Multi-task UNet: Jointly Boosting Saliency Prediction and Disease Classification on Chest X-ray Images

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Abstract

Human visual attention has recently shown its distinct capability in boosting machine learning models. However, studies that aim to facilitate medical tasks with human visual attention are still scarce. To support the use of visual attention, this paper describes a novel deep learning model for visual saliency prediction on chest X-ray (CXR) images. To cope with data deficiency, we exploit the multi-task learning method and tackles disease classification on CXR simultaneously. For a more robust training process, we propose a further optimized multi-task learning scheme to better handle model overfitting. Experiments show our proposed deep learning model with our new learning scheme can outperform existing methods dedicated either for saliency prediction or image classification. The code used in this paper is available at https://github.com/hz-zhu/MT-UNet.

Keywords: Saliency Prediction, Disease Classification, X-ray Imaging, Deep Learning, Multi-task learning

1. Introduction

Recent work in machine learning and computer vision have demonstrated advantages of integrating human attention with artificial neural network models, as studies show that many machine vision tasks, i.e., image segmentation, image captioning, object recognition, etc., can benefit from adding human visual attention (Liu and Milanova, 2018).

Visual attention is the ability inherited in biological visual systems to selectively recognize regions or features on scenes relevant to a specific task (Borji et al., 2012), where “bottom-up” attention (also called exogenous attention) focuses on physical properties in the visual input that are salient and distinguishable, and “top-down” attention (also called endogenous attention) generally refers to mental strategies adopted by the visual systems to accomplish the intended visual tasks (Paneri and Gregoriou, 2017). Early research on saliency prediction aims to understand attentions triggered by visual features and patterns, and thus “bottom-up” attention is the research focus (Borji et al., 2012). More recent attempts, empowered by interdisciplinary efforts, start to study both “bottom-up” and “top-down” attentions, and therefore the terms, saliency prediction and visual attention prediction, are used interchangeably (Sun et al., 2021). In this paper, we use the term saliency prediction as the prediction of human visual attentions allocations when viewing
2D images, containing both “bottom-up” and “top-down” attentions. 2D heatmap is usually used to represent human visual attention distribution. Note that saliency prediction studied in this paper is different from neural network’s saliency/attention which can be visualized through class activation mapping (CAM) by Zhou et al. (2016) and other methods (Simonyan et al., 2013; Fu et al., 2019; Selvaraju et al., 2016). With the establishment of several benchmark datasets, data driven approaches demonstrated major advancements in saliency prediction (review in Borji (2019) and Wang et al. (2019)). However, saliency prediction for natural scenes is the primary focus, and more needs to be done in the medical domain. Hence, we intend to study the saliency prediction for examining chest X-ray (CXR) images, one of the most common radiology tasks worldwide.

CXR imaging is commonly used for the diagnosis of cardio and/or respiratory abnormalities; it is capable of identifying multiple conditions through a single shot, i.e., COVID-19, pneumonia, heart enlargement, etc. (Çallı et al., 2021). There exists multiple public CXR datasets (Irvin et al., 2019; Wang et al., 2017). However, the creation of large comprehensive medical datasets is labour intensive, and requires significant medical resources which are usually scarce (Castro et al., 2020). Consequently, medical datasets are rarely as abundant as that for non-medical fields. Thus, machine learning approaches applied on medical datasets need to address the problem of data scarcity. In this paper, we exploit the multi-task learning for solution.

Multi-task learning is known for its inductive transfer characteristics that can drive strong representation learning and generalization of each component task (Caruana, 1997). Therefore, multi-task learning methods partially alleviates some of the major shortcomings in deep learning, i.e., high demands for data sufficiency and heavy computation loads (Crawshaw, 2020). However, to apply multi-task learning methods successfully, challenges still exist, which can be the proper selection of component tasks, the architecture of the network, the optimization of the training schemes and many others (Zhang and Yang, 2021; Crawshaw, 2020). This paper investigates the proper configuration of a multi-task learning model that can tackle visual saliency prediction and image classification simultaneously.

The main contributions of this paper are: 1) development of a new deep convolutional neural network (DCNN) architecture for CXR image saliency prediction and classification based on UNet (Ronneberger et al., 2015), and 2) proposal of an optimized multi-task learning scheme that handles overfitting. Our method aims to outperform the state-of-the-art networks dedicated either for saliency prediction or image classification.

2. Background

2.1. Saliency prediction with deep learning

DCNN is the leading machine learning method applied to saliency prediction (Pan et al., 2016; Kümmерer et al., 2016; Jia and Bruce, 2020; Kroner et al., 2020). Besides, transfer learning with pre-trained networks was observed to boost the performance of saliency prediction (Oyama and Yamanaka, 2017; Kümmерer et al., 2016; Oyama and Yamanaka, 2018). A majority of DCNN approaches are for natural scene saliency prediction, and so far, only a few studied the saliency prediction for medical images. By Cai et al. (2018), the generative adversarial network is used to predict expert sonographer’s saliency when performing standard fetal head plane detection on ultrasound (US) images. However, the
saliency prediction is used as a secondary task to assist the primary detection task, and thus, the saliency prediction performance failed to outperform benchmark prediction methods in several key metrics. Similarly, by Karargyris et al. (2021), as a proof-of-concept study, the gaze data is used as an auxiliary task for CXR image classification, and the performance of saliency prediction is not reported in the study.

2.2. CXR image classification with deep learning

Public datasets for CXR images enabled data driven approaches for automatic image analysis and diagnosis (Serte et al., 2020; Li et al., 2020). Advancements in standardized image classification networks, i.e., ResNet (He et al., 2016), DenseNet (Huang et al., 2017), and EfficientNet (Tan and Le, 2019), facilitate CXR image classification. Yet, CXR image classification remains challenging, as CXR images are noisy, and may contain subtle features that are difficult to recognize even by experts (Çallı et al., 2021; Khan et al., 2021).

3. Multi-task Learning Method

As stated in Section 1, component task selection, network architecture design, and training scheme are key factors for multi-task learning. We select the classification task together with the saliency prediction based on the fact that attention patterns are task specific (Karessli et al., 2017). Radiologists are likely to exhibit distinguishable visual behaviors when different patient conditions are shown on CXR images (McLaughlin et al., 2017). This section introduces our multi-task UNet (MT-UNet) architecture, and derives a better multi-task training scheme for saliency prediction and image classification.
3.1. Multi-task UNet

Figure 1 shows the architecture of the proposed MT-UNet. The network takes CXR images, $x \in \mathbb{R}^{1 \times H \times W}$, where $H$ and $W$ are image dimensions, as input, and produces two outputs, predicted saliency $y_s \in \mathbb{R}^{1 \times H \times W}$, and predicted classification $y_c \in \mathbb{R}^C$, where $C$ is the number of classes. As the ground truth for $y_s$ is human visual attention distribution, represented as a 2D matrix whose elements are non-negative and sum to 1, $y_s$ is normalized by Softmax before output from MT-UNet. Softmax is also applied to $y_c$ before output so that the classification outcome can be interpreted as class probability. For the simplicity of notation, batch dimensions are neglected.

The proposed MT-UNet is derived from standard UNet architecture (Ronneberger et al., 2015). As a well-known image-to-image deep learning model, the UNet structure has been adopted for various tasks. For example, the UNet is appended with additional structures for visual scene understanding (Jha et al., 2020), the features from the bottleneck (middle of the UNet) are extracted for image classification tasks (Karargyris et al., 2021), and by combining UNet with Pyramid Net (Lin et al., 2017), features at different depth are aggregated for enhanced segmentation (Moradi et al., 2019). What’s more, the encoder-decoder structure of UNet is utilized for multi-task learning, where the encoder structure is used to learn representative features, along with designated decoder structures or classification heads for image reconstruction, segmentation, and/or classification (Zhou et al., 2021; Amyar et al., 2020). In our design, we apply classification heads (shaded in light green in Figure 1), which are added not only to the bottleneck but also the ending part of the UNet architecture. This additional classification specific structures aggregates middle and higher-level features for classification, exploiting features learnt at different depths. The attention heads perform global average pooling operations to the 4D tensors, followed by concatenation, and two linear transforms (dense layers) with dropout (rate=25%) in the middle to produce classification outcomes. The MT-UNet belongs to the hard parameter sharing structure in multi-task learning, where different tasks share the same trainable parameters before branched out to each tasks’ specific parameters (Vandenhende et al., 2021). Having more trainable parameters in task specific structures may improve the performance for that task at a cost of introducing additional parameters and increasing computational load (Crawshaw, 2020; Vandenhende et al., 2021). In our design, we wish to avoid heavy structures with lots of task specific parameters, and therefore, task specific structures are minimized. In Figure 1, we use yellow and green shades to denote network structures dedicated for saliency prediction and classification, respectively.

3.2. Multi-task Training Scheme

Balancing the losses between tasks in a multi-task training process has a direct impact on the training outcome (Vandenhende et al., 2021). There exist multi-task training schemes (Kendall et al., 2018; Chen et al., 2018; Guo et al., 2018; Sener and Koltun, 2018), and among which, we adopt the uncertainty based balancing scheme (Kendall et al., 2018) with the modification proposed in (Liebel and Körner, 2018). Hence, the loss function is:

$$L = \frac{1}{\sigma_s^2} L_s + \frac{1}{\sigma_c^2} L_c + \ln(\sigma_s + 1) + \ln(\sigma_c + 1)$$

(1)
where $L_s$ and $L_c$ are loss values for $y_s$ and $y_c$, respectively; $\sigma_s > 0$ and $\sigma_c > 0$ are trainable scalars estimating the uncertainty of $L_s$ and $L_c$, respectively; $\sigma_s$ and $\sigma_c$ are initialized to 1; $\ln(\sigma_s+1)$ and $\ln(\sigma_c+1)$ are regularizing terms to avoid arbitrary decrease of $\sigma_s$ and $\sigma_c$. With Equation (1), we know that $\sigma$ values can dynamically weigh losses of different amplitudes during training, and loss with low uncertainty (small $\sigma$ value) is prioritized in the training process. $\mathcal{L} > 0$. Given $y_s$ and $y_c$ with their ground truth $\bar{y}_s$ and $\bar{y}_c$, respectively, the loss functions are:

$$L_s = H(y_s, y_s) - H(\bar{y}_s),$$ (2)

$$L_c = H(y_c, y_c)$$ (3)

where $H(Q, R) = -\sum_i Q_i \ln(R_i)$ stands for cross entropy of two discrete distributions $Q$ and $R$, both with $n$ elements; $H(Q) = H(Q, Q)$ stands for the entropy, or self cross entropy, of discrete distribution $Q$. $L_s$ is the Kullback-Leibler divergence (KLD) loss, and $L_c$ is the cross-entropy loss. By observing Equation (2) and Equation (3), we know that only the cross entropy terms, $H(\cdot, \cdot)$, generate gradient when updating network parameters, as the term $-H(\bar{y}_s)$ in $L_s$ is a constant and has zero gradient. Therefore, we extend the method in (Kendall et al., 2018), and use $\frac{1}{\sigma^2}$ to scale a KLD loss ($L_s$) as that for a cross-entropy loss ($L_c$).

Although the training scheme in Equation (1) yields many successful applications, overfitting for multi-task networks still can jeopardize the training process, especially for small datasets (Wang et al., 2020). Multiple factors can cause overfitting, among witch, learning rate, $r > 0$, shows the most significant impact (Li et al., 2019). Also, $r$ generally has significant influences on the training outcome (Smith, 2018), making it one of the most important hyper-parameters for a training process. When training MT-UNet, $r$ is moderated by several factors. The first factor is the use of an optimizer. Many optimizers, i.e., Adam (Kingma and Ba, 2014) and RMSProp (Tieleman et al., 2012), deploy the momentum mechanism or its variants, which can adaptively adjust the effective learning rate, $r_e$, during training. As a learning rate scheduler is often used for more efficient training, it is the second factor to influence $r$. The influence of $r$ from a learning rate scheduler can be adaptive, i.e., reduce learning rate on plateau (RLRP), or more arbitrary, i.e., cosine annealing with warm restarts (Loshchilov and Hutter, 2016). By observing Equation (1), we know that an uncertainly estimator $\sigma$ for a loss $L$ also serves as a learning rate adaptor for $L$, which is the third factor. More specifically, given a loss value $L$ with learning rate $r$, the effective learning rate for parameters with a scaled loss value $L_{\sigma^2}$ is $\frac{r}{\sigma^2}$.

Decreasing $r$ upon overfitting can alleviate its effects (Smith, 2018; Duffner and Garcia, 2007), but Equation (1) leads to increased learning rate upon overfitting, further worsening the training process. This happens because training loss decreases when overfitting occurs, reducing its variance at the same time. Thus, $\sigma$ decreases accordingly, which increases the effective learning rate, thus creating a vicious circle of overfitting. More detailed mathematical derivation is presented in Appendix A. This phenomenon can be observed in Figure 2, where changes of losses and $\sigma$ values during a training process following Equation (1) are presented. We can see from Figure 2(a), at epoch 40, after an initial decrease in both the training and validation losses, the training loss start to acceleratedly decrease while the validation loss start to amplify, which is a vicious circle of overfitting. A RLRP scheduler
can halt the vicious circle by resetting the model parameters to a former epoch and reducing \( r \). Yet, even with reduced \( r \), a vicious circle of overfitting can remerge in later epochs.

Figure 2: Training process visualization with Equation (1)

To alleviate overfitting, we propose the use of the following equations to replace Equation (1):

\[
\mathcal{L} = \frac{1}{\sigma_s^2} L_s + L_c + \ln(\sigma_s + 1),
\]

\( (4) \)

\[
\mathcal{L} = L_s + \frac{1}{\sigma_c^2} L_c + \ln(\sigma_c + 1).
\]

\( (5) \)

The essence of Equations (4) and (5) is to fix the uncertainty term for one loss in Equation (1) to 1, so that the flexibility in changing effective learning rate is reduced. With the uncertainty term fixed for one component loss, Equations (4) and (5) demonstrate the ability to alleviate overfitting and stabilize the training process. It is worth noting that Equations (4) and (5) cannot be used interchangeably. We need to test both equations to check which can achieve better performances, as depending on the dataset and training process, overfitting can occur of different severity in all component tasks. In this study, training process with Equation (5) achieves the best performance. Ablation study of this method is presented in Section 5.

4. Dataset and Evaluation Methods

We use the “chest X-ray dataset with eye-tracking and report dictation” (Karargyris et al., 2021) shared via PhysioNet (Moody et al., 2000) in this study. The dataset was derived from the MIMIC-CXR dataset (Johnson et al., 2019a,b) with additional gaze tracking and dictation from an expert radiologist. 1083 CXR images are included in the dataset, and accompanying each image, there are tracked gaze data; a diagnostic label (either normal, pneumonia, or enlarged heart); segmentation of lungs, mediastinum, and aortic knob; and radiologist’s audio with dictation. The CXR images in the dataset are in resolutions of various sizes, i.e., 3056 × 2044, and we down sample and/or pad each image to 640 × 416. A GP3 gaze tracker by Gazepoint (Vancouver, Canada) was used for the collection of gaze data. The tracker has an accuracy of around 1° of visual angle, and has a 60 Hz sampling rate (Zhu et al., 2019).

Several metrics have been used for the evaluation of saliency prediction performances, and they can be classified into location-based metrics and distribution-based metrics (Bylinskii et al., 2018). Due to the tracking inaccuracy of the GP3 gaze tracker, location-based
metrics is not suited for this study. Therefore, in this paper, we follow suggestions in (Bylinskii et al., 2018) and use KLD for performance evaluation. We also include histogram similarity (HS), and Pearson’s correlation coefficient (PCC) for reference purposes. For the evaluation of classification performances, we use the area under curve (AUC) metrics for multi-class classifications (Hand and Till, 2001; Fawcett, 2006), and the classification accuracy (ACC) metrics. We also include the AUC metrics for each class: normal, enlarged heart, and pneumonia, denoted as AUC-Y1, AUC-Y2, and AUC-Y3, respectively. In this paper, all metrics values are presented as median statistics followed by standard deviations behind the ± sign. Metrics with up-pointing arrow ↑ indicates greater values reflect better performances, and vice versa. Best metrics are emboldened.

5. Experiments and Result

5.1. Benchmark comparison

In this subsection, we compare the performance of MT-UNet, with benchmark networks for CXR image classification and saliency prediction. Detailed training settings are presented in Appendix B.

For CXR image classification, the benchmark networks are chosen from the top performing networks for CXR image classification examined in (El Asnaoui et al., 2021), which are ResNet50 (He et al., 2016) and Inception-ResNet v2 (abbreviated as IRNetV2 in this paper) (Szegedy et al., 2017). Following Karargyris et al. (2021), we also include a state-of-the-art general purpose classification network: EfficientNetV2-S (abbreviated as EffNetV2-S) (Tan and Le, 2021) for comparison. For completeness, classification using standard UNet with additional classification head (denoted as UNetC) is included. Results are presented in Table 1, and We can see that MT-UNet outperforms the other classification networks.

For CXR image saliency prediction, comparison was conducted with 3 state-of-the-art saliency prediction models, which are SimpleNet (Reddy et al., 2020), MSINet (Kroner et al., 2020) and VGGSSM (Cao et al., 2020). Saliency prediction using standard UNet (denoted as UNetS) is also included for reference. Table 2 shows the result, where MT-UNet outperforms the rest. Visual comparisons for saliency prediction results are presented through Table 4 in Appendix C.

| Metrics   | MT-UNet         | UNetC     | EffNetV2-S | IRNetV2  | ResNet50   |
|-----------|-----------------|-----------|------------|----------|------------|
| ACC ↑     | **0.670 ± 0.018** | 0.593 ± 0.009 | 0.640 ± 0.037 | 0.640 ± 0.017 | 0.613 ± 0.013 |
| AUC ↑     | **0.843 ± 0.012** | 0.780 ± 0.006 | 0.826 ± 0.015 | 0.824 ± 0.014 | 0.816 ± 0.010 |
| AUC-Y1 ↑  | **0.864 ± 0.014** | 0.841 ± 0.007 | 0.852 ± 0.013 | 0.862 ± 0.016 | 0.845 ± 0.015 |
| AUC-Y2 ↑  | **0.912 ± 0.008** | 0.840 ± 0.003 | 0.901 ± 0.015 | 0.897 ± 0.011 | 0.896 ± 0.015 |
| AUC-Y3 ↑  | **0.711 ± 0.027** | 0.597 ± 0.018 | 0.653 ± 0.017 | 0.633 ± 0.036 | 0.622 ± 0.022 |

Table 1: Performance comparison between classification models.
Table 2: Performance comparison between saliency prediction models.

| Metrics | MT-UNet  | UNetS    | SimpleNet | MSINet   | VGGSSM   |
|---------|----------|----------|-----------|----------|----------|
| KLD ↓   | 0.726 ± 0.004 | 0.750 ± 0.002 | 0.758 ± 0.009 | 0.748 ± 0.003 | 0.743 ± 0.007 |
| PCC ↑   | 0.569 ± 0.004 | 0.552 ± 0.002 | 0.545 ± 0.008 | 0.557 ± 0.002 | 0.561 ± 0.005 |
| HS ↑    | 0.548 ± 0.001 | 0.540 ± 0.001 | 0.541 ± 0.002 | 0.545 ± 0.001 | 0.545 ± 0.003 |

5.2. Ablation study

To validate the modified multi-task learning scheme, ablation study is performed. The multi-task learning schemes following Equations (1), (4) and (5) are compared, and they are denoted as MTLS1, MTLS2, and MTLS3, respectively. Please note that the best-performing MTLS3 is used for benchmark comparison in Section 5.1. Figure 3 in Appendix C shows the training process for MTLS2 and MTLS3. With Figures 2 and 3, we can see that overfitting occurs both for MTLS1 and MTLS2, but the overfitting is reduced in MTLS3. The training processes shown in Figures 2 and 3 are with optimized hyper-parameters. The resulting performances are compared in Table 3 in Appendix C. We can see that MTLS3 outperforms the rest learning schemes both in classification and in saliency prediction.

To validate the effects of using classification head that aggregates features from different depths, we create ablated versions of MT-UNet that use features from either the bottleneck or the top layer of the MT-UNet for classification, denoted as MT-UNetB and MT-UNetT, respectively. Results are presented in Table 3 in Appendix C. We can see that MT-UNet generally performs better than MT-UNetT and MT-UNetB.

6. Discussion

In this paper, we build the MT-UNet model and propose a further optimized multi-tasking learning scheme for saliency prediction and disease classification with CXR images. While a multi-task learning model has the potential of enhancing the performances for all component tasks, a proper training scheme is one of the key factors to fully unveil its potentiality. As shown in Table 3, MT-UNet with the standard multi-task learning scheme may barely outperform existing models for saliency prediction or image classification.

Several future work could be done to improve this study. The first would be the expansion of the gaze tracking dataset for medical images. So far, only 1083 CXR images are publicly available with radiologist’s gaze behavior, limiting extensive studies of gaze-tracking assisted machine learning methods in the medical field. Also, more dedicated studies on multi-task learning methods, especially for small datasets, can be helpful for medical machine learning tasks. Overfitting and data deficiency are the lingering challenges encountered by many studies. A better multi-task learning method may handle these challenges more easily.

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References

Amine Amyar, Romain Modzelewski, Hua Li, and Su Ruan. Multi-task deep learning based ct imaging analysis for covid-19 pneumonia: Classification and segmentation. Computers in Biology and Medicine, 126:104037, 2020.

Ali Borji. Saliency prediction in the deep learning era: Successes and limitations. IEEE transactions on pattern analysis and machine intelligence, 2019.

Ali Borji, Dicky N Sihite, and Laurent Itti. Quantitative analysis of human-model agreement in visual saliency modeling: A comparative study. IEEE Transactions on Image Processing, 22(1):55–69, 2012.

Zoya Bylinskii, Tilke Judd, Aude Oliva, Antonio Torralba, and Frédo Durand. What do different evaluation metrics tell us about saliency models? IEEE transactions on pattern analysis and machine intelligence, 41(3):740–757, 2018.

Yifan Cai, Harshita Sharma, Pierre Chatelain, and J Alison Noble. Multi-task sonoeyenet: detection of fetal standardized planes assisted by generated sonographer attention maps. In International conference on medical image computing and computer-assisted intervention, pages 871–879. Springer, 2018.

Erdi Çalli, Ecem Sogancioglu, Bram van Ginneken, Kicky G van Leeuwen, and Keelin Murphy. Deep learning for chest x-ray analysis: A survey. Medical Image Analysis, page 102125, 2021.

Ge Cao, Qing Tang, and Kang-hyun Jo. Aggregated deep saliency prediction by self-attention network. In International Conference on Intelligent Computing, pages 87–97. Springer, 2020.

Rich Caruana. Multitask learning. Machine learning, 28(1):41–75, 1997.

Daniel C Castro, Ian Walker, and Ben Glocker. Causality matters in medical imaging. Nature Communications, 11(1):1–10, 2020.

Zhao Chen, Vijay Badrinarayanan, Chen-Yu Lee, and Andrew Rabinovich. Gradnorm: Gradient normalization for adaptive loss balancing in deep multitask networks. In International Conference on Machine Learning, pages 794–803. PMLR, 2018.

Michael Crawshaw. Multi-task learning with deep neural networks: A survey. arXiv preprint arXiv:2009.09796, 2020.

Stefan Duffner and Christophe Garcia. An online backpropagation algorithm with validation error-based adaptive learning rate. In International Conference on Artificial Neural Networks, pages 249–258. Springer, 2007.
Khalid El Asnaoui, Youness Chawki, and Ali Idri. Automated methods for detection and classification pneumonia based on x-ray images using deep learning. In Artificial Intelligence and Blockchain for Future Cybersecurity Applications, pages 257–284. Springer, 2021.

Tom Fawcett. An introduction to roc analysis. Pattern recognition letters, 27(8):861–874, 2006.

Kun Fu, Wei Dai, Yue Zhang, Zhirui Wang, Menglong Yan, and Xian Sun. Multicam: Multiple class activation mapping for aircraft recognition in remote sensing images. Remote Sensing, 11(5):544, 2019.

Michelle Guo, Albert Haque, De-An Huang, Serena Yeung, and Li Fei-Fei. Dynamic task prioritization for multitask learning. In Proceedings of the European Conference on Computer Vision (ECCV), pages 270–287, 2018.

David J Hand and Robert J Till. A simple generalisation of the area under the roc curve for multiple class classification problems. Machine learning, 45(2):171–186, 2001.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016.

Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q Weinberger. Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 4700–4708, 2017.

Jeremy Irvin, Pranav Rajpurkar, Michael Ko, Yifan Yu, Silviana Ciurea-Ilcus, Chris Chute, Henrik Marklund, Behzad Haghigho, Robyn Ball, Katie Shpanskaya, et al. CheXpert: A large chest radiograph dataset with uncertainty labels and expert comparison. In Proceedings of the AAAI conference on artificial intelligence, volume 33, pages 590–597, 2019.

Ankit Jha, Awanish Kumar, Shivam Pande, Biplab Banerjee, and Subhasish Chaudhuri. Mt-unet: A novel u-net based multi-task architecture for visual scene understanding. In 2020 IEEE International Conference on Image Processing (ICIP), pages 2191–2195. IEEE, 2020.

Sen Jia and Neil DB Bruce. Eml-net: An expandable multi-layer network for saliency prediction. Image and Vision Computing, 95:103887, 2020.

Alistair EW Johnson, Tom J Pollard, Seth J Berkowitz, Nathaniel R Greenbaum, Matthew P Lungren, Chih-ying Deng, Roger G Mark, and Steven Horng. Mimic-cxr, a de-identified publicly available database of chest radiographs with free-text reports. Scientific data, 6(1):1–8, 2019a.

Alistair EW Johnson, Tom J Pollard, Nathaniel R Greenbaum, Matthew P Lungren, Chih-ying Deng, Yifan Peng, Zhiyong Lu, Roger G Mark, Seth J Berkowitz, and Steven Horng. Mimic-cxr-jpg, a large publicly available database of labeled chest radiographs. arXiv preprint arXiv:1901.07042, 2019b.
Alexandros Karargyris, Satyananda Kashyap, Ismini Lourentzou, Joy T Wu, Arjun Sharma, Matthew Tong, Shafiq Abedin, David Beymer, Vandana Mukherjee, Elizabeth A Krupinski, et al. Creation and validation of a chest x-ray dataset with eye-tracking and report dictation for ai development. *Scientific data*, 8(1):1–18, 2021.

Nour Karessli, Zeynep Akata, Bernt Schiele, and Andreas Bulling. Gaze embeddings for zero-shot image classification. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4525–4534, 2017.

Alex Kendall, Yarin Gal, and Roberto Cipolla. Multi-task learning using uncertainty to weigh losses for scene geometry and semantics. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 7482–7491, 2018.

Wasif Khan, Nazar Zaki, and Luqman Ali. Intelligent pneumonia identification from chest x-rays: A systematic literature review. *IEEE Access*, 2021.

Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

Alexander Kroner, Mario Senden, Kurt Driessen, and Rainer Goebel. Contextual encoder–decoder network for visual saliency prediction. *Neural Networks*, 129:261–270, 2020.

Matthias Kümmerer, Thomas SA Wallis, and Matthias Bethge. Deepgaze ii: Reading fixations from deep features trained on object recognition. *arXiv preprint arXiv:1610.01563*, 2016.

Haidong Li, Jiongcheng Li, Xiaoming Guan, Binghao Liang, Yuting Lai, and Xinglong Luo. Research on overfitting of deep learning. In *2019 15th International Conference on Computational Intelligence and Security (CIS)*, pages 78–81. IEEE, 2019.

Yuanyuan Li, Zhenyan Zhang, Cong Dai, Qiang Dong, and Samireh Badrigilan. Accuracy of deep learning for automated detection of pneumonia using chest x-ray images: a systematic review and meta-analysis. *Computers in Biology and Medicine*, page 103898, 2020.

Lukas Liebel and Marco Körner. Auxiliary tasks in multi-task learning. *arXiv preprint arXiv:1805.06334*, 2018.

Tsung-Yi Lin, Piotr Dollár, Ross Girshick, Kaiming He, Bharath Hariharan, and Serge Belongie. Feature pyramid networks for object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2117–2125, 2017.

X Liu and M Milanova. Visual attention in deep learning: a review. *Int Rob Auto J*, 4(3):154–155, 2018.

Ilya Loshchilov and Frank Hutter. Sgdr: Stochastic gradient descent with warm restarts. *arXiv preprint arXiv:1608.03983*, 2016.
Laura McLaughlin, Raymond Bond, Ciara Hughes, Jonathan McConnell, and Sonyia McFadden. Computing eye gaze metrics for the automatic assessment of radiographer performance during x-ray image interpretation. *International journal of medical informatics*, 105:11–21, 2017.

GB Moody, RG Mark, and AL Goldberger. Physionet: A research resource for studies of complex physiologic and biomedical signals. In *Computers in Cardiology 2000. Vol. 27 (Cat. 00CH37163)*, pages 179–182. IEEE, 2000.

Shakiba Moradi, Mostafa Ghelich Oghli, Azin Alizadehasl, Isaac Shiri, Niki Oveisi, Mehrdad Oveisi, Majid Maleki, and Jan Dhooge. Mfp-unet: A novel deep learning based approach for left ventricle segmentation in echocardiography. *Physica Medica*, 67:58–69, 2019.

Taiki Oyama and Takao Yamanaka. Fully convolutional densenet for saliency-map prediction. In *2017 4th IAPR Asian Conference on Pattern Recognition (ACPR)*, pages 334–339. IEEE, 2017.

Taiki Oyama and Takao Yamanaka. Influence of image classification accuracy on saliency map estimation. *CAAI Transactions on Intelligence Technology*, 3(3):140–152, 2018.

Junting Pan, Elisa Sayrol, Xavier Giro-i Nieto, Kevin McGuinness, and Noel E O’Connor. Shallow and deep convolutional networks for saliency prediction. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 598–606, 2016.

Sofia Paneri and Georgia G Gregoriou. Top-down control of visual attention by the prefrontal cortex: functional specialization and long-range interactions. *Frontiers in neuroscience*, 11:545, 2017.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. Pytorch: An imperative style, high-performance deep learning library. *Advances in neural information processing systems*, 32:8026–8037, 2019.

Navyasri Reddy, Samyak Jain, Pradeep Yarlagadda, and Vineet Gandhi. Tidying deep saliency prediction architectures. In *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 10241–10247. IEEE, 2020.

Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015.

Ramprasaath R Selvaraju, Abhishek Das, Ramakrishna Vedantam, Michael Cogswell, Devi Parikh, and Dhruv Batra. Grad-cam: Why did you say that? *arXiv preprint arXiv:1611.07450*, 2016.

Ozan Sener and Vladlen Koltun. Multi-task learning as multi-objective optimization. *arXiv preprint arXiv:1810.04650*, 2018.

Sertan Serte, Ali Serener, and Fadi Al-Turjman. Deep learning in medical imaging: A brief review. *Transactions on Emerging Telecommunications Technologies*, page e4080, 2020.
Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. Deep inside convolutional networks: Visualising image classification models and saliency maps. *arXiv preprint arXiv:1312.6034*, 2013.

Leslie N Smith. A disciplined approach to neural network hyper-parameters: Part 1–learning rate, batch size, momentum, and weight decay. *arXiv preprint arXiv:1803.09820*, 2018.

Yubao Sun, Mengyang Zhao, Kai Hu, and Shaojing Fan. Visual saliency prediction using multi-scale attention gated network. *Multimedia Systems*, pages 1–9, 2021.

Christian Szegedy, Sergey Ioffe, Vincent Vanhoucke, and Alexander A Alemi. Inception-v4, inception-resnet and the impact of residual connections on learning. In *Thirty-first AAAI conference on artificial intelligence*, 2017.

Mingxing Tan and Quoc Le. Efficientnet: Rethinking model scaling for convolutional neural networks. In *International Conference on Machine Learning*, pages 6105–6114. PMLR, 2019.

Mingxing Tan and Quoc V Le. Efficientnetv2: Smaller models and faster training. *arXiv preprint arXiv:2104.00298*, 2021.

Tijmen Tieleman, Geoffrey Hinton, et al. Lecture 6.5-rmsprop: Divide the gradient by a running average of its recent magnitude. *COURSERA: Neural networks for machine learning*, 4(2):26–31, 2012.

Simon Vandenhende, Stamatios Georgoulis, Wouter Van Gansbeke, Marc Proesmans, Dengxin Dai, and Luc Van Gool. Multi-task learning for dense prediction tasks: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2021.

Weiyao Wang, Du Tran, and Matt Feiszli. What makes training multi-modal classification networks hard? In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12695–12705, 2020.

Wenguan Wang, Jianbing Shen, Jianwen Xie, Ming-Ming Cheng, Haibin Ling, and Ali Borji. Revisiting video saliency prediction in the deep learning era. *IEEE transactions on pattern analysis and machine intelligence*, 43(1):220–237, 2019.

Xiaosong Wang, Yifan Peng, Le Lu, Zhiyong Lu, Mohammadhadi Bagheri, and Ronald M Summers. Chestx-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2097–2106, 2017.

Yu Zhang and Qiang Yang. A survey on multi-task learning. *IEEE Transactions on Knowledge and Data Engineering*, 2021.

Bolei Zhou, Aditya Khosla, Agata Lapedriza, Aude Oliva, and Antonio Torralba. Learning deep features for discriminative localization. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2921–2929, 2016.
Appendix A. Mathematical derivation of vicious circle for overfitting

Let $L \geq 0$ be the loss for a task, $T$, and $\sigma > 0$ be the variance estimator for $L$ used in Equation (1). Therefore, the loss for $T$ following Equation (1) can be expressed as:

$$L = \frac{L}{\sigma^2} + \ln(\sigma + 1).$$

(6)

The partial derivative of $L$ with respect to $\sigma$ is:

$$\frac{\partial L}{\partial \sigma} = -\frac{2L}{\sigma^3} + \frac{1}{\sigma + 1}.$$  

(7)

During a gradient based optimization process, to minimize $L$, $\sigma$ converges to the equilibrium value ($\sigma$ remains unchanged after gradient descend) which is achieved when $\frac{\partial L}{\partial \sigma} = 0$. Therefore, the following equation holds when $\sigma$ is at its equilibrium value, denoted as $\tilde{\sigma}$:

$$L = \frac{\tilde{\sigma}^3}{2\tilde{\sigma} + 2}.$$  

(8)

which is calculated by letting $\frac{\partial L}{\partial \sigma} = 0$. Let $f(\tilde{\sigma}) = L$, $\tilde{\sigma} > 0$, we can calculate that:

$$\frac{df(\tilde{\sigma})}{d\tilde{\sigma}} = \frac{\tilde{\sigma}^2(2\tilde{\sigma} + 3)}{2(\tilde{\sigma} + 1)^2} > 0, \quad \forall \tilde{\sigma} > 0.$$  

(9)

Therefore, we know that $f(\tilde{\sigma})$ is strictly monotonically increasing with respect to $\tilde{\sigma}$, and hence the inverse function of $f(\tilde{\sigma})$, $f^{-1}(\cdot)$, exists. More specifically, we have:

$$\tilde{\sigma} = f^{-1}(L).$$  

(10)

As a pair of inverse functions share the same monotonicity, we know that $\tilde{\sigma} = f^{-1}(L)$ is also strictly monotonically increasing. Thus, when $L$ decreases due to overfitting, we know that $\tilde{\sigma}$ will decrease accordingly, forcing $\sigma$ to decrease. The decreased $\sigma$ leads to an increase in the effective learning rate for $T$, forming a vicious circle of overfitting.

Appendix B. Training settings

We use the Adam optimizer with default parameters (Kingma and Ba, 2014) and the RLRP scheduler for all the training processes. The RLRP scheduler reduces 90% of the learning rate when validation loss stops improving for $P$ consecutive epochs, and reset model parameters to an earlier epoch when the network achieves the best validation loss. All training and
testing are performed with the PyTorch framework (Paszke et al., 2019). Hyper-parameters for optimizations are learning rate $r$, and $P$ in RLRP scheduler. The dataset is randomly partitioned into 70%, 10% and 20% subsections for training, validation and testing, respectively. The random data partitioning process preserves the balanced dataset characteristic, and all classes have equal share in all sub-datasets. All the results presented in this paper are based on at least 5 independent trainings with same hyper-parameters. NVIDIA V100 and A100 GPUs (Santa Clara, USA) were used.

Appendix C. Performance evaluation

| Metrics  | MTLS1   | MTLS2   | MTLS3   | MT-UNetB | MT-UNetT |
|----------|---------|---------|---------|----------|----------|
| KLD ↓    | 0.730 ± 0.007 | 0.738 ± 0.006 | **0.726** ± 0.004 | 0.730 ± 0.003 | 0.734 ± 0.007 |
| CC ↑     | 0.566 ± 0.005 | 0.563 ± 0.005 | **0.569** ± 0.004 | 0.568 ± 0.003 | 0.561 ± 0.007 |
| HS ↑     | 0.547 ± 0.002 | 0.545 ± 0.002 | **0.548** ± 0.001 | 0.548 ± 0.001 | 0.544 ± 0.003 |
| ACC ↑    | 0.649 ± 0.041 | 0.638 ± 0.019 | **0.670** ± 0.018 | 0.653 ± 0.013 | 0.649 ± 0.011 |
| AUC ↑    | 0.832 ± 0.019 | 0.832 ± 0.010 | 0.843 ± 0.012 | 0.836 ± 0.009 | **0.847** ± 0.008 |
| AUC-Y1 ↑ | 0.859 ± 0.014 | 0.861 ± 0.015 | 0.864 ± 0.014 | 0.859 ± 0.007 | **0.883** ± 0.005 |
| AUC-Y2 ↑ | 0.906 ± 0.016 | 0.913 ± 0.005 | **0.912** ± 0.008 | 0.907 ± 0.011 | 0.910 ± 0.006 |
| AUC-Y3 ↑ | 0.682 ± 0.035 | 0.672 ± 0.010 | **0.711** ± 0.027 | 0.694 ± 0.023 | 0.695 ± 0.025 |

Table 3: Ablation study performance comparison.

(a) MTLS2 losses (b) MTLS2 $\sigma$ (c) MTLS3 losses (d) MTLS3 $\sigma$

Figure 3: Multi-task learning schemes comparison
|                | Normal | Enlarged heart | Pneumonia |
|----------------|--------|----------------|-----------|
| **Truth**      | ![Normal](image1) | ![Enlarged heart](image2) | ![Pneumonia](image3) |
| **MT-UNet**    | ![Normal](image4) | ![Enlarged heart](image5) | ![Pneumonia](image6) |
| **UNet**       | ![Normal](image7) | ![Enlarged heart](image8) | ![Pneumonia](image9) |
| **SimpleNet**  | ![Normal](image10) | ![Enlarged heart](image11) | ![Pneumonia](image12) |
| **MSINet**     | ![Normal](image13) | ![Enlarged heart](image14) | ![Pneumonia](image15) |
| **VGGSSM**     | ![Normal](image16) | ![Enlarged heart](image17) | ![Pneumonia](image18) |

Table 4: Visualization of predicted saliency distributions. The ground truth and predicted saliency distributions are overlaid over CXR images. Jet colormap is used for saliency distributions where warmer (red and yellow) colors indicate higher concentration of saliency and colder (green and blue) colors indicate lower concentration of saliency.