Classification of high-resolution images with Local Binary Pattern and Convolutional Neural Network

T.Gladima Nisia, Dr. S.Rajesh

Abstract— In high-resolution satellite images, it is very important to classify the image accurately and classify each area of the image distinctly. However, it is not easy to identify complex patterns. To cope up this difficulty deep learning method is employed. Deep learning method is to automatically extract many features without any human intervention. Still the performance of the classification is enhanced by combining the deep features with texture features. The proposed system facilitates the deep feature learning strategy combined with texture-based classification. Here, texture features are extracted using Local Binary Pattern (LBP) and deep features by Convolutional Neural Network (CNN). The proposed system is implemented and the results are verified. Experimental results show that the efficiency of classification is improved when texture features are combined with deep learning approach.

Keywords—high-resolution image; deep learning; Convolutional neural network (CNN); image classification; Local binary pattern (LBP)

1. INTRODUCTION

Remote sensing (RS) images obtained by satellite sensor has detailed information about the different areas of the landscape. The rich spatial information present in the images needs accurate interpretation. Especially in urban area, the objects consist of different construction material. This different construction material will result in confused feature set. Thus, it becomes difficult to extract features from the remote sensing image to classify it [1] [2]. In the earlier, features extraction methods are Local Binary Patterns, run-length matrices (RLM) fractal analysis and gray level co-occurrence matrices (GLCM) [3]. When GLCM method was used, the system can extract texture features that describes spectral variations to necessary information for classification. Adaptive multiple feature method (AMFM) is formed by combining all these features.

From the observation of high-imageries, it is observed that it contains more richer information in spatial domain than in the spectral domain. So, the researchers are continued by applying spatial filters such as Gabor filters [4] and wavelet analysis [5] to RS images. The extracted spatial features are further used in the context of high-resolution images. Even though such features are extracted, for defining such elaborate features it still requires lots of experience and expert knowledge for humans. Also, find the most effective and efficient features from the elaborated features remain the hardest part for the recognition of different objects.

The identification of the objects from complex patterns of RS images is very difficult. So, the need for exploring more and more, efficient and representative image features from complex patterns, such as complex buildings in an urban area is growing. Thus, resulting in the automatic classification scheme for feature extraction. Different feature learning methods were introduced at different times. Cheriyadat [6] introduced a feature learning scheme of sparse coding from RS image for automatic feature extraction with predefined filter banks. Tuia et al. [7] introduced a model by using sparse-constrained support vector machine (SVM). But it needs for selecting the predefined features. In RS field, several studies were made using deep learning models, such as stacked autoencoder (SAE) and CNN for image classification. But the original SAE does not succeed in efficient image classification since it works by extracting one-dimensional spectral features and is not enough for image interpretation. Therefore, Chen et al. [8] used SAE for the efficient image classification of hyper spectral images by remodeling the SAE model by introducing spatial features. But when compared to SAE, the convolutional neural network performed well in spatial feature exploration and the accuracy is further improved.

Here thus the proposed system tends to utilize the CNN for the classification process. The system transforms the manually designed features into automatically extracted features using deep learning. The deep learning is achieved using CNN and thus resulting in the deep features from the RS images. The deep features extracted from CNN are fused with the texture features extracted using LBP[9]. Thus, the newly combined features are able to increase the classification accuracy of the process.

2. METHODOLOGY

The complexity of the classification increases, since we are dealing with the high-resolution satellite images. The proposed system uses the CNN for extracting the deep features. The overview of the proposed worked is given in

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Fig. 1. It concentrates mainly on extracting useful features from the high-resolution image given. The features extracted is done as two separate process.

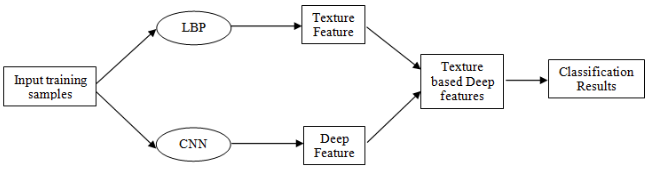


Fig. 1: Overview of the proposed system

A. Extraction of features using LBP:

The method divides the images into cells. The pixel value of each cell is compared with its neighboring pixel values in clockwise or anticlockwise directions. If pixel value exceeds neighbor value then replaces it with '0' else '1' (shown in Fig. 2(b)). The computation thus results in the 8-digit binary number. From this binary number the LBP value is calculated by multiplying reference binary value matrix with the matrix replaced with 1's and 0's. The process is explained in Fig 2(a), 2(b) and 2(c).

7	4	3
6	5	9
1	3	2

(a)

1	0	0
1	X	1
0	0	0

(b)

1	2	4
128	X	8
64	32	16

(c)

Fig. 2: (a) Original matrix (b) Matrix replaced with 1's and 0's (c) Reference binary value matrix

Pattern = 10010001 and LBP = (1*1)+(2*0)+(4*0)+(8*1)+(16*0)+(32*0)+(64*0)+(128*1) = 137. In the same way, the features are calculated for the whole image.

B. Extraction of features using CNN:

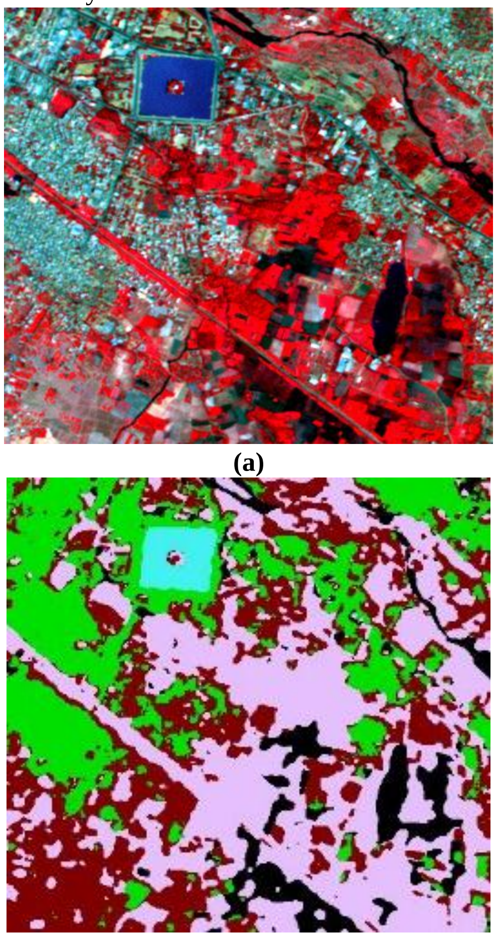
The convolutional neural networks are used for extracting the deep features without any human interaction. The layers associated with the CNN are Convolution layer, ReLu layer, Max pooling, fully connected, Softmax and classification layer. Here in Convolution layer the input image's matrix is convolved with a randomly chosen filter matrix by sliding it over. The product value is calculated between input matrix and filter matrix and they are summed up. In ReLu layer, the negative values of the convoluted matrix are made as zero and the remaining is left as such. Pooling layer is also called as down sampling layer. It takes a filter and applies it to the matrix from ReLu layer. The result of this is the maximum number in every sub region that the filter worked with. The remaining layer then classifies the pixel. The trained CNN is then tested using the test image. The test image thus produces the deep features. The features are taken to the next stage for classification.

C. Feature Fusion and Classification:

The features from LBP and CNN are combined together into a single feature set. The fusion operation is performed to combine those features from different process. These final features are used for classification of the images. In case of satellite images, the images are identified with different land usage/land coverage regions. The classification of the image is done using the CNN. The trained network is used to distinguish the image and label them.

III. EXPERIMENT STUDY AND RESULTS

The LISS IV image of Madurai consists of 5 different classes such as waste land, water body, urban area, vegetation, saline land. The training samples of different sample sizes such as 3x3, 5x5, 7x7 and 9x9 are tried. Finally, the training samples of size 7x7 are found to be efficient and is used to train the network. The number of filters is also altered with 20, 30, 40, 50, 60, 70 and 80 filters. Among which the efficient number of filters is found to be 50. The deep of the network is increased by adding further more number of convolutions, relu and pooling layers. After training we can classify the image using the trained network. The entire image is given for classification and the output is classified image with different color for different labels. The original image and the classified output image are as given in Fig. 3(a) and 3(b). The overall accuracy of the classification is 90%.



(a)

(b)

Fig. 3: (a) Original LISS IV input image (b) Classified output image

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IV. CONCLUSION

The proposed system thus efficiently classifies the high resolution LISS IV images. The most difficult part of the classification is feature extraction process. The efficiency of the whole process lies on the quality of the features extracted. So, the proposed system handled the issue in a great way by choosing the CNN for extracting the deep features. The accuracy is still improved by fusing the obtained deep features with texture features extracted using LBP. The system is tested using LISS IV Madurai image and the results are verified. The accuracy is improved when compared with other earlier approaches. In future, the classification accuracy can be still improved by combining some other features also with the deep features

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