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Semantic Segmentation of Remote Sensing Data using Data Mining Techniques for Geological Mapping

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Abstract— Conventional means of mineral exploration requires physical access to the region of interest, which is a labor-intensive process with many associated challenges. Furthermore, it results in geological maps with nominal precision and is limited by many factors. Remote sensing has emerged as a prominent tool for environment mapping, land cover, and land use mapping, but its applications in geological mapping are comparatively limited. However, due to the availability of non-commercial satellite data sources and cloud processing services, its applications are emerging in the mineral exploration and geological mapping community.

This study briefly explains the process of geological mapping using different data mining algorithms. Furthermore, it explores other data mining techniques for semantic segmentation of remote sensing data specifically for geological mapping. Moreover, this study categorizes them into three classes, i.e., conventional approaches, machine learning techniques, and deep learning techniques. The study contrast and compares these techniques factoring in their feasibility for lithological mapping and narrows them down to a couple of most prominent approaches in each category.

The findings of this study demonstrate the potential of semantic segmentation techniques for geological mapping with a review of practical case studies. Furthermore, it also explores future avenues for research in this domain. The study is beneficial for researchers in geographic information sciences and geological sciences, working on geological mapping, land cover/land use mapping, or environment mapping.

Index Terms— Remote Sensing, Geological Mapping, Limestone, Semantic Segmentation, Data Mining, Machine Learning, Deep Learning, Review

1 Introduction

Mminerals are found crystalline, normally formed by deposition of an element or a group of elements through some geological process. There are different types of rock-forming minerals but the most common are Olivine, Micas, Pyroxenes, Quartz, Amphiboles and Feldspar etc. others may include ferric, oxides of sulfides minerals [1]. Rock types can be classified into Sedimentary, Igneous and Metamorphic rocks each classified based on the process of formation. Sedimentary rocks are formed as a result of deposition of sediments, igneous are formed as a result of magmatic or volcanic activities and metamorphic rocks are a result of metamorphosis (change) by heat and pressure [2]. Mineral may occur on surface or subsurface depending on its process of formation. Surface minerals are comparatively easier to explore and map whereas for subsurface minerals indicator minerals exists which are used form it's mapping and exploration [3].

Geological mapping is the art and science of identification and mapping of rocks and minerals using remote sensing techniques [4]. Some geologies have economic significance and some not which requires the use of data mining techniques for its delineation. Large amount of multispectral and hyperspectral data is available which can be used for mineralogical mapping including data from non-commercial satellites such as ASTER, Sentinel and Landsat. Powerful computational sources such as cloud based remote sensing platform, Google Earth Engine (GEE), are also available for processing this data [5]. Many techniques for mining large amounts of data with parallel processing chains have been researched for identification of mineralogical hotspots. However, this domain is open for more research with great potential.

This study will explore a variety of literature on data mining techniques used for semantic segmentation for the purpose of geological mapping. The study has categorized literature in three broad classes i.e. Conventional Techniques, Machine Learning Techniques and Deep Learning Techniques. The study concludes with a summary of the literature review and some remarks about future venues for research.

2 Semantic Segmentation for Geological Mapping: An Overview

Semantic segmentation is the classification of each individual pixel in an image. It differs from conventional classification task in a sense that in semantic segmentation instead of the on label for the whole image, each pixel is labeled individually and clustered together to form a segment in the image [6]. Remote sensing differs from a normal image classification task because of a few important factors. First, the remote sensing data is composed of huge 3D matrices of pixel with very large dimensions thus processing each image as a whole might not be convenient [4]. Secondly, a single remote sensing image or scene conventionally consists of more than 3 visible bands. To explain further, a normal image is mainly composed of three-color bands i.e. Red, Green, Blue (RGB) [4]. Each band can be considered a black and white image with each pixel indicating the intensity of reflection in that wavelength region. In re-

International Journal of Scientific & Engineering Research, Volume 8, Issue 11, August-2020
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mote sensing images NIR, SWIR and TIR bands are also included which are very important for delineating different earthly objects. Specifically, in geological mapping visible bands holds nominal importance as compared to non-visible bands such as NIR, SWIR, and TIR which have larger wavelength as compared to visible bands and more sensitive to geological compositions [7].

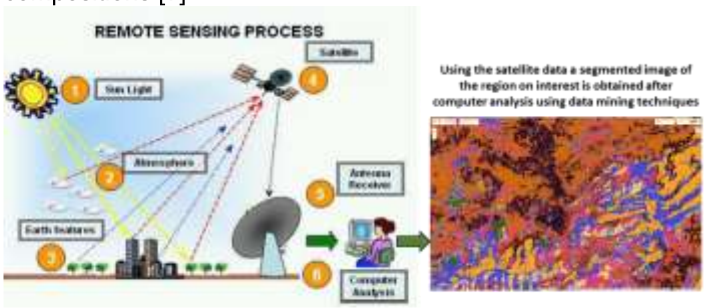

Figure 1 Remote sensing process schematic for geological mapping

To process remote sensing data some prerequisite steps are very important to bring it in the required shape and format. Remote sensing data is susceptible to a lot of errors and noise including Atmospheric, Radiometric and Geometric errors. A summary of the most commons noise in remote sensing data is given in the table below

Table 1 Common Noise and Interferences in Remote Sensing Data

Noise/Interference	Description	Ref
Crosstalk in ASTER	ASTER images are affected by the ‘crosstalk’ instrument problems i.e. the light from band 4 gets leaked into SWIR bands specifically band 5 and band 9.	[8]
Atmospheric Noise	The reflected or propagating radiations are interfered by aerosol, dust particles, atmospheric temperature or absorbed by different gasses in the atmosphere	[9]
Noise due to Thermal energy	Thermal noise occurs due to the heat in internal circuitry which causes the agitation in charge carriers, typically electron.	[10]
Shot Noise	The noise which is modelled by a poison process is called shot noise. This occurs due to the discrete nature of circuitry. In optical devices photon counting can also cause shot noise, where the associated factor is the particle nature of light.	[10]
Quantization Noise	When conversion from analogue to digital signal we quantize the signal at a quantization rate which is adjusted by the Least Significant Bit (LSB).	[10]

Without pre-processing remote sensing data processing will result in thematic maps plagued by errors and inconsistencies. There are several preprocessing techniques available specific to remote sensing imagery some of these are listed in the table below with a brief explanation and reference.

Table 2 Multi- and Hyperspectral Data Preprocessing

Technique	Description	Ref
Co-Registration	When we need to do temporal analysis multiple images of the same location at different time are studies and is called Co-Registration. Minerals property usually change with time due to geothermal and chemical alteration processes.	[11]
Savitzky-Golay filter	It is a simple but effective technique to remove cloud contamination and atmospheric variability noise in NDVI time-series analysis.	[12]
Wiener Filter	It reduces the mean squared error between the estimated random process and the desired one. In the referred study SAR image and Multi-band images are processed by wiener-based filters for classification.	[13]
Kalman Filter	Is an iterative mathematical algorithm which rapidly estimates the desired function from the data. Starting at an initial random estimate it will check the datapoint calculate its Error and Variances from the estimate and adjust its parameters. It will keep doing that iteratively until it can estimate the desired signal with as much precision and low error or variance as possible	[14]
Absolute Correction Methods using Radiative Transfer Codes	Used for the used to nullify the atmospheric error such as terrain illumination effect and the absorption and scattering effects.	[15]
ATREM, ATCOR 3	Atmospheric removal program (ATRAM) uses a predefined model of the atmosphere to remove its errors from satellite image. Atmospheric Correction Model 3 (ATCOR 3) uses a MODTRAN Radiative Transfer Code to allow for modeling the atmospheric conditions at the time of satellite overpass which	[16][17]

International Journal of Scientific & Engineering Research, Volume 8, Issue 11, August-2020
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	is used to correct errors due to aerosol, ozone, vapor, and atmospheric mass.	
Spectral Shape Matching Method (SSMM)	An algorithm developed by Korean study for atmospheric correction of remote sensing data based on a spectral shape matching technique.	[18]
Geometric Correction	The image captured at a location may not be exactly projected on the same location due to errors in its projection data. To solve that projection mathematics is used to calculate exact projection data and correct the errors.	[19]
Nearest Neighbor Resampling Algorithm (NNR)	A resampling algorithm to increase the spatial resolution of remote sensing data which can results in refined geological maps with sharp lithological boundaries.	[20]
Radiometric Correction	When images are captured some pixel may have errors due to sensor malfunction or due to on-board preprocessing. Radiometric correction are a set of techniques based on mean, mode or median or Machine Learning or Probabilistic methods to remove those errors.	[21]
Topographic Correction	A set of statistical or empirical methods used to fix DEM topographic errors in remote sensing data of rough terrains.	[22]

3 Conventional Techniques for Geological Mapping

The most common set of data mining techniques used for geological mapping includes False Color Composites i.e. mapping of non-color bands to color bands [23], band ratio which is basically performing mathematics with the image bands, Principal Component Analysis (PCA) which works with eigen decomposition of the image data [24], Independent Component Analysis (ICA) which is used in blind source separation using known spectral signature of mixed response [25], Minimum Noise Fraction (MNF) which uses eigen decomposition to calculate a rotation matrix and uses it to segregate noise in the data and decorrelation stretching which basically stretches the raw band data across its principal axis using a rotation matrix thus suppressing band-band correlation [26].

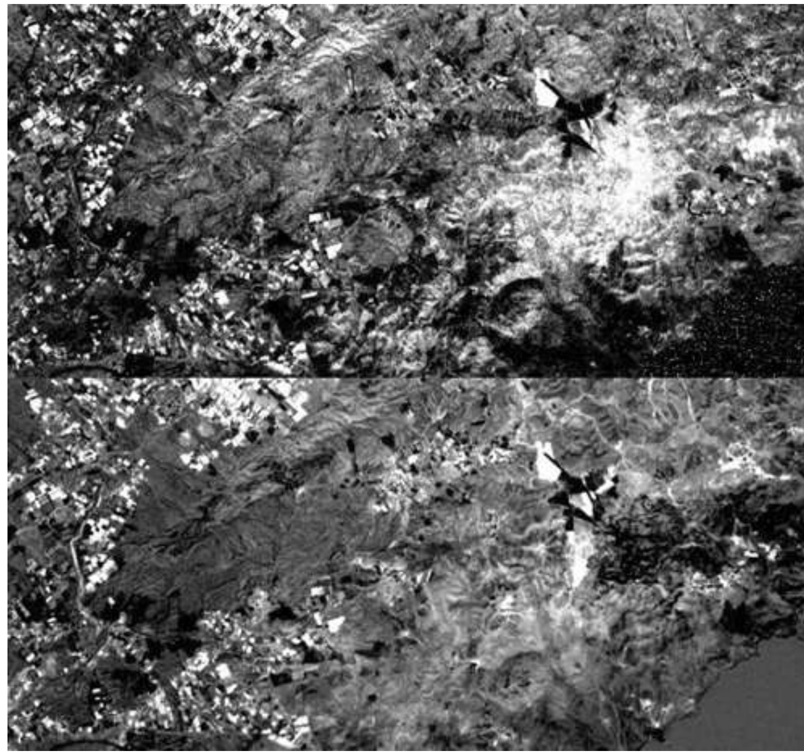

Figure 2 Example of Geological Product as a result of conventional techniques. Top to bottom (a) Band Ratio/Band Mathematics 3/1, (b) 5/7, PCA (c) PC3 of Landsat TM 1,3,4,5 (d) PC3 of Landsat TM 1,4,5,7 and (d) PC4 of Landsat TM 1,4,5,7 [27]

Although, this is a very limited set of techniques but a large amount of very successful algorithms is based on these basic techniques and considered their enhancements such as Crosta Techniques which is the most common variation of Principal Component Analysis in which Principal Components are selected based on eigen vector loadings analysis [28]. Crosta Technique was introduced basically for hydrothermal alteration mapping but it's success in mapping minerals have earned it a lot of significance in the geological mapping community.
Some more techniques have been covered in Table 3. Many other conventional techniques exist in literature which are commonly being used to this day for generating thematic maps of geologies.

Table 3 Conventional Remotes Sensing Techniques used in Geological Mapping

Technique	Description	Ref
Digital Elevation Model (DEM)	Digital Elevation Model based on SAR data used for Radiometric Correction of Satellite Images and elevation mapping. This can be used in combination with a variety of other techniques	[29]
Mixture Tuned Matched Filtering	Use Mixture Tuned Matched Filtering (MTMF) to perform Matched Filtering (MF) and to add an infeasibility image to the results. The infeasibility image is used to re-	[30]

International Journal of Scientific & Engineering Research, Volume 8, Issue 11, August-2020
ISSN 2229-5518

	duce the number of false positives that are sometimes found when using MF. Pixels with a high infeasibility are likely to be MF false positives. Correctly mapped pixels will have an MF score above the background distribution around zero and a low infeasibility value. The infeasibility values are in noise sigma units that vary in DN scale with an MF score (see the following figure).	
Minimum Noise Fraction Transform	Use MNF Rotation transforms to determine the inherent dimensionality of image data, to segregate noise in the data, and to reduce the computational requirements for subsequent processing. Matched Filtering (MF) using Minimum Noise Fraction to perform Matched Filtering (MF) and to add an infeasibility image to the results. The infeasibility image is used to reduce the number of false positives that are sometimes found when using MF. Pixels with a high infeasibility are likely to be MF false positives.	[31]

4 Machine Learning Techniques

The most commonly used supervised mapping techniques in geological mapping are conventional Machine Learning Algorithms (MLA) such as Support Vector Machines (SVM) [32], Classification and Regression Trees (CART) [33], Random Forrest (RF) [34] and Naïve Bayes (NB) [35] for their simplicity, robustness and ability to train on less amount of data.
For geological mapping the boundaries are very subtle and each pixel in a remote sensing image have accumulated response from different lithologies due to lower spatial resolution of non-commercial satellite data. Thus, to identify subtle spectral patterns which can delineate different lithologies calls for more robust techniques than conventional data mining algorithms i.e. Machine Learning Algorithms. Most commonly used MLA in remote sensing i.e. CART and RF are used for environmental and geological mapping but the fact that they are susceptible to noise makes it very challenging to reliably train these algorithms. Many unsupervised clustering techniques are used for data labeling and generating thematic maps such as active spatial clustering [36], X-Means and K-Means Clustering [37], multi objective genetic clustering [38], spatial and temporal clustering [34] etc. These techniques are beneficial in a way that they don't require manual data annotation and cluster alike spectral and spatial data together which can result in geological maps. However, their accuracy is not as good as supervised techniques which can classify each pixel based on the training data provided.

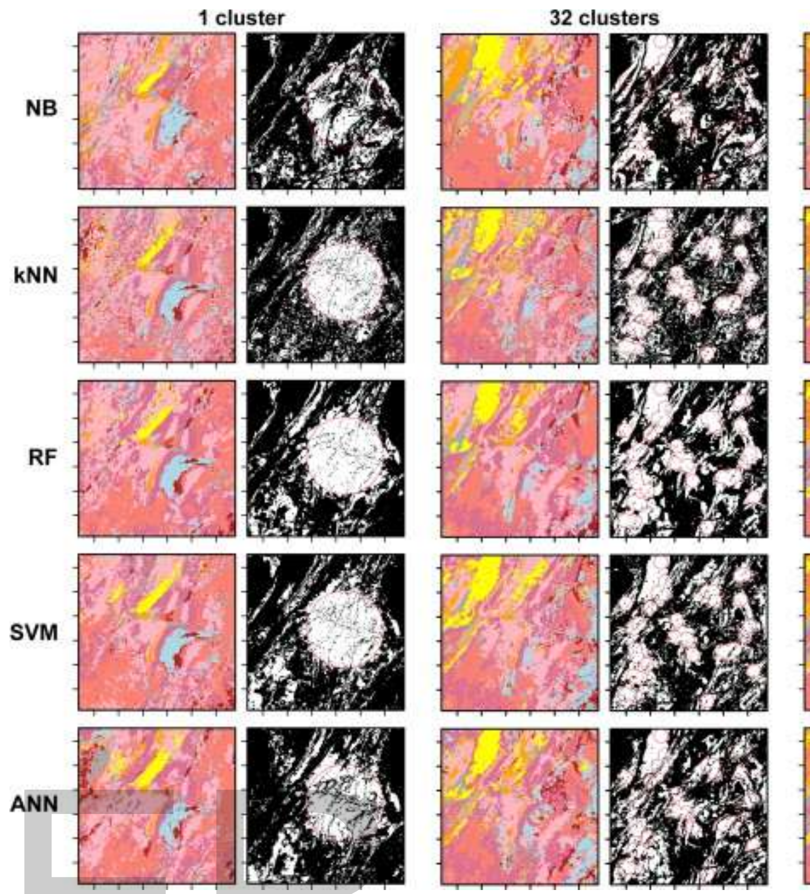

Figure 3 Visualization of lithological class predictions using multiple MLAs integrating geophysical data with number of cluster parameters [34]

Although, MLAs have proven to be effective in mapping lithologies. However, conventional MLAs are limited in case of geological mapping for the very reason that the geological compositions are subtle and the patterns required to delineate are deeply enmeshed in pixel data which requires more powerful techniques i.e. Deep Learning Algorithms (DLAs).

5 Deep Learning Techniques

Deep learning algorithm (DLAs) is a machine learning algorithm which is based on the functionality of biological neuron. It mimics the learning process of biological neural networks through mathematical operations. DLAs are massive parallel mathematical operation of summation and multiplication which processes the input data and performs predictions. It can be used for regression and classification. When it is used for classification of each individual pixel in an image then it is called semantic segmentation. DLAs are very powerful as long as large amount of training data and computational capacity is provided. Training data is dependent upon the complexity and structure of the algorithms. Similarly, computational time vary with the model structure.

To train a DLA for semantic segmentation of remote sensing image data. The data is converted into processable patches mostly of 255 by 255 dimensions with all the bands stacked as

International Journal of Scientific & Engineering Research, Volume 8, Issue 11, August-2020
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a third dimension. Each patch is flattened and fed into the input layer. The input layer performs massive multiplication and summation operation on the input data and generate output at each node of the input layer which is then passed through an activation function and then provided to the hidden layer.

$$y = f\left(\sum_{i=1}^{n} w_i x_i + w_0\right) \equiv f\left(\sum_{i=0}^{n} w_i x_i\right) \quad (1)$$

This process of multiplication and summation continues until we reach the output layer where an activation function converts the output of the final hidden layer into probabilities. There can be one or multiple nodes in the output layer depending upon the number of classes.

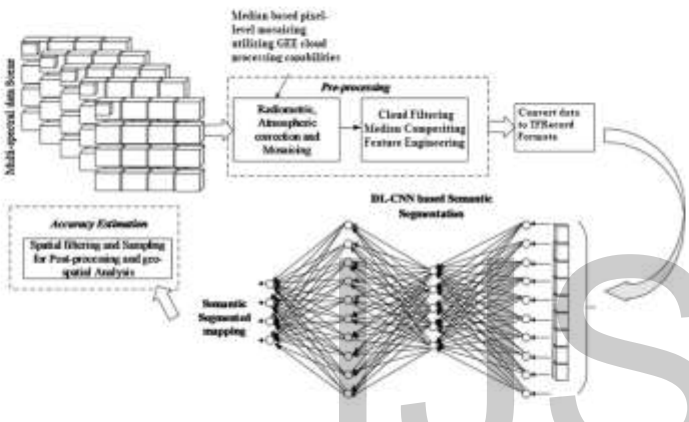

Figure 4 Machine Learning semantics segmentation process using deep learning approaches

DLAs have recently started being rigorously researched by the remote sensing community. From the simplest DLA i.e. Multi-layered perceptron model to a state-of-the-art Generative Adversarial Networks (GAN) and U-Net, every DLA algorithm is being tested for Geological mapping. Since, these have recently started emerging as dominant research topic thus there is still room for a lot of remote sensing specific DLA approaches which can outperform the standard. Still, DNN for Geochemical mapping [39], CNN for super-resolution [40], FCNN for semantic segmentation [6], Conditional GAN for Image to Digital Surface Model [41], probabilistic neural network for limestone mapping [42] are some of the state-of-the-art researches carried out in the recent 3 years.
Besides classification, clustering based semantic segmentation have also been carried out using deep learning approaches such as CNN based clustering [43], DNN for dune pattern mapping [44], DCNN for semi-supervised semantic segmentation [45] etc.
However, the work in DNN specifically for lithological classification and geological mapping is limited. Among, all other categories of data mining algorithm this is the most prominent and recent with huge demand for research, specifically in complex model structures, data preprocessing and feature engineering techniques.

6 Conclusions

Due to the many challenges associated with conventional mineral exploration techniques, remote sensing-based geological mapping has conquered all due to its feasibility in every aspect from cost to precision. Conventional remote sensing techniques have been very useful for geological mapping, but due to the emergence of Machine Learning algorithms, their use has become limited. Most of the time, they are integrated with MLAs to improve accuracies. Furthermore, deep learning approaches have recently started showing prominence in geological mapping research due to the availability of large amounts of data and computational capabilities. Since DLAs have recently dominated geological mapping research, there is still a lot of room for testing recently published models for semantic segmentation of remote sensing data. Specifically, U-Net and its variants can be used for remote sensing semantic segmentation object localization.

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International Journal of Scientific & Engineering Research, Volume 8, Issue 11, August-2020
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