Digital Naturalist - AI Enabled tool for Biodiversity Researchers

Literature survey

Introduction

The ever-growing number of digital sensors in the environment has led to an increase in the amount of digital data being generated. This includes data from satellites, weather stations, data from ‘‘internet of things’’ devices, and data collected by members of the public via smartphone applications, to name but a few. These new sources of data have contributed to the era of ‘‘Big Data’’ characterized by large volumes of data, of numerous types and quality, being generated at an increasing speed. This difficult for multimedia data which are typically much more complex than other data types. Largescale analysis of multimedia data has only been possible in recent years since the development of large computational facilities, both academic and commercial. Regardless, the analysis of multimedia data is often further complicated because of their nonstandardized methods of acquisition, with highly diverse devices, sensors, formats, scales, environmental contexts, and taxonomic scope. Building efficient, scalable, and robust approaches to solve these problems is a difficult scientific challenge at the forefront of data science and machine learning specifically. Artificial intelligence (AI) techniques have profoundly transformed our ability to extract information from visual data. AI techniques have been applied for a long time in security and industrial domains, for example, in iris recognition7 or the detection of faulty objects in manufacturing.8 They were nevertheless only recently made more widely accessible after their use in smartphone apps for face recognition9 and song identification.10 Combined with increasing access to cloudbased computation, AI techniques can now automatically analyse hundreds of thousands of visual data every day. AI can also be used to extract information from big data in order to address various challenges faced by society. Applications of AI to biological recording have to date typically focused on active sampling, that is, images collected specifically for the purpose of recording wildlife24 (e.g., wildlife recording apps or camera traps). However, this has neglected large amounts of image data that are not collected for the purposes of biological recording, but which nonetheless may contain useful information about biodiversity. AI naturalists, just like their human counterparts, may have their own biases which must be fully understood if the information that they generate is to be trusted and suitably utilized. For example, most AI systems can only detect or recognize already seen (or learned) objects or concepts. Benchmark datasets of images can be organized to precisely assess the limits of AI systems' ability, highlighting where human expertise is still required. Deep learning models (some of the most advanced AI algorithms) are developed with training datasets that allow them to capture discriminant visual patterns. Their performances are then strongly correlated to the quality and completeness of the datasets on which they are trained. Unbalanced, biased, or otherwise poor-quality training datasets will lead to underperforming algorithms in real conditions.27 During the learning phases, particular attention must be given to any relevant limitations of the training data, and the gap between these and the test data on which the developed algorithms will be evaluated.28 We present an AI naturalist developed to create biodiversity datasets from social media image data.

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[1]. "Bird classification using CNN" by Simon Haykin: This work presents a scenario with classification of birds using CNN technique based on color features. They used color images of birds with almost similar types. Image segmentation is carried in various stages. At first, the pixels are arranged and segmented on the basis of edges and spatial segmentation, where clustering is done. Next, the blocks are segmented using edge detection. The computational efficiency increases for image and training becomes easier. This approach provides with better and robust results for different images. Here they took sparrow for the case study and evaluated the features of it using the steps up listed. The experimental results classify the effectiveness of proposed approach to improve the segmentation quality in aspects of precision and computational time .

[2]. "Adapted approach for Species Classification" by Schmid Huber, J.: In this work, an adaptive approach for the identification of species is proposed and experimentally validated. Image processing technique is followed. In the first step K-Means clustering is used for image segmentation, in the second step some state of art features is extracted from segmented image, and finally images are classified under one of the classes by using multi-class support vector machine. The classification accuracy is achieved up to 89%.

[3]. “Detection And Classification of images using Detection Line” by Haibing Wu and Xiaodong Gu: In this study, they present an application of neural networks and image processing techniques for detecting and classifying images. Images were segmented by a detection line (DL) method. Six geometric features (i.e., the principal axis length, the secondary axis length, axis number, area, perimeter and compactness of the image), 3 color features (i.e., the mean gray level of image on the R, G, and B bands. The methodology presented herein effectively works for classifying image to an accuracy of 90.9% .

[4]. “Texture Classification from Random Features” by Gary Bradski and Adrian Kaehler: presented an approach for texture classification based on random projection, suitable for large texture database applications. A small set of random features are extracted from local image patches and those features are embedded into a bag-of-words model to perform texture classification .

[5]. “Classification and Grading of Image Using Texture Based Block-Wise Local Binary Patterns” by Paul Viola, Michael Jones: They proposed approach makes use of global textural feature viz., Local Binary Pattern for feature extraction. Initially, an image is divided into k number of blocks. Subsequently, the texture feature is extracted from each k blocks of the image. The k value is varied and has been fixed empirically. For experimentation purpose, the bird dataset is created using 4 different classes and experimentation is done for whole image and also with different blocks like 2, 4 and 8. Grading of Bird is done using Support Vector Machine classifier. Finally, the performance of the grading system is evaluated through metrics like accuracy, precision, recall and F-measure computed from the confusion matrix. The experimental results show that most promising result is obtained for 8 blocks of the image.

References

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