Supplementary Table S 2

Network	Input size	Parameters	Validation Accuracy	Held-out test Accuracy
This work	64 x 64 x 3	13,550	**0.954 ± 0.02**	**0.946 ± 0.01**
AlexNet	227 x 227 x 3	56.9 x 10^6	0.715 ± 0.02	0.672 ± 0.06
GoogLeNet	224 x 224 x 3	5.0 x 10^6	0.839 ± 0.03	0.688 ± 0.04
ResNet-50	224 x 224 x 3	23.6 x 10^6	0.905 ± 0.01	0.727 ± 0.04
ResNet-50 reduced params	224 x 224 x 3	5.9 x 10^6	0.917 ± 0.02	0.716 ± 0.05

Table S 2. Image-level performance evaluation for additional neural network architectures.

We assessed the image-level performance accuracy for neural network architectures including AlexNet (5), GoogLeNet (6), ResNet50 (7), and ResNet50 reduced params where we reduced the number of kernels by half at each layer. These networks have a larger field of view and higher capacity (more parameters) and they tend to easily overfit the training/validation dataset , even when using regularization techniques and aggressive data augmentation. This overfitting with high-capacity models is likely due to the small size of the dataset. The results are presented as the Mean ± SD of three models.

SUPPLEMENTAL REFERENCES

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