Bridging the Gap: Differentially Private Equivariant Deep Learning for Medical Image Analysis

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Abstract

Machine learning with formal privacy-preserving techniques like Differential Privacy (DP) allows one to derive valuable insights from sensitive medical imaging data while promising to protect patient privacy, but it usually comes at a sharp privacy-utility trade-off. In this work, we propose to use steerable equivariant convolutional networks for medical image analysis with DP. Their improved feature quality and parameter efficiency yield remarkable accuracy gains, narrowing the privacy-utility gap.

Keywords: Differential Privacy, Equivariant Convolutions, Steerable Kernels

1. Introduction

Deep learning-based medical imaging analysis has so-far been unable to fully leverage the advances in other fields of computer vision because many advanced applications require large datasets to obtain sufficient accuracy for diagnostic use. In medicine, procuring such datasets is problematic, as patient privacy mandates minimising the amount of data collected and/or shared. Privacy-enhancing technologies allow one to derive insights from sensitive datasets while protecting the individuals, and represent the best chance to date to incentivize data sharing in an ethical and responsible manner. Deep learning with Differential Privacy (DP) (Dwork and Roth, 2014; Abadi et al., 2016), a gold-standard technique for privacy preservation, enables analysts to train predictive models which can be shared for diagnostic purposes while offering formal guarantees about how much information can be extracted from their representations. However, DP leads to sharp utility trade-offs, as gradients are norm-bounded and noised, while noise scales proportionally to the number of model parameters, making training of large models disproportionately difficult. Thus, advanced deep learning techniques, able to learn robust and generalizable features under DP must be developed (Tramer and Boneh, 2020). Equivariant CNN (ECNN) architectures (to Euclidean transformations) (Cohen and Welling, 2016, 2017) exhibit greatly increased data efficiency, improved generalization and high parameter efficiency, especially in domains with high degrees of intra-image symmetry such as medical imaging. So far, no works have investigated the training of ECNNs under DP, even though their characteristics render them highly attractive for this use-case. In this paper, we initiate an empirical investigation into DP ECNNs using steerable kernels. Our results demonstrate that ECNNs have superior performance with a narrowed privacy-utility gap, even at smaller model sizes. We show that these beneficial attributes are a result of lower gradient sparsity, improved feature extraction characteristics and better model calibration.

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## 2. Results

For all experiments, we utilized the ResNet-9 architecture and privacy parameters \((\varepsilon = 7.42, \delta = 10^{-5})\) of Klause et al. (2022), adapted for equivariant training, and the MedMNIST dataset (Yang et al., 2021). Steerable ECNNs were implemented with regular representations and group pooling for the cyclic groups \(C_N\), with \(N\), the number of discrete rotations, restricted to \(N/2\) after the first residual layer (Weiler and Cesa, 2019), and with induced irreducible representations of frequency 1, induced gated non-linearities and induced norm-pooling for the \(O(2)\) group. All results are summarized in Table 1.

### Superior DP classification performance:
Steerable ECNNs generally outperformed their non-equivariant counterparts when training with DP, most notably on the colon pathology dataset, where an accuracy increase of \(\approx 9\%\) was observed. The \(O(2)\) group performed best on the blood cell and dermatology datasets, indicating that the benefit of higher equivariance outweighed the additional noise required due to the larger model size (240k vs. 90k parameters for \(C_{16}\)). Out of the cyclic groups, the \(C_4\) group performed especially well, indicating a good trade-off between equivariance and model size. Augmentations (performed as in Hoffer et al. (2020)) – on average – increased accuracy by 0.56% for DP ECNNs but decreased performance by 0.15% for non-equivariant models.

### Reduced private/non-private accuracy gap:
The DP validation accuracy was – on average – 5.5% lower for conventional CNNs compared to non-private training. ECNNs diminished this gap, with a reduction of only 2.8%, approaching the non-DP baseline set by Yang et al. (2021) on MedMNIST using much larger architectures like ResNet-50.

### Improved accuracy despite smaller model size:
DP ECNNs not only outperformed larger conventional CNNs, but even larger ECNNs. For instance, the 35k parameter \(C_4\) DP ECNN outperformed both the much larger 2,5M parameter conventional CNN but also the 2,3M parameter DP ECNN (Figure 1 left).

| Dataset          | Data Modality | Group | No Augmentation | Augmentation |
|------------------|---------------|-------|-----------------|--------------|
|                  |               |       | Non-DP          | DP           |
| Blood Cell Microscope |               | \{\varepsilon\} | 94.05% 89.19% 96.52% | 90.61%       |
|                  |               | \(C_1\) | 93.52% 89.98% 95.57% | 90.47%       |
|                  | MedMNIST      | \(C_4\) | 95.35% 91.30% 96.67% | 91.39%       |
| Dermatoscope     | \(C_8\)      | 95.32% 86.56% 96.30% | 92.39%       |
| Colon Pathology  | \(C_{16}\)   | 95.74% 91.48% 96.16% | 91.67%       |
|                  | O(2)          | 96.13% 92.51% 96.71% | 93.73%       |

| MedMNIST         | Dermatoscope  | \{\varepsilon\} | 76.79% 71.78% 78.48% | 72.41%       |
| Dermatoscope     | \(C_1\)      | 75.77% 72.84% 76.48% | 72.27%       |
| Colon Pathology  | \(C_4\)      | 75.18% 73.25% 77.84% | 74.17%       |
|                  | \(C_8\)      | 76.48% 72.79% 77.58% | 66.88%       |
|                  | \(C_{16}\)   | 76.86% 72.53% 77.57% | 70.64%       |
|                  | O(2)          | 77.24% 73.29% 77.98% | 72.45%       |
| Colon Pathology  | \{\varepsilon\} | 83.53% 80.11% 85.75% | 79.41%       |
|                  | \(C_1\)      | 82.35% 83.57% 82.22% | 83.68%       |
|                  | \(C_4\)      | 83.97% 86.89% 83.43% | 83.52%       |
|                  | \(C_8\)      | 85.11% 88.13% 85.23% | 88.75%       |
|                  | \(C_{16}\)   | 85.88% 89.14% 85.38% | 88.94%       |
|                  | O(2)          | 82.12% 77.91% 80.87% | 80.64%       |

Table 1: Validation accuracies of the ResNet-9 for a model layout of 8-16-32 channels.
Figure 1: Results on the colon pathology dataset for different DP conventional and $C_4$ equivariant model widths (left). $\ell_{10^{-5}}$ gradient sparsity during training (right).

Result Interpretation: Figure 1 (right) shows, that DP ECNNs converge faster during training, updating fewer weights. This is indicated by a higher gradient sparsity, as measured by the $\ell_{10^{-5}}$-norm, for the ECNN with the $C_4$ group. DP ECNNs also exhibited better model calibration (e.g. 41.17% lower Brier score in the aforementioned model). Moreover, a more robust feature extraction by the steerable kernels was observed, indicated by a higher magnitude filter impulse response (FIR) and an improved co-location of the FIR with the input features used for prediction (Figure 2). These findings corroborate the higher sample and feature efficiency of ECNNs even in the DP setting, explaining their superior performance.

Figure 2: Guided Backprop/Grad-CAM of the final model layer. Colon pathology dataset.

3. Conclusion

Our preliminary findings indicate that DP ECNNs can help close the privacy-utility gap in medical imaging tasks through the beneficial characteristics of equivariant convolutions and the resulting feature, sample and parameter efficiency. In future work, we intend to investigate a larger variety of datasets and models in medical imaging and beyond.
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