International Cartographic Association
Association Cartographique Internationale

A deep learning model for the recognition of depression wetland shape

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Keywords: deep learning, depression wetland, pan, shape recognition, convolutional neural network, image classification

Abstract:

Wetlands are aquatic ecosystems that provide important hydrological and biological functions and ecosystem services (de Klerk et al. 2016). These functions include flood attenuation, stream flow reduction, controls on erosion, water quality improvement and groundwater recharge (Ferreira 2010). However, wetlands globally are under pressure from anthropogenic forces and urgent strategies for the understanding, conservation and management of these resources are required (Dronova 2015).

Pans, or depression wetlands, are a type of endorheic wetland system characterised by having circular, oval, kidney or lobed shapes, a flat basin floor and a lack of water outlet (de Klerk et al. 2016). They are generally found in arid regions and serve as habitats for several types of flora and fauna, as well as serving as nutrient sinks and surface water storage (Wu & Lane 2017). There is currently no consensus on the mechanism of formation of pans, though it is understood that the shapes of pans are an indication of the processes that led to their formation, such as aeolian deflation (typically elliptical), geochemical processes (circular) or along abandoned drainage lines (linear) (Grenfell et al 2019). Having knowledge of the shapes of depression wetlands allows for more appropriate conservation and rehabilitation efforts, as well as better inputs to hydrological models and watershed management (Wu & Lane 2016).

While wetlands and pans have been studied with a variety of earth observation and spatial data analysis tools (Dronova 2015, Vanderhoof & Lane 2019), virtually no research has been done on developing tools for automated recognition of pan shape. While spatial datasets of wetland outlines commonly exist, it is often a highly time-consuming task to manually classify wetland polygons into shapes such as elongated, circular, ovoid, irregular, kidney or lobe-shaped. Just in South Africa alone this would entail manual interpretation of tens of thousands of wetlands (de Klerk et al. 2016). The aim of this study was to develop, train and evaluate a convolutional neural network (CNN) capable of automated recognition of depression wetland shape.

A dataset containing around 13,000 digitized pan polygons in South Africa was acquired from the South African National Biodiversity Institute (SANBI). A training dataset of 983 pans was created by randomly iterating through the main dataset and manually classifying samples as either elongated, irregular, ovoid or kidney shaped. To ensure balanced training classes, the iteration was continued until roughly 200 samples per class were collected. The polygon samples were converted to image chips and scaled to the same size. Data augmentation was performed in the form of rotations and flipping of the image chips, resulting in a training set of 5661 image chips and a validation set of 1415 image chips, leaving 780 image chips for the testing set. These subsets were randomly generated.

A variety of CNN architectures were evaluated as well as two chipset resolutions (64x64 and 256x256). Model performance was measured on the test set using overall accuracy, kappa, Matthews Correlation Coefficient (MCC) and balanced accuracy. The best model architecture achieved an overall test accuracy and kappa value of 0.93 and 0.91, respectively, with MCC and balanced accuracy values of 0.90 and 0.92, respectively. The optimal architecture and chipset size is shown in Table 1 below:

Chipset size	256x256
Convolutional layers and depths:	16, 32, 64, 64, 32, 32
Fully connected layer depths and activation functions	8 (ReLU), 4 (Softmax)

Table 1. Optimal model architecture

Abstracts of the International Cartographic Association, 6, 188, 2023.
31st International Cartographic Conference (ICC 2023), 13–18 August 2023, Cape Town, South Africa.
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Figure 1 below shows the training and validation accuracy of the optimal model. The model starts to overfit after around 50 epochs, and early stopping was employed to achieve optimal performance.

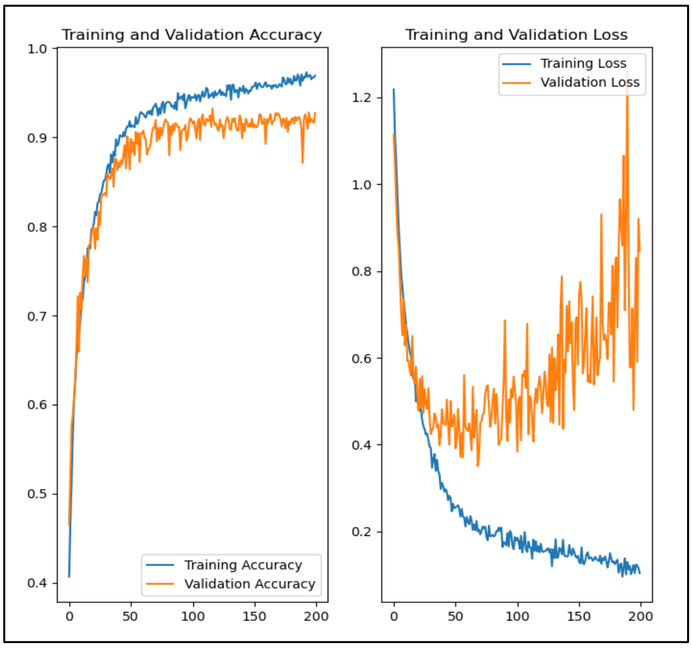

Figure 1. Optimal model training and validation accuracy per epoch

The model had minimal confusion between classes, though most confusion was seen between the irregular and kidney-shaped classes, followed by confusion between the ovoid and elongated classes. Given the morphological similarity of these classes, this is understandable. Human error in labelling these samples during the training data collection process could also have contributed to incorrect labels.

The results show that CNNs can be successfully used to the recognition of pan shape, especially when data augmentation and hyperparameter tuning is performed. This approach, and refinements thereof, is recommended for tasks where existing spatial databases of wetlands need to be labelled according to their shape. Access to this type of data can lead to improved understanding of wetland origins and morphology and allow for better data-driven management and conservation strategies.

Acknowledgements

The authors wish to thank Ms Nancy Job and the Freshwater Biodiversity Programme at the South African National Biodiversity Institute (SANBI) for providing the wetland dataset.

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https://doi.org/10.5194/ica-abs-6-188-2023 |