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A Survey on Airport Detection on Remote Sensing Images using Deep Convolutional Neural Network

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Abstract: ***This survey analyzed the use of deep convolutional neural networks (CNNs) in providing a solution for the problem of airport detection in remote sensing images (RSIs). In recent years, Deep CNNs is mostly used in many applications undertaken in the area of computer vision. Researchers generally detect airport detection as a pattern recognition problem, in which first distinctive features are extracted, and then one of the classifier is adopted to detect airports. As per the research in various field CNNs not only ensure a tuned feature vector, but also gives better classification accuracy. The method proposed in this paper first detects various regions on RSIs using Line Segment Detection algorithm and then uses these candidate regions to train CNN architecture with Matconv-net tool. The CNN model used has five convolution and three fully connected layers. Normalization and dropout layers were employed in order to build efficient architecture. A data augmentation strategy was used to reduce overfitting. Many experiments were performed to evaluate the performance of CNNs.***
Index terms: Airport detection, remote sensing images, convolutional neural net-work (CNN), line segment detector (LSD).

I. INTRODUCTION

Detecting the object in remote sensing images (RSIs) has become a frequently discussed topic in image analysis and pattern recognition [1-3]. Roads, airports, buildings, forests, and urban settlements are most often the objects of interest in RSIs, with airports being the most significant because of their civil and military applications. Many airport detection methods have been used, based on either edge/line segment detection [4] or texture image segmentation [1]. While the former detection methods are motivated by airport runways, the latter consider the special texture of airport regions. However, the line-based methods generally fail to distinguish betweenairport runways and roads [5]. In addition, segmentation-based methods generally use a sliding window, thus carry a computational burden [1]. Recently, several efficient airport detection algorithms have been proposed based on both line detection and texture feature extraction [6, 7].

These methods first use line segments or visual saliency or their combination for airport detection with various candidates of regions. Then, texture features are extracted from these regions [7, 8]. Finally, a classifier is adopted to classify the candidate regions into airports and non- airports based on the extracted features. More recently, a new topic called deep learning has attracted researchers in the machine learning community [9]. It has found various applications particularly in the classification of huge image datasets into large classes [9].

Convolutional neural network (CNN), an extension of biologically inspired multi-layer perceptron's (MLPs) [10], is considered an efficient image feature extractor. The typical CNN architecture consists of a number of convolution and pooling layers, followed by fully connected layers [10]. The convolution layers contain local filters, which are tuned during the training of the CNN architecture to exploit the strong spatial local correlation present in the input images.

CNNs are considered to be a leading technique in image classification and have state-of-the-art performance in many applications including handwritten digit recognition [11], traffic signs classification [12], and 1000 class Image Net dataset classification and localization [9]. However, to the authors' knowledge, CNN has not been applied to the problem of airport detection. Therefore, this survey proposes a deep CNN-based airport detection system, having a two-stage airport detection scheme inspired from the existing efficient schemes [5].

The first stage of the proposed method aimed to locate various candidate airport regions in the input RSI. For this stage, the methodology proposed in Ref. [5] was applied, so in that firstly used candidate airport region extraction method by improving the line segment detection (LSD) algorithm given in Ref. [13]. In the second stage, popular deep CNN architecture [9], AlexNet, was employed for verification purposes. AlexNet consists of five layers of CNN and three fully-connected layers for large-scale image classification [9].

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II. METHOD

The proposed method is formed by mainly four steps that is Region proposal, Dataset Acqusition , feature extraction, and finally Training using Deep Convolutional Neural Network(CNN), All the tested optical satellite images were collected from Google Earth of 2000×2000.

III. CONVOLUTIONAL NEURAL NETWORK

Recently, CNN has become a popular tool for image classification/recognition and image retrieval applications. Although MLPs can be used for similar purposes, to obtain sufficient generalization performance, it is better to consider prior knowledge within the network architecture [10]. CNN aims to incorporate input image spatial information between pixels into the network architecture. It contains two basic operations; convolution and pooling, which are embedded in the sequential layers of the network. Performing convolution and pooling operations consecutively constructs high-level features, on which classification is performed. Classification is performed in the fully connected layers of the CNN architecture. However, during CNN training, a large number of parameters require adjustment.

To keep the number of parameters tractable, the weights of convolutional nodes in the same map are shared. Training of the CNN is handled using the conventional back propagation algorithm. CNN has three different types of layer:

1) *Convolution Layer*: Known as the core layer of the CNN architecture, the convolution layer has a number of trainable filters. During the training of the CNN, each filter is convolved across the width and height of the input tensor in the forward pass. After the convolution operation, two-dimensional activation maps of the filters are constructed. As a result, the network learns the filters that are activated when a specific feature type is seen at a spatial position in the input.
2) *Pooling Layer*: Another important concept of the CNN architecture is pooling. It forms a non-linear down-sampling. Although the pooling operation can be handled with several non-linear functions, the most common is max pooling in which the input image is partitioned into a set of rectangle sub- regions. For each sub-region, a maximum value is set as the output in order to reduce the spatial size of the input. This also reduces the number of parameters and amount of computation required.
3) Fully Connected Layer: After several convolution and pooling layers, the classification process is handled in a fully connected layer. The neurons in the fully connected layer have full connections to all activations in the previous layers and can be computed with a matrix multiplication followed by a bias offset.

IV. EXPERIMENTAL SETUP

A. *Architecture of the CNN*

The input of the CNN was a fixed size 224×224×3 pixel color image. The mean color image, computed on training color images, is subtracted from each pixel. The CNN model has five convolution layers and three fully connected layers. The first convolution layer employs 64 filters of size 11×11. The convolution stride is four pixels. The rectification linear unit (RELU) and local response normalization layers follow the first and second convolution layers. There are five max- pooling layers in the architecture, which follow some of the convolution layers. The pooling operation is performed over a 3×3 pixel window, with stride 2. The second convolution layer filters the output of the previous layer by using 256 filters of size 5×5. The convolution stride is one pixel and spatial padding is two pixels. The third convolution layer also employs 256 filters of size 3×3. The convolution stride and spatial padding are one pixel. A RELU layer follows the third convolution layer. The fourth and fifth convolution layers have the same structure as the third convolution layer. As mentioned earlier, three fully connected layers follow the convolution layers. Each fully connected layer has 4096 nodes. Dropout probability is selected as 0.5. A loss layer is used as the last layer.

B. *Dataset Construction*

Various experiments were conducted to evaluate the performance of the proposed method on real RSIs obtained from Google Earth that contain airports in various parts of the world [14]. The sizes of the airport images were 2000×2000 with a resolution of 1 m. A total of 92 images were collected, of which 48 were randomly selected for training and 44 were used for testing. The candidate regions on the input images were extracted using the improved LSD algorithm proposed in Ref. [5] and were normalized to 224×224×3 pixels. The labeling of the candidate regions was handled visually. If 40% of a candidate region overlapped with a true airport region, then that candidate region was labeled as positive (airport); otherwise, the candidate was assumed as negative (non- airport). In total, 89 airport regions and 251 non-airport regions were labeled in the training images, and 68 airport regions and 245 non-airport regions were labeled in the test images.

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C. Dataset Augmentation

The training dataset was artificially enlarged to reduce overfitting. Firstly, input images were flipped on the X, Y, and XY axes. Then, the input images were rotated $+90^{o}$ and -90^{o}, and the rotated images were flipped on the Y axis. The end results comprised 8×(89+251)=2720 images. Figure 3 illustrates an example of data augmentation flipping on the X, Y, and XY axes. No enlargement operation was applied to the dataset.

D. Result

MATLAB 2013a was used. The MaTConvNet tool was used to generate the CNN model [13] with a stochastic gradient descent. The batch size of 70 training instances was considered during training.

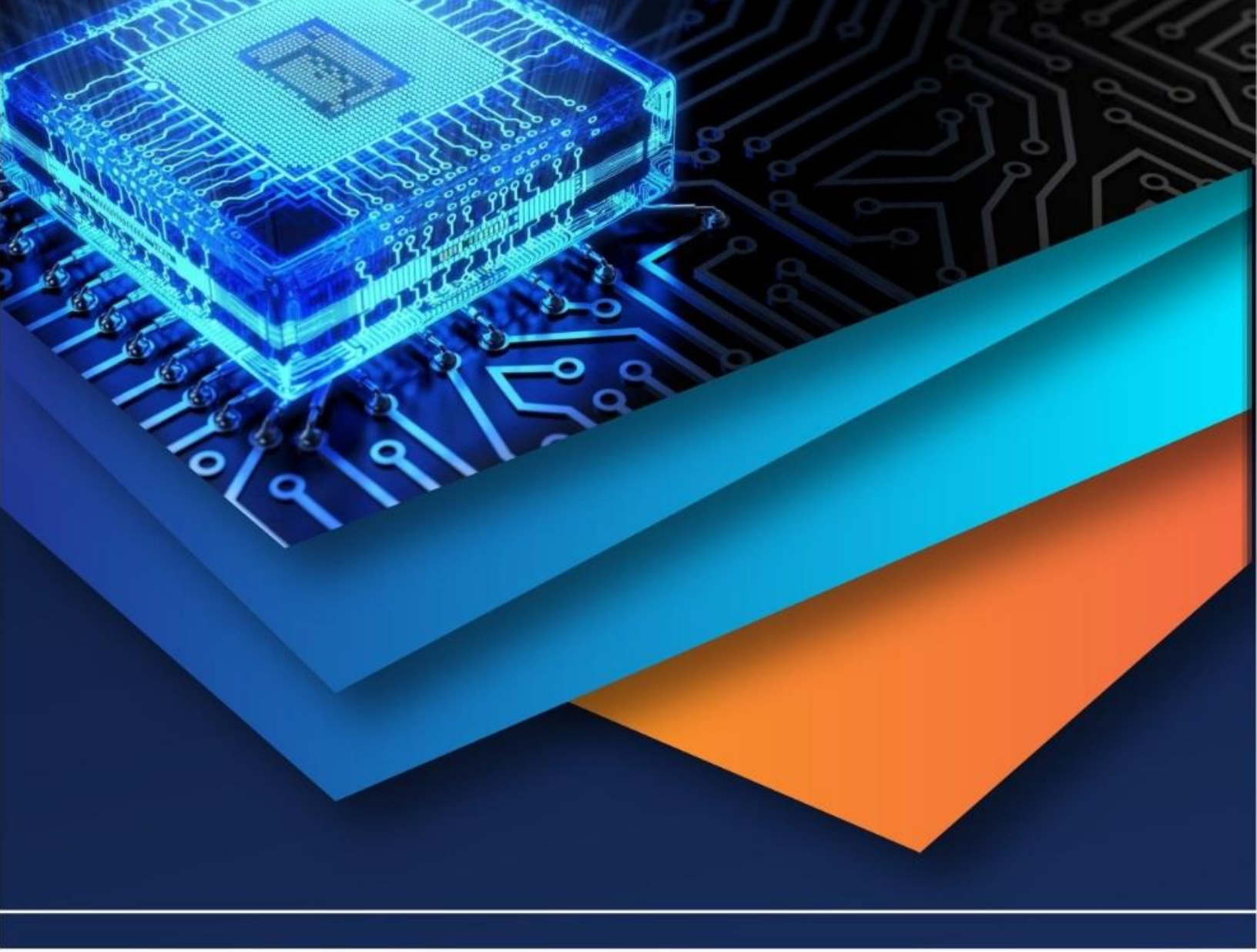
V. CONCLUSION

In this survey, the use of a deep CNN for the airport detection problem was investigated. After potential airport regions were detected, the CNN architecture was trained for airport recognition. The proposed CNN not only successfully extracted the distinct features that characterized airports, but also performed better in classification compared to the previous methods based on SIFT features and SVM classification. .

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