Automatic Identification of Footwear Class Characteristics

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Problem and Objectives

Goal: To automatically identify class characteristics of footwear outsole images.
Background: In shoe print analysis, it is often useful to determine the frequency of a given shoe print (or features of the print) in a local population. Machine learning tools, such as neural networks, are an inexpensive and efficient way to automatically identify these features, which may inform about the prevalence of such features.

Class Characteristics

Footwear class characteristics include the size and shape of geometric design elements. Size, orientation, and position of geometric elements are capable of distinguishing most shoes collected in samples from the general population [1], and can be used to speed up database searches for candidate shoe models [2].

Table 1: Geometric shapes, modified from [3]

An automated algorithm which can identify these features in shoe images could be used to assemble an open-access database of shoe models searchable by image upload or feature selection. Spatial relationships between geometric features could be added to further reduce the number of shoes with the same characteristics.

Convolutional Neural Network

- A convolutional neural network (CNN) is a tool for deep learning that is well-suited to image analysis.
- Inspired by the brain, CNNs learn global patterns using a hierarchy of local feature detection and pooling
- VGG16 is a CNN [4] pre-trained on ~1.3 million images spanning 1,000 categories from ImageNet [5].

Image source: https://bit.ly/2AmjF6K

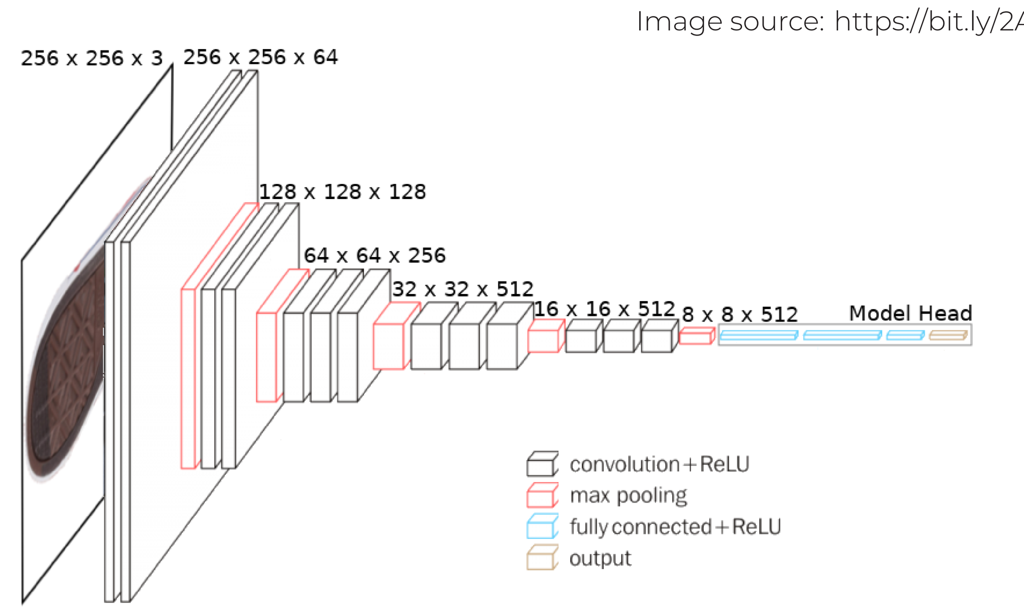

Figure 1: Architecture of VGG16

Data

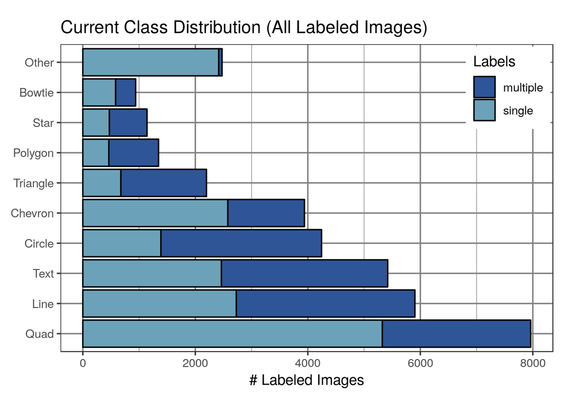

Figure 2: Label Frequency

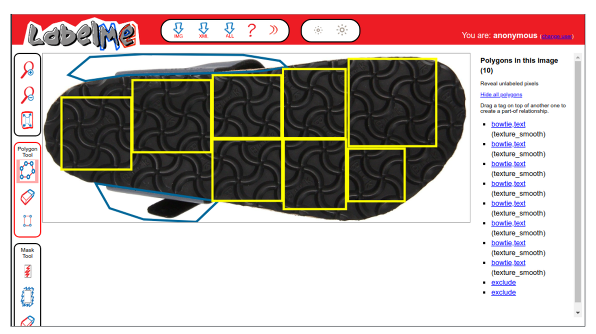

Figure 3: LabelMe Tool [6]

- 25,000 multi-label images from 2,200 shoes
- Training set: 60%, downsampled to get approximately equal numbers of each label
- Validation set: 20%, used during training
- Test set: 20%, used after training

Training

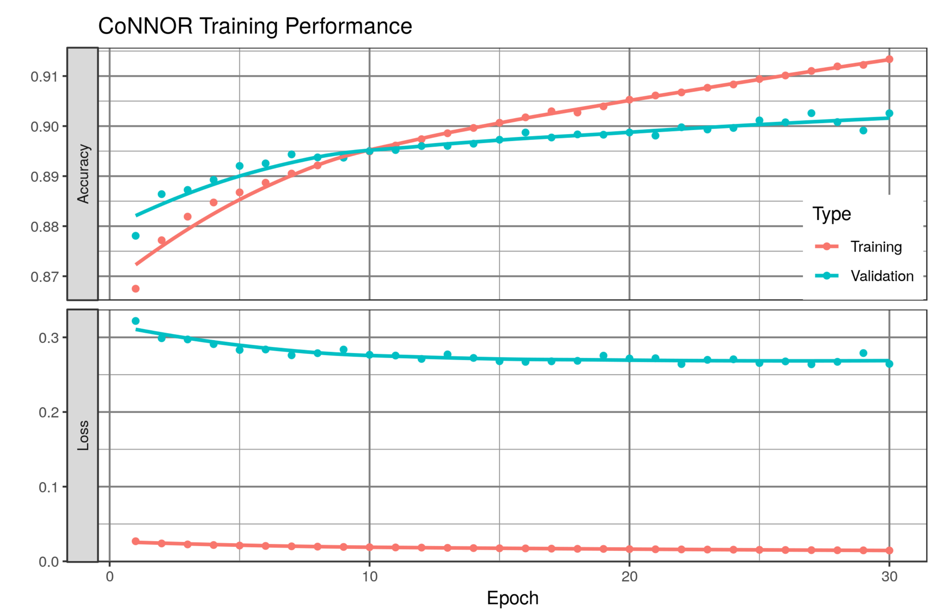

Figure 4: Training and Validation accuracy and loss for each epoch of the fitting process.

Prediction Accuracy

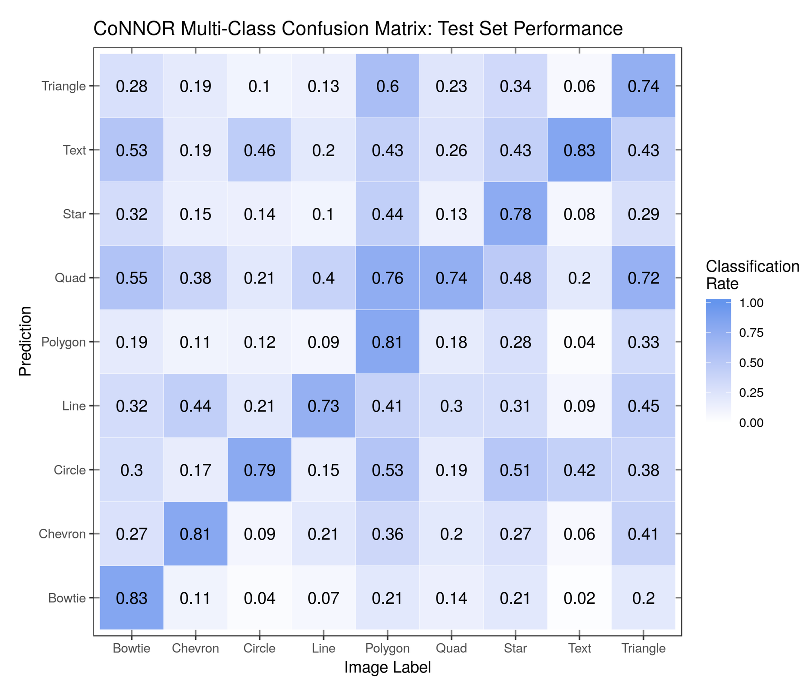

Figure 5: Percent of test images identified as containing a class with probability $\geq$ equal error rate, after accounting for multiple labels

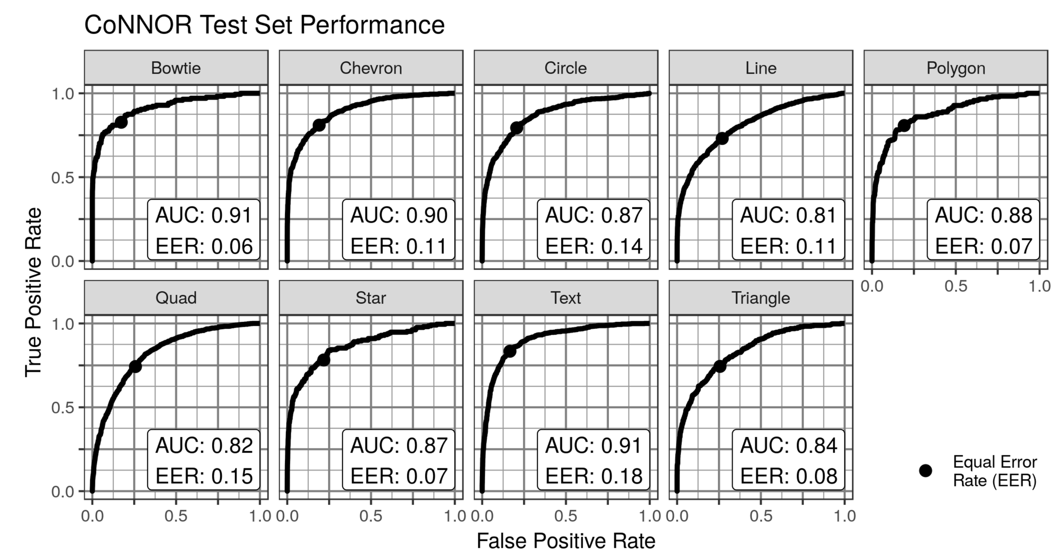

Figure 6: True Positive Rate by False Positive Rate of classification for each class

Distance

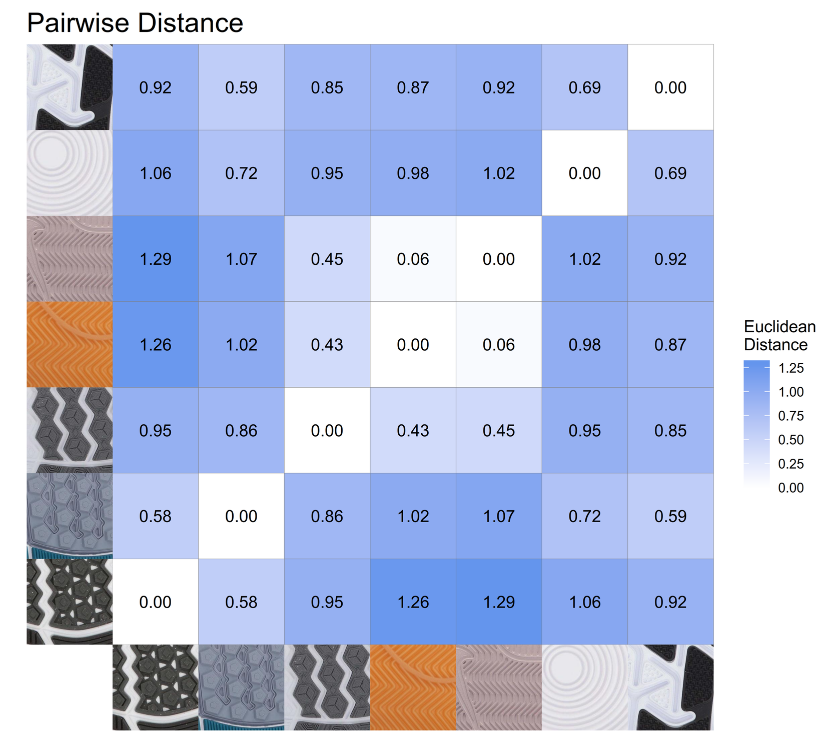

Figure 7: Pairwise Euclidean Distance between selected example images

Future Applications

- Features for statistical models to assess match strength
- Speed up database searches
- Estimate frequency of class characteristics given information about local population

References

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[5] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision (IJCV)*, 115(3):211–252, 2015.

[6] Bryan C. Russell, Antonio Torralba, Kevin P. Murphy, and William T. Freeman. Labelme: A database and web-based tool for image annotation. *Int. J. Comput. Vision*, 77(1-3):157–173, May 2008.

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