A Future Perspective for Automated Detection of Archaeology using Deep Learning with Remote Sensor Data

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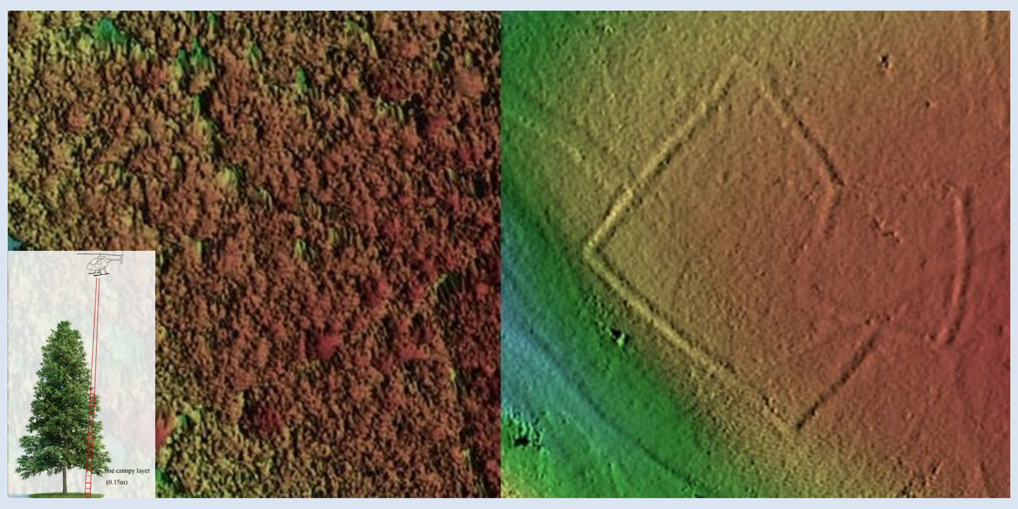
Background

An essential aspect of archaeology is the protection of sites from looters, extensive agriculture and erosion. Under this constant threat of destruction, it is of utmost importance that sites are located. This is mostly done on the ground or by manually scanning through remote sensing data such as **aerial images** or **LiDAR** derived elevation models (fig. 1-2).



Need for automated detection of archaeological sites[1];

- **Time consuming task**
- **Highly specialised**
- **Interpretation bias**
- **'Too much' data**

Fig. 1 The LiDAR survey data shows slight elevation differences under forest canopy.

Fig. 2 Cropmarks and their anatomy shown on an aerial image.

Data challenge

Within this novel research, the potential of **deep learning** for the detection of archaeological sites (especially barrows) is being assessed.

Generally this task requires a lot of training data but recently it was shown that this can be done with **less**[2]. In our case study 287 barrow locations are known in a 60 km² area of the New Forest (fig. 3). Our current strategy to overcome the data challenge focusses on;

- **Data augmentation**
- **Transfer learning**

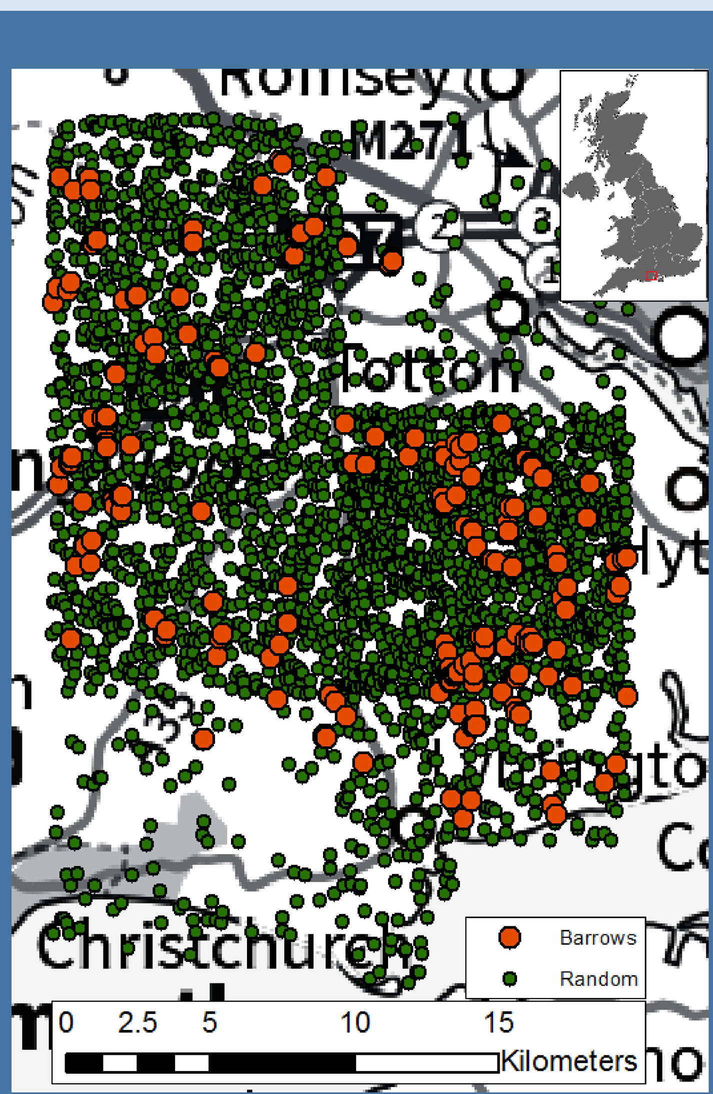


Fig. 3 Case study area

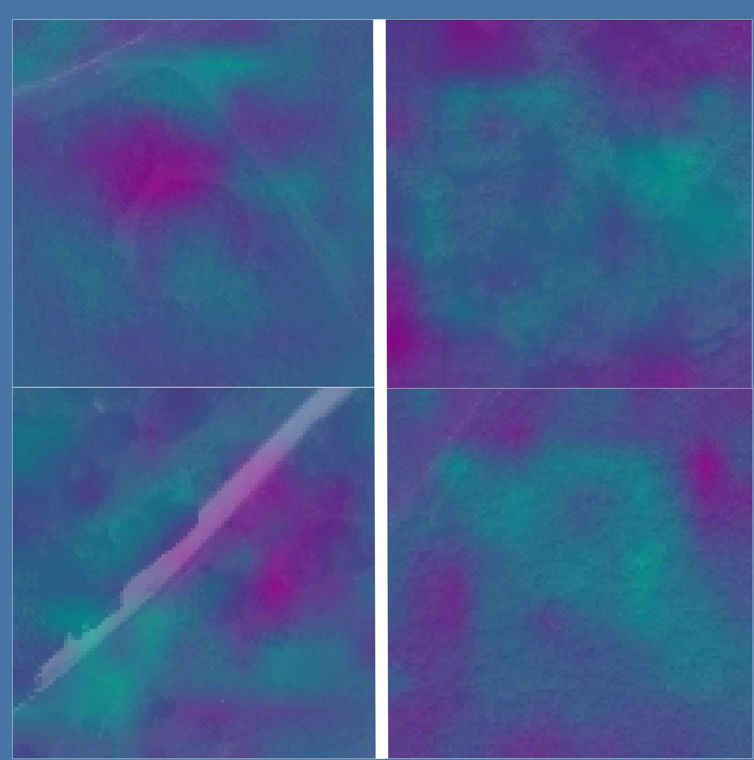
At a later stage we hope to include other types of remote sensing data such as LIDAR and the multispectral bands of the aerial imagery. In this way we can increase the dimensionality of the networks and hopefully compensate the limited number of objects.

Preliminary results

The preliminary results show a **significant improvement** to the known automated methods on similar objects and it proves that **deep learning can be successfully applied** to detect archaeological sites from aerial images.

Details

- 287 known barrow locations
- 2870 images after data augmentation
- 3-band aerial imagery (0.5cm)
- Transfer learning (VGG on ImageNet)
- Fully convolutional network (fig. 5)
- **Validation accuracy of 85%**



Correctly classified an obvious barrow (top) and a barrow despite the modern road (bottom)

Misclassified manually these would also be missed due to trees (top) and shrubs (bottom)

Fig. 4 Heat maps generated from the last convolutional layer of the network in fig. 5.

Layer (type)	Output Shape
Batch normalization	(None, 512, 15, 15)
Convolution	(None, 128, 15, 15)
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Batch normalization	(None, 128, 15, 15)
Convolution	(None, 128, 15, 15)
Batch normalization	(None, 128, 15, 15)
Convolution	(None, 2, 15, 15)
Global Average Pooling	(None, 2)
Softmax activation	(None, 2)

Fig. 5 This table shows the fully connected network which remains its output shape to create heat maps.

Future perspective

In this research, a new method is proposed to automated detection of archaeology which is robust and allows for improvements by;

- **expanding the area**
- **including other object types**
- **including other remote sensing data or time slices**

In the long term this means that we can now look forward to a countrywide detection model which could make automated discoveries when new remote sensing data is released (fig. 6).

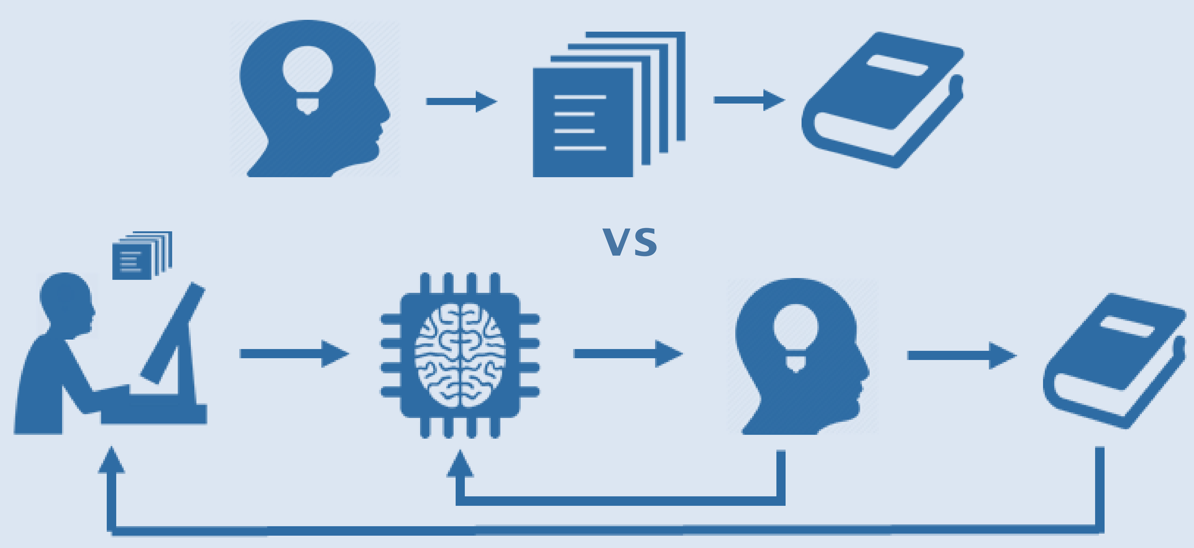

Fig. 6 A vision on how we will move from manual interpretation of remote sensing data towards an automated workflow.

References

[1] Bennett, R., Cowley, D., & De Laet, V. (2014). The data explosion: Tackling the taboo of automatic feature recognition in airborne survey data. *Antiquity, 88* (341), 896-905. doi:10.1017/S0003598X00050766

[2] Razavian, A. S., Azizpour, H., Sullivan, J., & Carlsson, S. (2014). CNN features off-the-shelf: An astounding baseline for recognition. IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, 512-519

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