Computer vs human: Deep learning versus perceptual training for the detection of neck of femur fractures

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Abstract

Introduction: To evaluate the accuracy of deep convolutional neural networks (DCNNs) for detecting neck of femur (NoF) fractures on radiographs, in comparison with perceptual training in medically-naive individuals.

Methods: This study extends a previous study that conducted perceptual training in medically-naive individuals for the detection of NoF fractures on a variety of dataset sizes. The same anteroposterior hip radiograph dataset was used to train two DCNNs (AlexNet and GoogLeNet) to detect NoF fractures. For direct comparison with perceptual training results, deep learning was completed across a variety of dataset sizes (200, 320 and 640 images) with images split into training (80%) and validation (20%). An additional 160 images were used as the final test set. Multiple pre-processing and augmentation techniques were utilised.

Results: AlexNet and GoogLeNet DCNNs NoF fracture detection accuracy increased with larger training dataset sizes and mildly with augmentation. Accuracy increased from 81.9% and 88.1% to 89.4% and 94.4% for AlexNet and GoogLeNet respectively. Similarly, the test accuracy for the perceptual training in top-performing medically-naive individuals increased from 87.6% to 90.5% when trained on 640 images compared with 200 images.

Conclusions: Single detection tasks in radiology are commonly used in DCNN research with their results often used to make broader claims about machine learning being able to perform as well as subspecialty radiologists. This study suggests that as impressive as recognising fractures is for a DCNN, similar learning can be achieved by top-performing medically-naive humans with less than 1 hour of perceptual training.

Key words: femoral neck fractures; learning; radiology; supervised machine learning; X-rays.
healthcare\textsuperscript{1} with examples including dermatology for skin lesion identification,\textsuperscript{2} ophthalmology for the detection of diabetic retinopathy,\textsuperscript{3} orthopaedics for hand and ankle fractures\textsuperscript{4} and in radiology for interpreting chest X-rays for tuberculosis\textsuperscript{5} and interpreting CT and MRI for detecting strokes\textsuperscript{6} to name a few.

Our study was a continuation of one in which we performed perceptual training on medically-naive undergraduate students to detect neck of femur (NoF) fractures.\textsuperscript{9} Perceptual training is the method of improving one’s perceptual skills to allow for an enhanced capacity to identify or categorise images without being provided explicit rules.\textsuperscript{10,11} An example of a perceptual skill is gender identification based on facial appearance.\textsuperscript{12,13} Although ordinarily easy to perform, it can be difficult to verbalise and explicitly teach. The prior study found that top-performing students, with less than 1 hour of training, had comparable accuracy to board-certified radiologists in the detection of NoF fractures.

From a learning perspective, perceptual training and supervised machine learning operate in a very similar manner.\textsuperscript{14} The subject, human or DCNN, is presented with a large number of training images, one-by-one, attempts to classify each image according to a pre-set criterion (e.g. whether it contains a NoF fracture) and is informed whether they were correct. The subject then learns, based on this feedback. Learning can be increased by increasing the number of training images.\textsuperscript{14}

The purpose of the study is to evaluate the accuracy of DCNNs for detecting NoF fractures on radiographs, in comparison with perceptual training in medically-naive individuals when trained on the same set of radiographic images.

**Methods**

**Prior perceptual training study**

The study followed on from one by Chen et al.\textsuperscript{9} that conducted perceptual training in 142 medically-naive undergraduate students for the detection of neck of femur fractures on a variety of dataset sizes. The students had no prior knowledge of X-ray interpretation. The study found that top-performing medically-naive students could detect NoF fractures as accurately as radiology residents and board-certified radiology consultants with 48 minutes and 52 minutes of training respectively.

**Dataset**

The same dataset that was originally produced for the perceptual training study was used for this study. The images were from The Royal Melbourne Hospital radiographic archive for emergency presentations where patients had surgically confirmed NoF fractures. All presentation AP pelvic X-rays were de-identified and digitised using FujiFilm Synapse PACS v4.5 software. As seen in Figure 1, two non-overlapping hip region images (for left and right) were cropped from the pelvic radiograph allowing one image to have a fracture and the other without. Radiographs were excluded if there was an underlying pathology (excluding osteoporosis or osteoarthritis) or metalware in either the fractured or unfractured hip. In total there were 805 images in the dataset, 403 with a fracture and 402 without.

**Deep learning methods**

**Processing environment**

The image dataset was handled in 8-bit Portable Network Graphics format. The processing of the images was performed on a Windows 10 (Microsoft Corporation, Redmont, WA, USA) operating system using MATLAB R2018a (The MathWorks Inc, Natick, MA, USA) with its Neural Network Toolbox and Parallel Processing Toolbox. To adequately handle processing of the DCNN, the computer had a GeForce GTX 1070 graphics processor (Nvidia Corporation, Santa Clara, CA, USA).

**Dataset sizes**

To allow direct comparison with the perceptual training study by Chen et al.,\textsuperscript{9} deep learning sample sizes were 200, 320 and 640 images, with images split into training (80%) and validation (20%). A separate group of 160 images were used as the final test set. Training, validation and test sets were randomised using inbuilt randomisation functions in MATLAB with equal proportions of fractured and non-fractured images in each.

**Pre-processing**

All dataset images underwent pre-processing to standardise them to be of equivalent size and proportions. All images of left-sided hips were mirrored to be right-sided. The images were also manually cropped to roughly standardise the size and location of the femoral head (see Fig. 1).

**Image augmentation**

To reduce the potential of over fitting of the trained network to the training data, MATLAB’s inbuilt image database augmentation algorithms were used. Training images were randomly mirrored (horizontally and/or vertically) and randomly rotated up to 15 degrees bidirectionally.

**DCNN architecture**

Two pre-trained DCNN architectures, with prior training using the ImageNet database,\textsuperscript{7} were used for the study.
AlexNet\textsuperscript{15} and GoogLeNet\textsuperscript{16} are two open-source frameworks that have been developed and used in a variety of research scenarios, including the detection of tuberculosis changes in chest X-rays.\textsuperscript{3} The final three layers were replaced to allow the pre-trained networks to be applied to detect NoF fractures.

Solver parameters

Hyperparameters were optimised using a grid search approach. The following solver parameters were selected: 50 Epochs; stochastic gradient descent; initial learning rate of 0.001 with 20\% drop every 10 epochs. Each pre-trained DCNN was trained 5 times for each training size with the optimal model chosen based on highest validation accuracy obtained.

Statistical methods

All statistical analysis was performed using MedCalc (MedCalc v. 18.5, MedCalc Software, Ostend, Belgium). Comparison of accuracy based on sample size, augmentation or DCNN used ‘N-1’ Chi-squared test.\textsuperscript{17} The receiver operating characteristic curves and AUC were determined for the test dataset for each DCNN.\textsuperscript{18} Ninety five percent confidence intervals and comparisons of AUCs for receiver operating characteristic curves, were calculated using a nonparametric approach.\textsuperscript{19}

Results

Deep learning results

Across all training dataset sizes, the GoogLeNet DCNN outperformed the AlexNet DCNN (overall accuracy 90.6\% vs 85.3\%, respectively, $P < 0.01$). Larger training sample sizes improved accuracy with 640 images in the training set outperforming 200 images (90.9\% vs 85.5\%, respectively, $P < 0.01$). However, the image augmentation that was implemented did not provide any significant difference (accuracy with augmentation vs accuracy without augmentation, 89.1\% vs 86.9\%, respectively, $P = 0.14$).

A summary of the Area Under Curve (AUC) results for the two DCNNs is shown in Table 1. Figure 2 shows a comparison of Receiver Operating Characteristic (ROC) curves for AlexNet and GoogLeNet DCNNs.

Deep learning benchmarking

Figure 3 compares AlexNet and GoogLeNet results with those previously obtained from perceptual training and

![Example Pelvic xray](image)

Fig. 1. Original AP pelvic radiographs were selected from the Royal Melbourne Hospital PACS archive for isolated neck of femur fractures. As shown in the figure, both hip regions were manually cropped from the pelvic radiograph to create two separate hip radiographs. Hips were labeled as either fractured or standard (non-fractured) and flipped as required to mimic right-sided orientation.
radiology specialists and trainees. The test accuracy for the perceptual training in top-performing medically-naive individuals increased from 87.6% to 90.5% when trained on 640 images compared with 200 images. When these top-performing individuals were allowed to train on the 640-image dataset twice (1280 images in total), they achieved an average accuracy of 94.5% and exceeded the average accuracy achieved by board-certified radiologists (93.5%) and radiology residents (92.9%).

Table 1. Area Under Curve test dataset

<table>
<thead>
<tr>
<th>Dataset size‡</th>
<th>Without augmentation</th>
<th>With augmentation†</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>200</td>
<td>320</td>
</tr>
<tr>
<td>AlexNet</td>
<td>0.91 (0.86, 0.95)</td>
<td>0.92 (0.87, 0.96)</td>
</tr>
<tr>
<td>GoogLeNet</td>
<td>0.93 (0.88, 0.96)</td>
<td>0.96 (0.92, 0.99)</td>
</tr>
</tbody>
</table>

Data in parentheses are the 95% confidence interval.
†Additional augmentation of random mirroring of images (horizontally and/or vertically) and random rotation up to 15 degrees bidirectionally.
‡Includes the combined training and validation dataset size with a ratio of 80:20, respectively.

Discussion

The results obtained from the study in regard to deep learning when comparing the pre-trained AlexNet and GoogLeNet models were, by and large, as predicted. Accuracy improved through increasing the sample size, augmentation played a minor role in improving the models and GoogLeNet outperformed AlexNet. Impressively, the pre-trained DCNNs were able to detect neck of femur fractures with similar levels as radiology residents and
board-certified radiologists, with the top-performing GoogLeNet model outperforming them both.

Although this is certainly an impressive result, especially considering that this was achieved with a relatively small sample size and using generic network architectures, it is important to frame the achievement in terms of how much human training this represents. In this case, a more accurate description is that these DCNNs performed as well as some medically-naive humans trained for less than an hour.

We believe that it is important to reframe the success of AI achievement in this way, not to devalue the impressive strides forward that AI has accomplished of late, but to put it in the context of normal human learning.

Deep learning’s full capability at image detection and classification are almost certainly underrepresented in this study. Firstly, the image dataset is magnitudes smaller than what would be usual when training deep learning models. Ideally testing and validation datasets should be at least in the thousands, if not tens of thousands of images. This would have been unrealistic for our study. To allow for direct comparison to perceptual learning, we would have needed to train humans on the same number of images. To put this in perspective, if each image took 2.77 seconds (the average time per image taken during perceptual training in the current study), it would take 7 hours and 42 minutes without breaks to train each individual with 10,000 images. The increased image dataset would also rely on there being sufficient radiographs in our hospital to create the training set. The DCNN models chosen in the study, were selected as they are relatively easily implemented, have been well researched and have been applied in medical imaging studies prior.

This study highlights the importance of pathology detection in radiology, but that it is only one, albeit important, aspect to the interpretation of medical imaging. The ability of medically-naive individuals, through perceptual training, and computers, through deep learning, to detect fractures at an accuracy matching or exceeding that of radiology residents and board-certified radiologists only highlights that more can be done to improve specialists’ ability to detect pathology. Radiology needs to mitigate the well documented high levels of systemic radiological error (between 2–20%) and embrace utilising tools like machine learning and concentrated perceptual training sessions to improve radiologists’ diagnostic accuracy.

In conclusion, single detection tasks in radiology are commonly used in DCNN research with their results often used to make broader claims about machine learning being able to perform, as well as, subspecialty radiologists. This study suggests that as impressive as recognising fractures is for a DCNN, similar learning can be achieved by top-performing medically-naive humans with less than 1 hour of perceptual training.

Acknowledgements

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References


