hyperspectral imagery, automated building footprint detection, automated road detection and smart city enhancement using machine learning and deep learning techniques. In the feature, we are planning to find out the best algorithms of machine learning techniques, classic approach and implement the dimensionality reduction using hyperspectral imagery..

REFERENCES

[1]. Volchok, B. A., and Chernyak, M. M. (1968). Transfer of microwave radiation in clouds and precipitation. *Transfer of Microwave Radiation in the Atmosphere, NASA TT F-590*, 90-97.

[2]. Wilheit, T. T., Chang, A. T. C., V. Rao, M. S., Rodgers, E. B., and Theon, J. S. (1977). A satellite technique for quantitatively mapping rainfall rates over the oceans. *Journal of applied meteorology*, *16*(5), 551-560.

[3]. Liu, S., Du, Q., Tong, X., Samat, A., Pan, H., and Ma, X. (2017). Band selection-based dimensionality reduction for change detection in multi-temporal hyperspectral images. *Remote Sensing*, *9*(10), 1008.

[4]. Archibald, R., and Fann, G. (2007). Feature selection and classification of hyperspectral images with support vector machines. *IEEE Geoscience and remote sensing letters*, *4*(4), 674-677.

[5]. Hsu, P. (2004, July). Feature extraction of hyperspectral images using matching pursuit. In *Proc. Of the XXth ISPRS Congress, Istanbul*.

[6]. Bradley, P., Keller, S., and Weinmann, M. (2018). Unsupervised feature selection based on ultrametricity and sparse training data: A case study for the classification of high-dimensional hyperspectral data. *Remote Sensing*, *10*(10), 1564.

[7]. Mena, J. B. (2003). State of the art on automatic road extraction for GIS update: a novel classification. *Pattern recognition letters*, *24*(16), 3037-3058.

[8]. Harsanyi, J. C., and Chang, C. I. (1994). Hyperspectral image classification and dimensionality reduction: an orthogonal subspace projection approach. *IEEE Transactions on Geoscience and remote sensing*, *32* (4), 779-785.

[9]. Kumar, S., Ghosh, J., and Crawford, M. M. (2002). The hierarchical fusion of multiple classifiers for hyperspectral data analysis. *Pattern Analysis & Applications*, *5*(2), 210-220.

[10]. Kaarna, A., Toivanen, P., and Keränen, P. (2006). Compression and classification methods for hyperspectral images. *Pattern Recognition and Image Analysis*, *16*(3), 413-424.

[11.] Paclik, P., Leitner, R., and Duin, R. P. (2006). A study on the design of object sorting algorithms in the industrial application using hyperspectral imaging. *Journal of Real-Time Image Processing*, *1*(2), 101-108.

[12]. Hsu, P. (2004, July). Feature extraction of hyperspectral images using matching pursuit. In *Proc. of the XXth ISPRS Congress, Istanbul*.

[13]. Zhou, S., Zhang, J., and Su, B. (2008, July). Dimensionality reduction and classification based on an ant colony algorithm for hyperspectral remote sensing image. In *IGARSS 2008-2008 IEEE International Geoscience and Remote Sensing Symposium (Vol.5, pp.V-393). IEEE.* [14]. Khoshelham, K., Nardinocchi, C., Frontoni, E., Mancini, A., and Zingaretti, P. (2010). Performance evaluation of automated approaches to building detection in multi-source aerial data. *ISPRS Journal of Photogrammetry and Remote Sensing*, *65* (1), 123-133.

[15]. Huang, X., and Zhang, L. (2011). A multidirectional and multiscale morphological index for automatic building extraction from multispectral GeoEye-1 imagery. *Photogrammetric Engineering and Remote Sensing*, *77* (7), 721-732.
[16]. Cahill, N. D., Start, D. B., and Chew, S. E. (2014, June). Modularity versus Laplacian Eigenmaps for dimensionality reduction and classification of hyperspectral imagery. In *2014 6th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS)* (pp. 1-4). IEEE.
[17]. Wieland, M., and Pittore, M. (2014). Performance evaluation of machine learning algorithms for urban pattern recognition from multi-spectral satellite images. *Remote Sensing*, *6*(4), 2912-2939.
[18]. Liang, H., & Li, Q. (2016). Hyperspectral imagery classification using sparse representations of convolutional neural network features. *Remote Sensing*, *8*(2), 99.
[19]. Vakalopoulou, M., Karantzalos, K., Komodakis, N., and Paragios, N. (2015, July). Building detection in very high-resolution multispectral data with deep learning features. In *2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)* (pp. 1873-1876). IEEE.
[20]. Zhao, W., and Du, S. (2016). Spectral–spatial feature extraction for hyperspectral image classification: A dimension reduction and deep learning approach. *IEEE Transactions on Geoscience and Remote Sensing*, *54*(8), 4544-4554.
[21]. Mughees, A., Ali, A., and Tao, L. (2017, September). Hyperspectral image classification via shape-adaptive deep learning. In *2017 IEEE International Conference on Image Processing (ICIP)* (pp. 375-379). IEEE.
[22]. Yang, C., Bruzzone, L., Zhao, H., Tan, Y., and Guan, R. (2018). Superpixel-based unsupervised band selection for classification of hyperspectral images. *IEEE Transactions on Geoscience and Remote Sensing*, *56*(12), 7230-7245.
[23]. Liu, X., Sun, Q., Meng, Y., Fu, M., and Bourennane, S. (2018). Hyperspectral image classification based on parameter-optimized 3D-CNNs combined with transfer learning and virtual samples. *Remote Sensing*, *10*(9), 1425.
[24]. ORTAÇ, G., and ÖZCAN, G. A Comparative Study for Hyperspectral Data Classification with Deep Learning and Dimensionality Reduction Techniques. *Uludağ University Journal of The Faculty of Engineering*, *23*(3), 73-90.
[25]. Thomas M.. Lillesand, and Ralph W.. Kiefer. (2000). *Remote Sensing and Image Interpretation*. John Wiley & Sons.
[26]. Mather, P. M., and Koch, M. (2004). *Computer processing of remotely-sensed images: an introduction*. John Wiley & Sons.
[27]. Huang, H., Li, Z., and Pan, Y. (2019). Multi-Feature Manifold Discriminant Analysis for Hyperspectral Image Classification. *Remote Sensing*, *11*(6), 651.
[28]. Zhang, L., Su, H., and Shen, J. (2019). Hyperspectral Dimensionality Reduction Based on Multiscale Superpixelwise Kernel Principal Component Analysis. *Remote Sensing*, *11*(10), 1219.
[29]. Li, W., He, C., Fang, J., Zheng, J., Fu, H., and Yu, L. (2019). Semantic Segmentation-Based Building Footprint Extraction Using Very High-Resolution Satellite Images and Multi-Source GIS Data. *Remote Sensing*, *11*(4), 403.
[30]. Dijkstra, K., van de Loosdrecht, J., Schomaker, L. R. B., and Wiering, M. A. (2019). Hyperspectral demosaicking and crosstalk correction using deep learning. *Machine Vision and Applications*, *30*(1), 1-21.
[31]. Charmisha, K. S., Sowmya, V., and Soman, K. P. (2018, January). Dimensionally reduced features for hyperspectral image classification using deep learning. In *International Conference on Communications and Cyber-Physical Engineering 2018* (pp. 171-179). Springer, Singapore.
[32]. Li, T., Leng, J., Kong, L., Guo, S., Bai, G., and Wang, K. (2019). DCNR: deep cube CNN with random forest for hyperspectral image classification. *Multimedia Tools and Applications*, *78*(3), 3411-3433.
[33]. Ergul, U., and Bilgin, G. (2019). MCK-ELM: multiple composite kernel extreme learning machine for hyperspectral images. *Neural Computing and Applications*, 1-11.
[34]. Gewali, U. B., Monteiro, S. T., and Saber, E. (2018). Machine learning based hyperspectral image analysis: a survey. *arXiv preprint arXiv:1802.08701*.
[35]. Zhao, Y., Yuan, Y., and Wang, Q. (2019). Fast Spectral Clustering for Unsupervised Hyperspectral Image Classification. *Remote Sensing*, *11*(4), 399.
[36]. Fang, B., Li, Y., Zhang, H., and Chan, J. C. W. (2019). Hyperspectral Images Classification Based on Dense Convolutional Networks with Spectral-Wise Attention Mechanism. *Remote Sensing*, *11*(2), 159.
[37]. McCoy, J. T., and Auret, L. (2019). Machine learning applications in minerals processing: A review. *Minerals Engineering*, *132*, 95-109.

[38]. Schuegraf, P., and Bittner, K. (2019). Automatic Building Footprint Extraction from Multi-Resolution Remote Sensing Images Using a Hybrid FCN. *ISPRS International Journal of Geo-Information*, *8*(4), 191.

[39]. Man, Q., and Dong, P. (2019). Extraction of Urban Objects in Cloud Shadows on the basis of Fusion of Airborne LiDAR and Hyperspectral Data. *Remote Sensing*, *11*(6), 713.

[40]. Astuti, N. R. D. P., and Mardhia, M. M. (2019). Multilevel thresholding hyperspectral image segmentation based on independent component analysis and swarm optimization methods. *International Journal of Advances in Intelligent Informatics*, *5*(1), 66-75.

[41]. Appice, A., and Malerba, D. (2019). Segmentation-aided classification of hyperspectral data using spatial dependency of spectral bands. *ISPRS journal of Photogrammetry and remote sensing*, *147*, 215-231.

[42]. Cao, X., Xiong, T., and Jiao, L. (2016). Supervised band selection using local spatial information for hyperspectral image. *IEEE Geoscience and Remote Sensing Letters*, *13*(3), 329-333.

[43]. Liu, S., Bruzzone, L., Bovolo, F., and Du, P. (2012, June). Unsupervised hierarchical spectral analysis for change detection in hyperspectral images. In *2012 4th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS)* (pp. 1-4). IEEE.

[44]. Gao, Q., Lim, S., and Jia, X. (2018). Hyperspectral image classification using convolutional neural networks and multiple feature learning. *Remote Sensing*, *10*(2), 299.

[45]. Fernandez, D., Gonzalez, C., Mozos, D., and Lopez, S. (2016). FPGA implementation of the principal component analysis algorithm for dimensionality reduction of hyperspectral images. *Journal of Real-Time Image Processing*, 1-12.

[46]. Sellami, A., Farah, I. R., and Solaiman, B. (2017). An Adaptive Dimensionality Reduction Approach for Hyperspectral Imagery Semantic Interpretation. *World Academy of Science, Engineering and Technology, International Journal of Computer, Electrical, Automation, Control and Information Engineering*, *11*(2), 213-220.

[47]. Tian, T., Gao, L., Song, W., Choo, K. K. R., and He, J. (2018). Feature extraction and classification of VHR images with attribute profiles and convolutional neural networks. *Multimedia Tools and Applications*, *77* (14), 18637-18656.

[48]. Rajasekaran Rajkumar, K.Govinda, Anushka Jindal, Rushil Mehtani, Jolly Masih, Maddineni Charan Sai: *Visualization Effect of Changing Climatic Trends on Natural Calamities:Hurricanes*. DOI:10.36872/LEPI/V50I3/201022

[49]. Paoletti, M. E., Haut, J. M., Plaza, J., and Plaza, A. (2018). A new deep convolutional neural network for fast hyperspectral image classification. *ISPRS journal of Photogrammetry and remote sensing*, *145*, 120-147.

[50]. Medjahed, S. A., and Ouali, M. (2018). Band selection based on optimization approach for hyperspectral image classification. *The Egyptian Journal of Remote Sensing and Space Science*, *21*(3), 413-418.

[51]. Li, S., Hao, Q., Kang, X., and Benediktsson, J. A. (2018). Gaussian pyramid based multiscale feature fusion for hyperspectral image classification. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *11*(9), 3312-3324.

[52]. Haut, J. M., Paoletti, M. E., Plaza, J., and Plaza, A. (2018). Fast dimensionality reduction and classification of hyperspectral images with extreme learning machines. *Journal of Real-Time Image Processing*, *15*(3), 439-462.

[53]. Guo, Y., Cao, H., Han, S., Sun, Y., & Bai, Y. (2018). Spectral–spatial hyperspectralimage classification with k-nearest neighbor and guided filter. *IEEE Access*, *6*, 18582-18591.

[54]. Shamila. S. N. S., Mahendran, D. S., and Sathik, M. M. (2019). Image and Video Frame Extraction System Based on Improved Deep Learning Technique. *International Journal on Emerging Technologies*, 10(3), 384-390.

[55]. Vishwakarma, G., and Thakur, G. S. (2019). Comparative Performance Analysis of Combined SVM-PCA for Content-based Video Classification by Utilizing Inception V3. *International Journal on Emerging Technologies*, 10(3), 397-403.

[56] Liu, P., Liu, X., Liu, M., Shi, Q., Yang, J., Xu, X., and Zhang, Y. (2019). Building Footprint Extraction from High-Resolution Images via Spatial Residual Inception Convolutional Neural Network. *Remote Sensing*, *11*(7), 830.