

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].

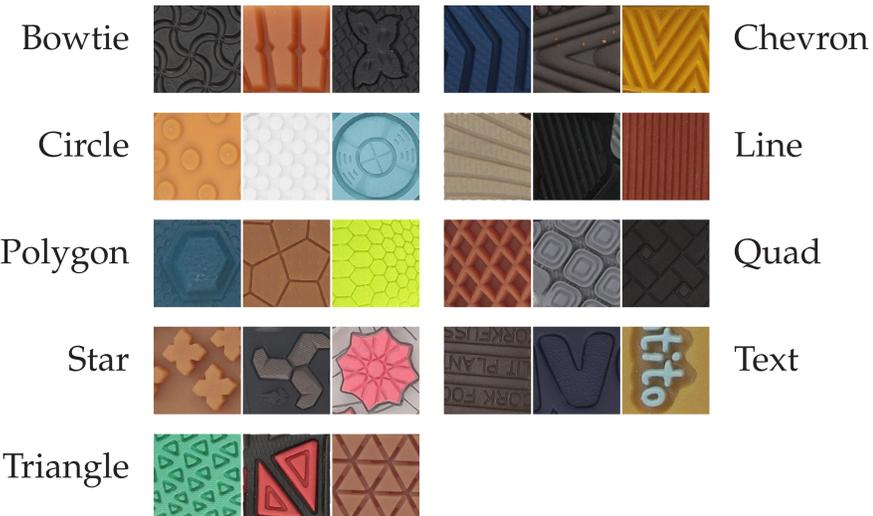


Table 1: Geometric Elements. Categories modified from [3]

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 Networks

- 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 ImageNet, an image database with more than 14 million images spanning 20,000+ categories [5].

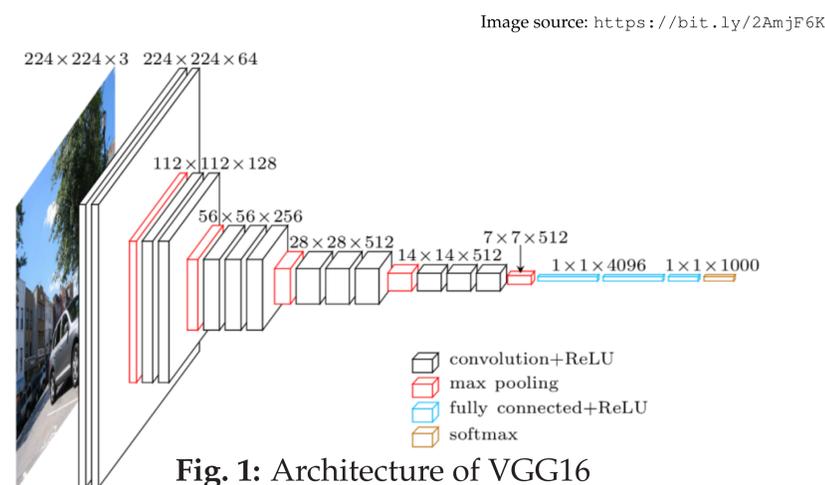


Fig. 1: Architecture of VGG16

Prediction Accuracy

Predictions	bowtie	chevron	circle	line	polygon	quad	star	text	triangle
triangle	0.02	0.1	0.03	0.08	0.09	0.17	0.08	0.03	0.49
text	0.06	0.06	0.14	0.04	0.03	0.09	0.03	0.64	0.09
star	0.1	0.04	0.06	0.03	0.1	0.05	0.57	0.06	0.05
quad	0.2	0.33	0.08	0.23	0.26	0.69	0.11	0.12	0.36
polygon	0.02	0.03	0.05	0.02	0.54	0.09	0.11	0	0.07
line	0.04	0.21	0.05	0.58	0.06	0.21	0.07	0.07	0.12
circle	0.05	0.02	0.61	0.02	0.07	0.05	0.09	0.11	0.06
chevron	0.05	0.64	0.02	0.08	0.05	0.12	0.05	0.03	0.1
bowtie	0.69	0.06	0.03	0.02	0.06	0.06	0.12	0.01	0.08

Truth

Fig. 4: Percent of test images identified as containing a class with probability ≥ 0.2 , after accounting for multiple labels

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

- [1] Sheida Hancock, Rian Morgan-Smith, and John Buckleton. The interpretation of shoeprint comparison class correspondences. *Science and Justice*, 52(4):243–248, 2012.
- [2] Maria Pavlou and Nigel M Allinson. Automatic extraction and classification of footwear patterns. In *International Conference on Intelligent Data Engineering and Automated Learning*, pages 721–728. Springer, 2006.
- [3] Susan Gross, Dane Jeppesen, and Cedric Neumann. The variability and significance of class characteristics in footwear impressions. *Journal of Forensic Identification*, 63(3):332, 2013.
- [4] Karen Simonyan and Andrew Zisserman. Very Deep Convolutional Networks for Large-Scale Image Recognition. September 2014.
- [5] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhibeng 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.

Data

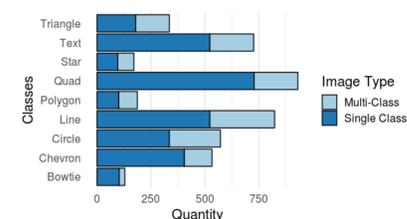


Fig. 2: Label Frequency

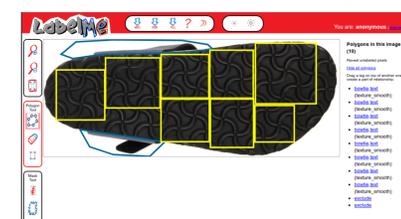


Fig. 3: LabelMe Tool [6]

- 24,000 multi-label images from 2,200 shoes
- Training set: 50%, downsampled to get approximately equal numbers of each label
- Validation set: 25%, used during training
- Test set: 25%, used after training