ARTIFICIAL INTELLIGENCE

DIGITAL NATURALIST - AI ENABLED TOOL FOR BIODIVERSITY RESEARCHERS

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

Literature Survey

This project aims to identifiy a different kinds of flora and fauna in nature. Being able to identify the flora and fauna around us often leads to an interest in protecting wild spaces, and collecting and sharing information about the species using artificial intelligence

Nguyen et al. [1] used 2 CNN based models, one to detect presence of wildlife called the wildlife detector (binary classifier) and one to identify the species of the wildlife found called the wildlife identifier (multiclass classifier) using Lite AlexNet, VGG-16, and ResNet-50. The wildlife detector task did an exceedingly great work in replacing manual filtering of images. The animal identification results have shown a good performance in identifying the most common three and six species of animals. But this performance was not sufficient to build a fully automatic recognition and the dataset used was slightly unbalanced (68% having animal presence).

Huang et al. [2] used a transfer learning-based method using Inception-ResNet-v2 to detect and classify endemic bird species and to distinguish them from other object domains. To enhance the performance and decrease overfitting in the selected model, a mechanism to swap the misclassified samples of training and validation was used. The designed model was reinforced with multistage model validation by swapping misclassified data between the training and validation datasets to achieve better results in the detection and classification of birds. But the identification of global endemic bird species was not fulfilled as the model was biased towards species of a region.

Gogul et al. [3] used Convolutional Neural Networks (CNN) to recognize flower species. Feature extraction of flower images was performed using a Transfer Learning approach. Machine learning classifiers such as Logistic Regression or Random Forest was used on top of it to yield a higher accuracy rate. This approach helped in minimizing the hardware requirement needed to perform the computationally intensive task of training a CNN. It was observed that CNN combined with Transfer Learning approach as feature extractor outperformed all the handcrafted feature extraction methods.

de Arruda et al. [4] identified regions of interest using the segmentation of thermal and RGB images by means of the SLIC algorithm. Such regions were projected onto the network feature map of the Fast R-CNN network after which, a maximum pooling was performed to adjust the final size of the features with the fully connected layer. VGGNet architecture with 16 layers was used for the final species identification. The approach achieved better results when compared with the original Fast R-CNN for 8 animal species. Approach included the use of thermal imaging that helped improve the results when compared with the Fast R-CNN. But the CNN required a large dataset to be trained to provide the observed accuracy.

Liu et al. [5] talked about a deep-learning approach called the PestNet. It consisted of three major parts. First, a novel module channel-spatial attention (CSA) was to be fused into the CNN backbone for feature extraction and enhancement. The second one was called region proposal network (RPN) that was adopted for providing region proposals as potential pest positions based on extracted feature maps from images. Position-sensitive score map (PSSM), the third component, was used to replace fully connected (FC) layers for pest classification and bounding box regression. The features were extracted and learned from original images automatically without any pre-processing rather than being hand-crafted. It yielded only moderate performance in case of noisy images and tiny objects.

Zhang et al. [6] used a path-based learning algorithm to enable joint learning of deep CNNs (for feature extraction) and tree classifier (over plant taxonomy) in an end-to-end fashion. The method used a tree classifier which was computationally less expensive than a flat approach such as N-way softmax. A path-based back propagation method was used to achieve joint learning of deep network and tree classifiers in an end-to-end fashion, so that the critical issue of inter-error propagation could be addressed effectively.

Jeon et al. [7] talked about effective image augmentation to get the best results. The colour image of a plant leaf was first transformed into a grayscale image and then converted to a binary one through binarization, and the contour then extracted. It used GoogleNet CNN Model for classification of images. Overfitting was avoided using batch normalization. Image cropping reduced the amount of computation used by the GPU to minimize the foreground portion. It classified leaves of different shapes and/or having different levels of discoloration with a significant accuracy.