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Fossil charcoal particle identification and classification by two convolutional neural networks

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Abstract

Fire is a significant natural and cultural phenomenon, affecting spatial scales from local to global, and is represented in most palaeoenvironmental records by fossil charcoal. Analysis is resource-intensive and requires high-level expert knowledge. This study is a preliminary investigation of the application of artificial neural networks to fossil charcoal particle analysis, utilizing a U-Net variant for charcoal particle identification and VGG for particle classification by morphology. Both neural networks performed well, reaching ~96 % accuracy for particle identification and ~75 % accuracy for classification. Future work will include expansion of the training dataset, including total number of particles and number of sites. The development and application of this automated system will increase the efficiency of fossil charcoal analysis.

Keywords

Fossil charcoal analysis; palaeolimnology; palaeofire; artificial neural networks; Quaternary; global; sedimentology, lakes, lagoons & swamps

Introduction

Fire has existed on Earth for over 400 million years (Bowman et al. 2009:481) and is an important environmental process interconnected to climate, vegetation structure, and carbon cycling (Beringer et al. 2015; Bowman et al. 2009; Veenendaal et al. 2017). Fire occurrence is also linked to people; humans have had a long and complex history with fire (Bowman et al. 2011; Scott et al. 2016), including the widespread use of fire as a landscape management tool (e.g. Anderson 1994; Archibald et al. 2012; Montiel and Kraus 2010; Rolland 2004; Rull et al. 2015). Moss and Kershaw (2000), for example, suggest the impacts of Australian indigenous use of fire in the landscape can be seen over 38,000 years ago in the palaeoenvironmental record. Both natural and anthropogenic fire are connected to significant issues for asset management, conservation and cultural practice.

Fossil charcoal is an important palaeofire proxy. It has high preservation potential (Conedera et al. 2009; Mooney and Tinner 2011; Whitlock and Larsen 2001), and charcoal records are available worldwide (see Global Paleofire Working Group 2017 as well as Power et al. 2010, for depictions of the spatial and temporal scope of global charcoal records). Analysis of fossil charcoal, including identification of the type of vegetation that burned to create it, allows for the creation of long term fire records contextualised by fuel type (e.g. Aleman et al. 2013; Crawford and Belcher 2014; Jensen et al. 2007). Such information allows for a greater understanding of fire and vegetation dynamics across time and space. However, traditional (optical) charcoal analysis is a time-intensive process; fossil charcoal is commonly quantified on pollen slides (particles <125 μm diameter) or wet sieved and suspended in water, with charcoal abundance measurements taken via microscope as either particle counts or area measurements (see Mooney and Tinner 2011; Stevenson and Haberle 2005). Increasing the speed of charcoal analysis will enable researchers to process a larger volume of samples in a given time frame, allowing for higher resolution records and broader sampling potential.

Recent developments in artificial neural networks have led to their successful application to problems across a diverse range of disciplines (e.g. review of developments and applications including finance, bioinformatics and environmental risk, Bassis et al. 2014; engineering, Mehrjoo et al. 2008; medical imaging, Wu et al. 2017). Drawing from these developments and using them as a framework for this study, the identification and classification process of fossil charcoal particles is an ideal candidate for automation using neural networks.

Background and Related Work

While volumes of preserved charcoal (number of fossil charcoal particles) help indicate the amount of fire in past landscape, the fuel source (vegetation type) of a fossil charcoal particle is significant as this reflects the composition of the surrounding environment. The aspect ratio of a macroscopic (>125 µm) charcoal particle provides this data, with more elongated particles identified as grass-derived and blockier particles as wood- or leaf-derived (e.g. Umbanhowar and McGrath 1998; Aleman et al. 2013; Crawford and Belcher 2014; Leys et al. 2017). The threshold ratio for a particle to be considered elongate is a matter of debate, ranging from a length-width ratio of 2 or greater (Aleman et al. 2013) through to 3.7 (Crawford and Belcher 2014).

An alternative method of fuel identification is classification by morphology (morphotypes) (e.g. Jensen et al. 2007). Enache and Cumming (2006) present a 7-type classification scheme based on morphological differences such as elongate versus blocky, geometric versus irregular, and the presence of internal structure such as voids. Mustaphi and Pisaric (2014) expand this to 27 different morphotypes including types specific to a temperate biome, such as type C1 (charred conifer needles). Enache and Cumming's (2006) morphotype classifications are a simpler system applicable to a broader range of environments.

The current standard for automated quantification of charcoal particles is ImageJ, originally developed by the US National Institutes of Health (Schneider et al. 2012; for examples of its application see Barr et al. 2017; Crawford and Belcher 2016; Halsall et al. 2018; Hawthorne and Mitchell 2016; Stevenson and Haberle 2005). The input image is a petri dish containing charcoal, and potentially other non-black particles; ImageJ output contains the total number of dark particles and particle area based on a user-defined threshold (Abramoff et al. 2004; Ferreira and Rasband 2011; see Mooney and Tinner 2011:11 for instructions on charcoal analysis using one of ImageJ's predecessors, Scion Image). Image classification, as is required for identifying morphotypes, is currently beyond the capabilities of ImageJ.

Few studies have applied neural networks to palaeoenvironmental problems. In palaeolimnology, Racca et al. (2003) use a multi-layer perceptron neural network to reduce diatom taxa for calibration purposes. Maruyama et al. (2018) use a convolutional neural network as a feature extractor to identify the species of native wood charcoal pieces, created from samples of modern trees. Weller et al. (2007) apply a supervised neural network to identification of sedimentary organic matter within pollen slides. A preliminary study automating pollen analysis by a neural network is presented by France et al. (2000). To date, no published studies have utilized neural networks for charcoal particle identification or classification.

Methods

In this study, two Convolutional Neural Networks (CNN) are used to identify and categorise charcoal particles: a variant of U-Net, and VGG, implemented in Keras with a Tensorflow backend (Abadi et al. 2015).

The U-Net variant is used to first mask, per pixel, charcoal particles so as to eliminate image artifacts or non-charcoal particles that made it through the filtering process. U-Net is an autoencoder network that uses multiple alternating layers of convolutions followed by max pooling to "encode" features from an image input. In our case, strided subimages of 512x512x3 pixels are encoded down to a feature space of 16x16x256. Once encoded into the feature space the network then "decodes" using alternating layers of upsampling, deconvolution (Zeiler et al. 2010) followed by the copy and crop of encoder layer outputs, sometimes referred to as skip connections, found in the U-Net architecture (Ronneberger et al. 2015). Training the network with binary images, representing "charcoal particle" and "not charcoal particle", the network learns how to encode and decode information in images to generate the binary masks itself and generalises to images that are outside the training data.

Due to the nature of charcoal particles being of high contrast, and the lack of similar looking distractors in the dataset, we deviated from the default U-Net architecture by removing the use of multiple layers of convolution and deconvolution between up-samples and down-samples. This drastically reduces the number of operations that the network needs to perform and still provided adequate results for the purposes of segmenting out individual particles for VGG to classify.

VGG is a very deep convolutional network for image recognition and is considered a staple for image based classification (Simonyan and Zisserman 2014). To accelerate the training process we used the pre-trained version of VGG16 that comes with Keras and locked the first 25 layers. Referred to in the literature as transfer learning (Weiss et al. 2016), the initial layers of VGG encode simple shapes such as lines, gradients and basic textures, hence avoiding spending time relearning those features from scratch while also reducing the amount of training data needed. Transfer learning does have a limitation in that the input images must conform to the same size that VGG16 was originally trained on; therefore, cropped individual particles are scaled to fit the 221 x 221 image size that VGG expects.

Implementation

Sample Collection and Preparation

Samples were taken from Holocene sediment cores collected from three wetlands in tropical northern Australia: Sanamere Lagoon (11.117°S, 142.35°E), Big Willum Swamp (12.657°S, 141.998°E) and Marura Sinkhole (13.409°S, 135.774°E). Sediment samples were prepared for fossil charcoal analysis following the method outlined by Stevenson and Haberle (2005); samples were placed in mid-strength (~5 % concentration) bleach for 72 hours before wet sieving to isolate the >63 µm fraction. Samples were suspended in water and photographed through a dissecting microscope using a DSLR and lens adapter.

The morphotype classification system devised by Enache and Cumming (2006) was selected for charcoal classification in this study (Figure 1). Two of the seven morphotypes (types B and D) were excluded from this study as they were insufficiently represented in the training dataset.

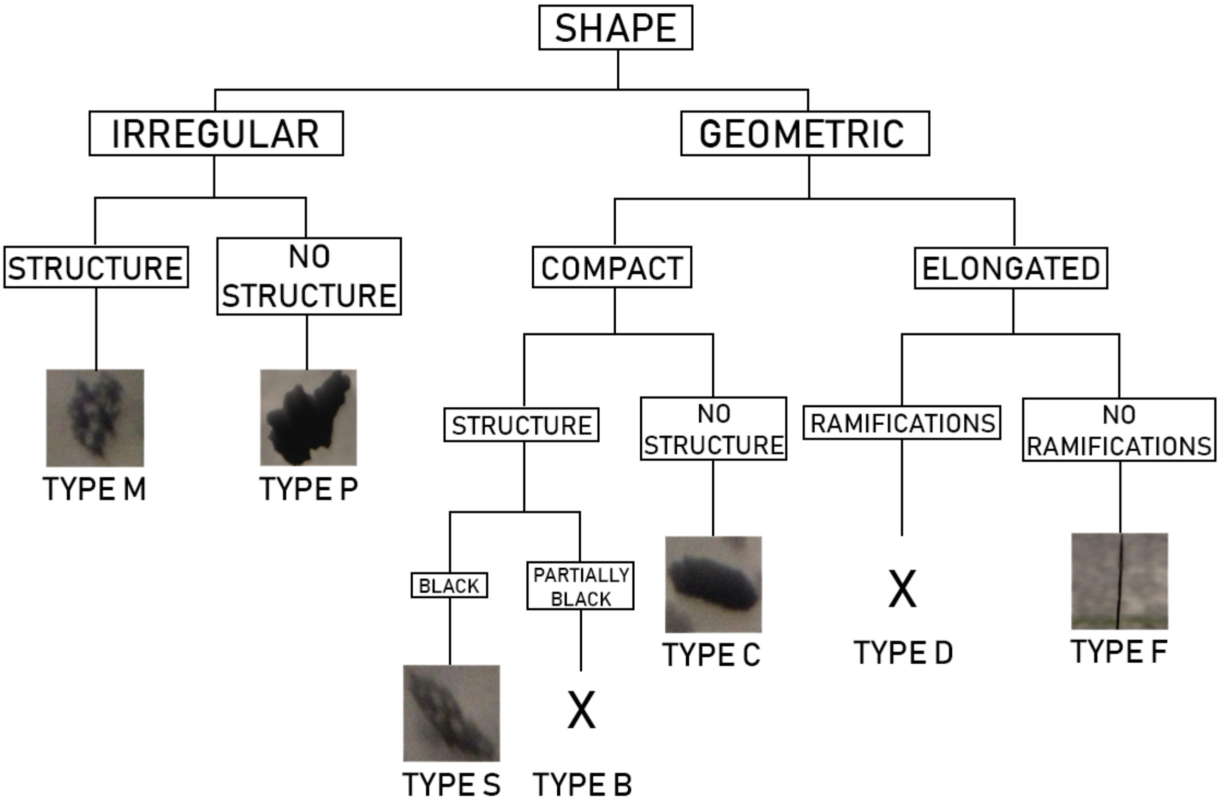

Figure 1: Morphotype classification system of Enache and Cumming (2006) used in this study with example particle photographs from the validation dataset (adapted from Enache and Cumming 2006:285).

Network Training

To prepare the input dataset for the U-Net network, each photograph of suspended samples was manually labelled with binary masks indicating the locations of any present charcoal particles. These masks were then used to segment the training data and extract images of each individual charcoal particle, in the same manner that the final system segments images based on masks generated by the trained U-Net network. The individual charcoal particle images were then manually classified by morphotype to form the input dataset for VGG.

The overall dataset for each network - 976 images for the U-Net network divided into 1714 individual particle images for VGG - was then separated into training and validation datasets, with 90% of images allocated to the training dataset (Table 1) and the remaining 10% of images allocated to the validation dataset. The selection of the individual images in each allocation was randomly computed in order to prevent biases in the trained networks due to over- or under-representation of any given classification label.

Table 1: Number of particle images of each morphotype classification in the network training dataset.

Morphotype	Images
Type C	403
Type F	465
Type M	196
Type P	167
Type S	483

Both the U-Net network and VGG were trained using the popular RMSProp optimiser (Tieleman and Hinton 2012), selected due to its ability to adaptively control the learning rate during training without the need to manually adjust this parameter. The U-Net network was trained from a blank state, whereas VGG was trained using transfer learning to accelerate the process, as stated previously. Each network was trained until the point at which its accuracy in predicting the classification labels of the validation dataset ceased to improve, as is standard practice for preventing overfitting and ensuring the generalisability of the trained networks (see Prechelt 1998).

Results

The trained U-Net network achieved 96.06% accuracy, while the trained VGG network achieved 75.15% accuracy (Figure 2).

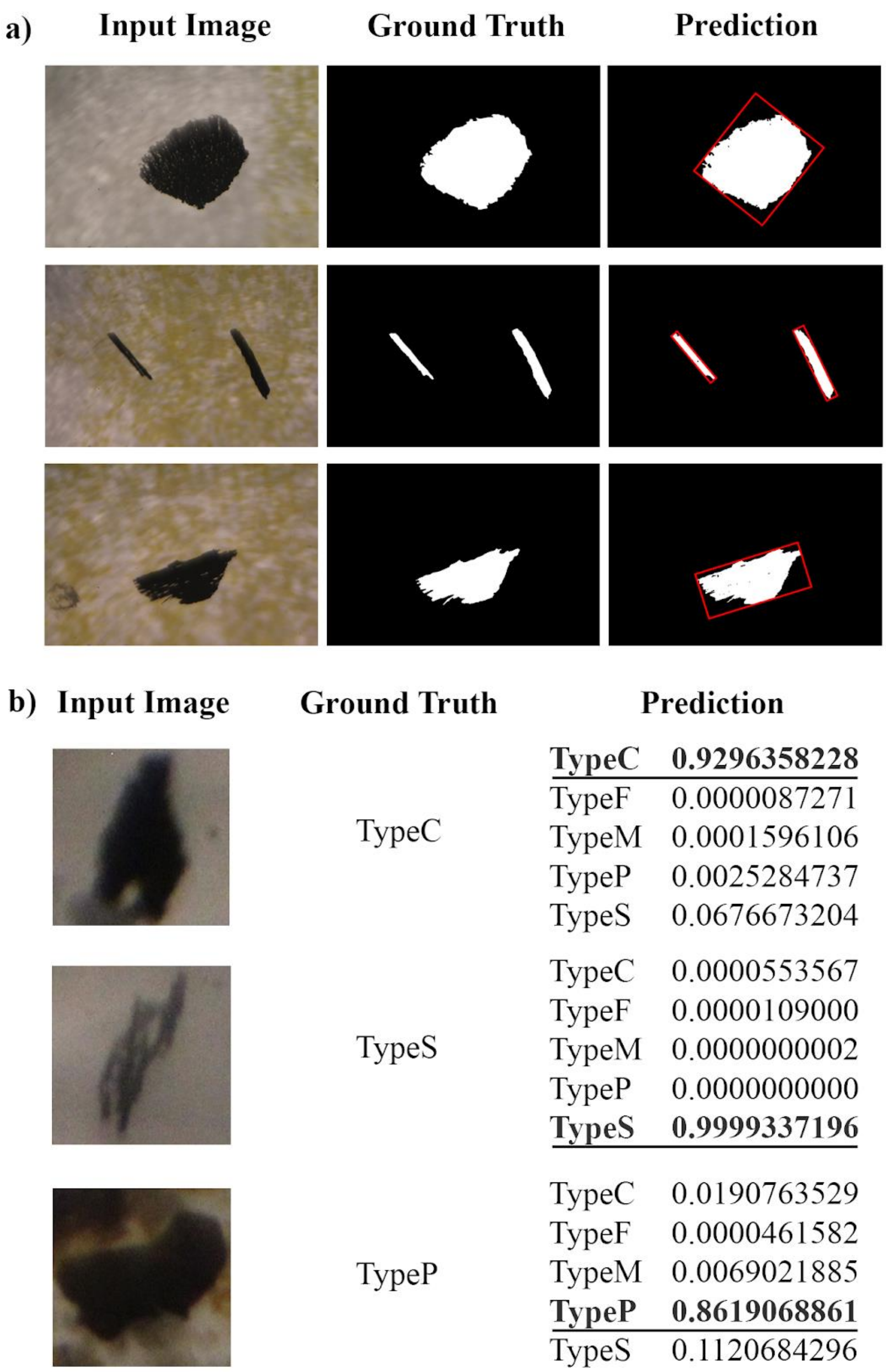

Figure 2: Example results from the validation datasets: a) U-Net network, with red bounding boxes around identified particles for segmentation, and b) VGG, with the highest probability classification underlined.

The U-Net network results were sliced by using a connected components algorithm (Grana et al. 2010) to isolate individual particles, shown in Figure 2 as a red bounding box. Identified particles measuring less than 63 x 63 µm were discarded, as samples were processed to only contain particles >63 µm (described in Sample Collection and Preparation above).

Discussion and Areas for Future Work

This study is a proof of concept for the application of neural networks to charcoal particle analysis. Our initial results demonstrate the feasibility of this methodology, with high accuracy achieved by U-Net for charcoal identification and VGG for morphotype classification. In combination with an appropriate mechanical apparatus for particle photography such as an automated stage, this methodology has the potential to significantly accelerate particle analysis workflows, reducing the number of hours that human experts must spend on labour-intensive visual inspection and providing a foundation for more complex and comprehensive analysis tasks.

As a proof of concept, the scope of this initial study is limited with respect to available image data. Training dataset images in this study are relatively clean with minimal non-charcoal particles and dark organics present. While this is the ideal result of sample preparation for charcoal analysis, the robustness of charcoal identification by U-Net could be improved by the inclusion in the training dataset of images containing more non-charcoal particles. Our training dataset also excludes morphotypes B (partially black, structured geometric) and D (elongate with ramifications) due to a lack of sufficient training images for these morphotypes.

Future work could include an expansion of the training dataset to include a greater number of images from more sites, covering a larger geographic area and more diverse particle assemblages. With the increase of images, the reliance on transfer learning to detect simple features could potentially be mitigated and a more specialized network could be used in the place of VGG. A larger dataset would also likely provide sufficient samples to encompass the morphologies not present in the dataset for this study. To improve the scalability and accessibility of this expanded dataset, an online charcoal image library could also be created, facilitating contributions by international researchers and providing a central repository for researchers wishing to utilise the dataset to train neural networks. As a first step towards this goal, we have made the source code and training data for this study available online, accompanied by comprehensive instructions for reproducing our results. These resources can be found at: https://github.com/adamrehn/charcoal-morphotypes.

Conclusion

The automated classification presented in this experimental study provides a fast and flexible method of charcoal analysis. This two-stage pre-trained network utilising a broadly applicable morphotype classification system can be applied to samples from any site without requiring the creation of additional training datasets. Alternatively, these neural networks can be trained using any morphotype system, including classifications that may be more region- or biome-specific.

Automated charcoal identification and classification using neural networks will increase the efficiency of charcoal analysis, enabling higher sampling resolutions and/or the analysis of more sites and sediment cores. This study presents a promising preliminary investigation into the application of neural networks to the automation of charcoal particle analysis, ultimately feeding into a broad shift to utilizing artificial neural networks to address increasingly complex analytical problems.

Data Availability

The training dataset of processed charcoal particle images used in this paper is available via the following:

Rehn, E.; Rehn, A. (2019): Fossil charcoal particle training data for neural networks. James Cook University. (dataset). http://doi.org/10.25903/5d006c1494cf9.

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