Explainable Deep Learning for Detection of Fairy Circles

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RESEARCH OBJECTIVE

Large barren soil circles (so-called fairy circles), up to 12 meters in diameter and visible in satellite images, are a prominent feature of semiarid landscapes around the world, including the Namib Desert, the outback of Australia, and the southwestern US (see Fig. 1). Such fairy circles are ecologically important, because fairy circles are a sensitive climate indicator. Moreover, they are global with confirmed occurrences in the Namibian grassland, Australia's desert outback, and the semiarid southwestern United States. To take advantage of this climate indicator, **our long-term goal** is to create a global database of fairy circles for monitoring their changes over time. Ground survey is not an option, as many of these places are hard or impossible to access.

Fig 1. Example of fairy circles in Nevada Location (left) and normal barren land (right)

INTRODUCTION

Detection of fairy circles is considered as an object detection problem in a large-scale image in Computer Vision. Most computer vision methods heavily relies on a large set of images with pixel-level labels (i.e., strongly supervised data), which is time-consuming and labor-intensive [1]. Recently, advanced deep convolutional neural networks have proposed novel solutions to handle weakly supervised data, which does not require pixel-level labels, but only image-level labels. Most of the weakly supervised object detection methods use the approach of Class Activation Maps (CAM) [2]. However, a challenging problem with CAM is to fail to capture entire regions of an object; Instead, they capture only most discriminative regions of the object (see Fig. 2).

We propose a novel attention-based explainable deep neural network approach that effectively learns essential features from weakly supervised data by paying more attention to features that help in localizing the entire regions of an object [3]. The key contributions of the proposed approach are:

1) Capturing the most important features related to an object from multiple attention modules.
2) Localizing the entire regions of an object from background over a large resolution satellite image.

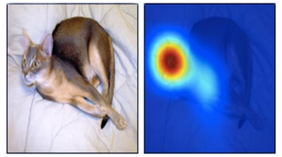

Fig 2: cat image (left) and CAM of cat (right)

METHOD

The pipeline of the proposed method (see Fig 3) consists of:

1. Patch images are extracted by sliding a small window over a given input image, and then a backbone network is trained using the patches.
2. The proposed model includes multiple self-attention (SA) modules (see Fig 4) on the optimized backbone model, inspired by the self-attention generative adversarial networks [4]. A self-attention module is a combination of a set of conventional convolutions with 1 x 1 kernel sizes, softmax function, and matrix multiplications. The SA module takes the feature maps from the convolution layers as input and generates enhanced attention maps.
3. The proposed model also includes a bilinear interpolation and stack layer to resize the enhanced attention maps from multiple SA modules to the desired shape and stack up the feature maps for effective object detection.
4. During the test phase, the patch images are passed through the model and, then we extracted the attention maps which are again multiplied by an appropriate average Hann window [5] and superimposed on original image.

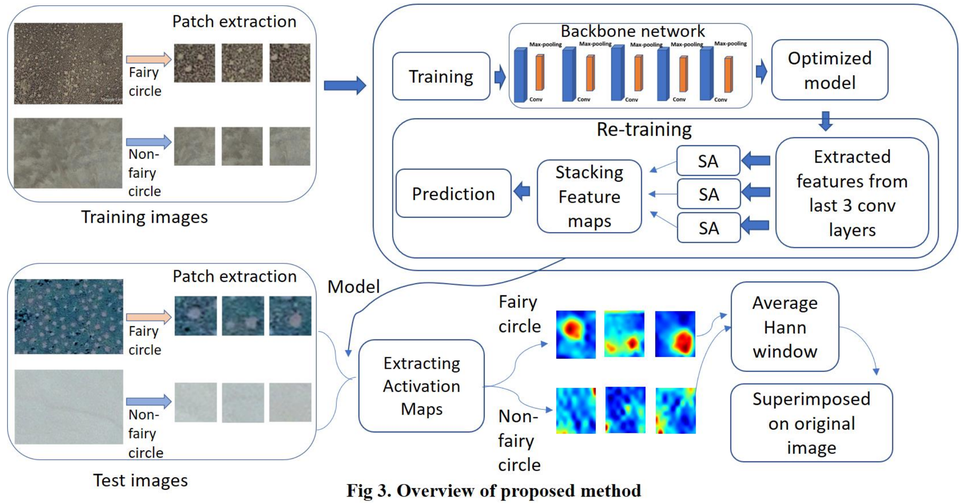

Fig 3. Overview of proposed method

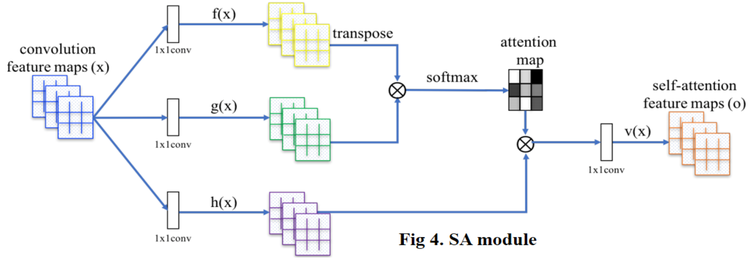

Fig 4. SA module

RESULTS

We compared the superimposed attention maps of fairy circles regions and non-fairy circle regions from Australia's desert outback. Our approach detected the entire regions with higher activation scores towards the fairy circle object.

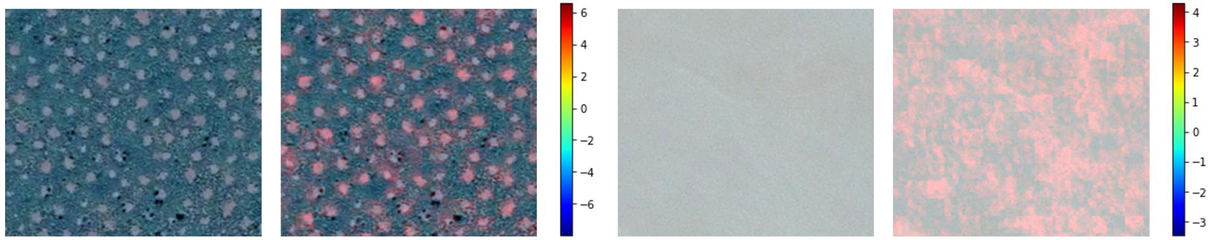

Fig 5. (a) Original image of fairy circles, (b) Attention maps superimposed on the original fairy circles, (c) original images of non-fairy circles, and (d) attention maps superimposed on the original non-fairy circles.

CONCLUSION

Our proposed explainable deep learning model can efficiently detect fairy circle objects over a large satellite image without strongly supervised data. The newly introduced multiple SA modules yielded significant results in localizing entire fairy circle objects. The proposed method can be easily integrated into any neural network architectures. Future efforts in this research will be to create a global database of fairy circles monitoring their changes over time.

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