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Image Classification of High Resolution Satellite Imagery Using Deep Learning Approach

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Abstract— *Extracting the information from earth's surface is main goal of remote sensing. There are various artificial techniques which are helpful for extracting information. Compared to those artificial methods, this paper represents method which learns the features naturally. Basically method is deep learning which can learn features layer by layer. Deep Learning is latest approach in classification. Deep learning method can successfully implemented in the area of high dimensional data, hyper spectral data classification. It shows excellent performance as compared to that shallow architecture. Deep learning leads to better accuracy as compared to other approaches.*

Keywords— *AutoEncoder, backpropagation, deep learning, multilayer perceptron.*

I. INTRODUCTION

Formation of Horizontal (H) and Vertical (V) pulses makes a Fully POLSAR image. Fully POLSAR Image consists of transmission of Horizontal and vertical polarized pulses. By using phase and amplitude between polarizations, a whole characterization of the target can obtained [1]. HH, HV, VH and VV these four combinations of polarization are captured. POLSAR imaging can hold more information of physical properties of the target. This information is helpful for getting better result in classification [2]. Feature extraction and classification techniques are most important part of POLSAR image classification. Features are most essential thing for the performance of POLSAR image classification. There are two categories by which POLSAR features can obtain. First category contains scattering matrix, coherent matrix and backscattering intensity while other category contains H/ *a* decomposition [3], four-component decomposition [4]. Feature extraction plays important role in POLSAR classification method. Deep Learning solves main problem in a series of simple many sub problems. Many levels of non-linear leads to depth of the architecture [5]. Deep learning algorithm learns an abstract complex features from a series of multiple layers. The number of abstraction levels gives authority to a structure for recognizing complex functions mapping directly from input data to the output data. At each level, features can be added to next layer from previous layer in the network. Feature extraction is layer wise and like a shallow learning, not dealing all the features at a one time. Deep learning is best way to understand complex representation. In Deep learning method, first simple features are learned and after that complex features processing takes place. In 2006, the concept of deep learning is introduced [6], which is received in both industry and academics with passion and severity. In Machine learning, Deep learning is a new field for research, the main motivation is foundation of neural network which copy the way the human brain works. Deep Learning Methods shows major potential in the various fields like speech recognition, image recognition, natural language processing and text searching. Deep learning can use vastly for POLSAR classification and recognition tasks. This paper represents deep learning method for POLSAR Image classification. Study area and Dataset explain in section II. Methodology explains in section III. Experimental results are given in section IV. Finally Conclusion is given in section V.

II. STUDY AREA AND DATASET

For this study we have chosen urban area of "Thibodaux, New Orleans" as shown in figure 1.

Fig. 1. Optical imagery courtesy of Google Earth.

The dataset chosen is an L-Band full polarimetric image. The crop of image is selected for classification as shown in figure 2.

Crop of image consist of water bodies, urban areas of different orientations, Mangroves and forested areas.

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Fig. 2. Pauli composite RGB of the UAVSAR L-Band Dataset [By JPL Team NASA].

III. Methodology

A. *Deep Learning*

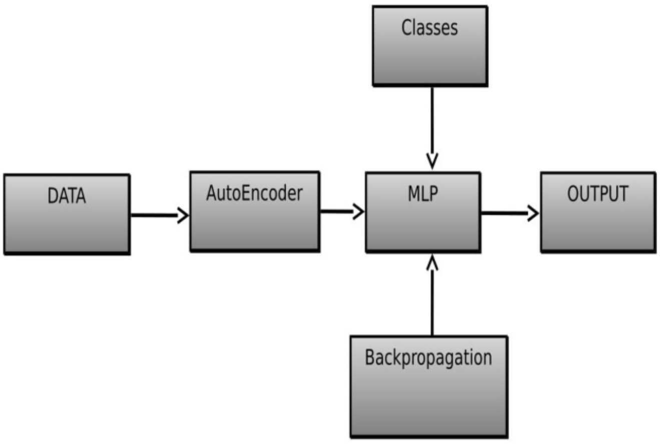

Fig. 3. Flowchart of deep learning.

- *Autoencoder* (AE)

An Autoencoder's [7] main focus is feature extraction. By using this, Autoencoder reconstruct original input signal. An Autoencoder consist of hidden layers for feature extraction and there is another hidden layer which follows previous layers designed to reconstruct the original input signal. Autoencoder trains the network. This paper uses many layers of Autoencoders and produces a deep model of input data on output of the last layer. It consists of layer-wise training. Working of every layer in AE depends on output of previous layer. Stacking of input-to-hidden layers makes a stacked Autoencoder. In this paper, Training of network takes place over 100000 iterations. Objective of training is output should be approximately equal to input.

- *MLP Classifier*

Feedforward artificial neural network is base of Multilayer perceptron classifier. MLPC contains many layers of nodes. In the network every layer is appended to the next layer. Input layer consist of Nodes that contains input data. With the help of every node's bias b and weights w, other Nodes in the network maps inputs to the outputs. This operation is performed using linear combination of inputs. An activation function is applied on it. For learning the network MLP classifier uses back-propagation [8] algorithm. MLPC with K+1 layers can be written in matrix form as:

$$y(x) = f_K(...f_2(w_2^T f_1(w_1^T x + b_1) + b_2).... + b_k)$$

Intermediate layers consist of nodes which uses sigmoid (logistic) function:

$$f(Z_i) = \frac{1}{1+e^{-z_i}}$$

Output layer consist of node which uses softmax function:

$$f(Z_i) = \frac{e^{z_i}}{\sum_{k=1}^{N} e^{z_k}}$$

N = the number of classes.

MLP classifier consists of 3 layers. MLP Classifier consists of input layer which consist of 8 nodes. Hidden layer consist of 400 hidden units. Output layer designed for four class classification. MLPC make a use of back propagation for learning the model. Logistic loss function used for optimization.

IV. Experimental Results

Four classes are selected for this study, namely: Urban (Red), Mangrove (Pink), Water (Blue), Bareland (green). Result is shown in figure 3.

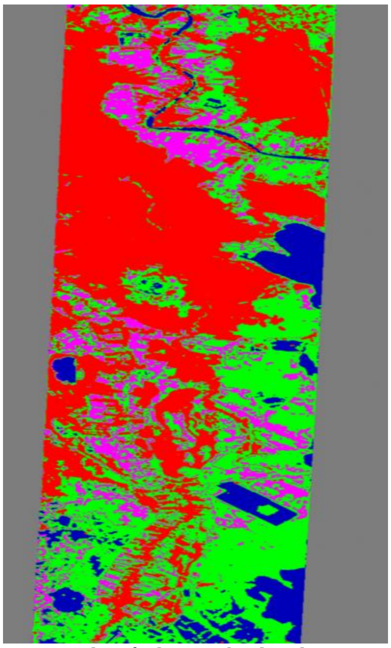

Fig. 4. Classified output by deep learning.

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This network was able to obtain accuracy of 92% over 100000 iterations. Thus MLP classifier can be differentiate between all four classes apart from target orientation.

V. Conclusion

Deep Learning shows excellent performance as compare to other approaches like SVM, Wishart Distribution. Autoencoder can extract the sharp features. In AutoEncoder, as number of hidden layers increases no of features can detected more. With the help of many numbers of hidden layers in autoencoder one can extract sharp features. Deep learning Method improves classification accuracy as compared to shallow approaches. Performance of Deep Learning is helpful in various challenges faced by classification and recognition. Thematic Map can be generated with the help of fully automated urban area classification with SAR, which is useful for urban sprawl and planning studies. Deep learning is able to set fast and actual unsupervised object recognition methods.

Acknowledgment

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Substitute the correct groups and datasets.

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