CheXphotogenic: Generalization of Deep Learning Models for Chest X-ray Interpretation to Photos of Chest X-rays

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Abstract
The use of smartphones to take photographs of chest x-rays represents an appealing solution for scaled deployment of deep learning models for chest x-ray interpretation. However, the performance of chest x-ray algorithms on photos of chest x-rays has not been thoroughly investigated. In this study, we measured the diagnostic performance for 8 different chest x-ray models when applied to photos of chest x-rays. All models were developed by different groups and submitted to the CheXpert challenge, and re-applied to smartphone photos of x-rays in the CheXphoto dataset without further tuning. We found that several models had a drop in performance when applied to photos of chest x-rays, but even with this drop, some models still performed comparably to radiologists. Further investigation could be directed towards understanding how different model training procedures may affect model generalization to photos of chest x-rays.

1. Introduction
Chest x-rays are the most common imaging examination in the world, critical for diagnosis and management of many diseases. With over 2 billion chest x-rays performed globally annually, many clinics in both developing and developed countries lack sufficient trained radiologists to perform timely x-ray interpretation. Automating cognitive tasks in medical imaging interpretation with deep learning models could improve access, efficiency, and augment existing workflows (Rajpurkar et al., 2018; Nam et al., 2018; Singh et al., 2018; Qin et al., 2018). However, a major obstacle to clinical adoption of such technologies is in model deployment, an effort often frustrated by vast heterogeneity of clinical workflows across the world (Kelly et al., 2019). Chest x-ray models are developed and validated using digital x-rays with many deployment solutions relying on heavily integrated yet often disparate infrastructures (Qin et al., 2019; Lakhani and Sundaram, 2017; Kallianos et al., 2019; Kashyap et al., 2019; Shih et al., 2019).

One appealing solution to scaled deployment across disparate clinical frameworks is to leverage the ubiquity of smartphones. Interpretation of medical imaging via cell phone photography is an existing “store-and-forward telemedicine” approach in which one or more photos of medical imaging are captured and sent as email attachments or instant messages by practitioners to obtain second opinions from specialists in routine clinical care (Goost et al., 2012; Vassallo et al.,

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Figure 1: MCC differences of 8 chest x-ray models on different pathologies between photos of the x-rays and the original x-rays with 95% confidence intervals.

Figure 2: MCC differences of the same models on photos of chest x-rays compared to radiologist performance with 95% confidence intervals.

1998). Smartphone photographs have been shown to be of sufficient diagnostic quality to allow for medical interpretation, thus leveraging deep learning models in automated interpretation of photos of medical imaging examinations may serve as an infrastructure agnostic approach to deployment, particularly in resource limited settings. However, significant technical barriers exist in automated interpretation of photos of chest x-rays. Photographs of x-rays introduce visual artifacts which are not commonly found in digital x-rays, such as altered viewing angles, variable lighting conditions, glare, moiré, rotations, translations, and blur (Phillips et al., 2020). These artifacts have been shown to reduce algorithm performance when input images are perceived through a camera (Kurakin et al., 2016).

We measured the diagnostic performance for 8 different chest x-ray models when applied to photos of chest x-rays. All models were developed by different groups and submitted to the CheXpert challenge, a large public competition for digital chest x-ray analysis (Irvin et al., 2019). We applied these models to a dataset of smartphone photos.
tos of 668 x-rays from 500 patients. Models were evaluated on their diagnostic performance in binary classification, as measured by Matthew’s Correlation Coefficient (MCC) (Chicco and Jurman, 2020), on the following pathologies selected in Irvin et al. (2019): atelectasis, cardiomegaly, consolidation, edema, and pleural effusion (Irvin et al., 2019).

We found that several chest x-ray models had a drop in performance when applied to smartphone photos of chest x-rays, but even with this drop, some models still performed comparably to radiologists.

2. Methods

Models. We investigated the generalization performance of 8 available models on the CheXpert competition (Irvin et al., 2019). CheXpert is a competition for automated chest x-ray interpretation that has been running since January 2019 featuring a strong radiologist-labeled reference standard. Many models have been submitted to the CheXpert leaderboard from both academic and industry teams. The top 8 available models of the 94 models on the CheXpert competition leaderboard as of November 2019 were selected. All of the selected models were ensembles with the number of models in the ensemble ranging from 8 to 32; the majority of these models featured Densely Connected Convolutional Networks (Huang et al., 2017).

Test Set. CheXpert used a hidden test set for official evaluation of models. Teams submitted their executable code, which was then run on a test set that was not publicly readable to preserve the integrity of the test results. We made use of the CodaLab platform to re-run these chest x-ray models. We evaluated these models on the CheXphoto (Phillips et al., 2020) test set, a dataset of photos of the x-rays from the CheXpert test set.

Table 1: AUC and MCC performance of models and radiologists on the standard x-rays and the photos of chest x-rays, with 95% confidence intervals.

| Comparison       | Result                          |
|------------------|--------------------------------|
| **AUC**          |                                |
| Photos           | 0.856 (0.840, 0.869)            |
| Standard         | 0.871 (0.855, 0.863)            |
| **AUC**          |                                |
| Standard-Photos  | 0.016 (0.012, 0.019)            |
| **MCC**          |                                |
| Photos           | 0.560 (0.528, 0.587)            |
| Standard         | 0.588 (0.560, 0.618)            |
| Radiologists     | 0.568 (0.542, 0.597)            |
| **MCC**          |                                |
| Standard-Photos  | 0.029 (0.014, 0.043)            |
| Radiologists-Photos | 0.009 (-0.022, 0.042)          |

Evaluation Metrics. Our primary evaluation metric was Matthew’s Correlation Coefficient (MCC), a statistical rate which produces a high score only if the prediction obtained good results in all of the four confusion matrix categories (true positives, false negatives, true negatives, and false positives); MCC is proportionally both to the size of positive elements and the size of negative elements in the dataset (Chicco and Jurman, 2020).

We reported the average MCC of 8 models for five pathologies, namely atelectasis, cardiomegaly, consolidation, edema, and pleural effusion. Additionally, in experiments comparing the models on standard chest x-rays to photos of chest x-rays, we reported the AUC and MCC of the models. In experiments comparing models to board-certified radiologists, we reported the difference in MCC for each of the five pathologies.

3. Results

In comparison of model performance on digital chest x-rays to photos, all eight models experienced a statistically significant drop in task performance on photos with an average drop of 0.036 MCC (95% CI 0.024, 0.048) (See Figure 1, Table 1). All models
had a statistically significant drop on at least one of the pathologies between native digital image to photos. One model had a statistically significant drop in performance on three pathologies: pleural effusion, edema, and consolidation. Two models had a significant drop on two pathologies: one on pleural effusion and edema, and the other on pleural effusion and cardiomegaly. The cardiomegaly and pleural effusion tasks led to decreased performance in five and four models respectively.

In comparison of performance of models on photos compared to radiologist performance, three out of eight models performed significantly worse than radiologists on average, and the other five had no significant difference (see Figure 2). On specific pathologies, there were some models that had a significantly higher performance than radiologists: two models on cardiomegaly, and one model on edema. Conversely, there were some models that had a significantly lower performance than radiologists: two models on cardiomegaly, and one model on consolidation. The pathology with the greatest number of models that had a significantly lower performance than radiologists was pleural effusion (seven models).

4. Discussion

Our results demonstrated that while most models experienced a significant drop in performance when applied to photos of chest x-rays compared to the native digital image, their performance was nonetheless largely equivalent to radiologist performance. We found that although there were thirteen times that models had a statistically significant drop in performance on photos on the different pathologies, the models had significantly lower performance than radiologists only 6 of those 13 times. Comparison to radiologist performance provides context in regard to clinical applicability: several models remained comparable to radiologist performance standard despite decreased performance on photos.

While using photos of chest x-rays to input into chest x-ray algorithms could enable any physician with a smartphone to get instant AI algorithm assistance, the performance of chest x-ray algorithms on photos of chest x-rays has not been thoroughly investigated. Several studies have highlighted the importance of generalizability of computer vision models with noise in (Hendrycks and Dietterich, 2019). Dodge and Karam (2017) demonstrated that deep neural networks perform poorly compared to humans on image classification on distorted images. Geirhos et al. (2019), Schmidt et al. (2018) have found that convolutional neural networks trained on specific image corruptions did not generalize, and the error patterns of network and human predictions were not similar on noisy and elastically deformed images. Our work makes significant contributions over another investigation of chest x-ray models (Rajpurkar et al., 2020). While their study considered the differences in AUC of models when applied to photos of x-rays, they did not (1) compare the resulting performances against radiologists, (2) investigate the drop in performances on specific tasks, or (3) analyze drops in performances of individual models across tasks.

Further investigation could be directed towards understanding how different model training procedures may affect model generalization to photos of chest x-rays, and understanding etiologies behind trends for changes in performance for specific pathologies or specific artifacts.

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