A scoping review of transfer learning research on medical image analysis using ImageNet

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Abstract

Objective: Employing transfer learning (TL) with convolutional neural networks (CNNs), well-trained on non-medical ImageNet dataset, has shown promising results for medical image analysis in recent years. We aimed to conduct a scoping review to identify these studies and summarize their characteristics in terms of the problem description, input, methodology, and outcome.

Materials and Methods: To identify relevant studies, MEDLINE, IEEE, and ACM digital library were searched. Two investigators independently reviewed articles to determine eligibility and to extract data according to a study protocol defined a priori.

Results: After screening of 8,421 articles, 102 met the inclusion criteria. Of 22 anatomical areas, eye (18%), breast (14%), and brain (12%) were the most commonly studied. Data augmentation was performed in 72% of fine-tuning TL studies versus 15% of the feature-extracting TL studies. Inception models were the most commonly used in breast related studies (50%), while VGGNet was the common in eye (44%), skin (50%) and tooth (57%) studies. AlexNet for brain (42%) and DenseNet for lung studies (38%) were the most frequently used models. Inception models were the most frequently used for studies that analyzed ultrasound (55%), endoscopy (57%), and skeletal system X-rays (57%). VGGNet was the most common for fundus (42%) and optical coherence tomography images (50%). AlexNet was the most frequent model for brain MRIs (36%) and breast X-Rays (50%). 35% of the studies compared their model with other well-trained CNN models and 33% of them provided visualization for interpretation.

Discussion: Various methods have been used in TL approaches from non-medical to medical image analysis. The findings of the scoping review can be used in future TL studies to guide the selection of appropriate research approaches, as well as identify research gaps and opportunities for innovation.

Keywords: medical imaging; transfer learning; convolutional neural network; ImageNet

1. Introduction

While convolutional neural networks (CNN) were initially explored in computer vision in the 1980s [1], it was not until 2012 that the ImageNet competition demonstrated the potential of using CNN for image analysis. Since then, CNN has become a popular machine learning approach for various applications including medical image analysis.

Full training of a CNN from scratch has two main requirements: 1) a large labeled dataset, and 2) extensive computational and memory resources. In clinical practice, such large labeled datasets are not always available.
Creating a large labeled dataset is labor intensive and the number of patients with a specific medical condition of interest might not be sufficient to create a large dataset [2].

An alternative approach to full training of CNN is transfer learning (TL). By leveraging TL, the knowledge gained from large non-medical data can be transferred to solve a targeted medical problem. More specifically, parameters of well-trained CNN models on non-medical ImageNet data with natural images (e.g., AlexNet[3], VGGNet[4] and ResNet[5]) can be transferred to a targeted CNN model to solve a medical imaging problem.

Previous literature reviews focused on the usage of non-TL based deep learning methods [6,7] and TL-based general machine learning methods for medical imaging [8]. Yet, previous reviews have not focused on TL-based deep learning methods from non-medical data (i.e., ImageNet) for medical image analysis. Employing CNN models well-trained on non-medical ImageNet data for medical image analysis is a recent emerging trend; a review on medical imaging analysis up to early 2017 [7] could not find more than a few TL studies on ImageNet. Therefore, this scoping review aimed to summarize medical image analysis studies that used TL approaches on ImageNet. Specifically, we extracted study characteristics such as input data (e.g., dataset size), CNN model, transferring knowledge (i.e., parameters), and performance measures. We aimed to answer the following research questions: 1) What medical image analysis tasks can benefit from using TL on ImageNet data? 2) What are the characteristics of the input data? 3) What TL process (e.g., in terms of the CNN models or transferred parameters) has been followed? 4) What are the outcomes (e.g., performance accuracy)?

2. Background

2.1. Convolutional Neural Networks

CNN is a machine learning method commonly used in machine vision and medical image analysis [9]. A CNN typically consists of an input layer, one to many convolution layers, pooling operations (or layers), and a fully connected layer [10]. More details about CNNs can be found in [11].

2.1.1. ImageNet

The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is a large scale object recognition challenge, which has been running annually since 2010 [12]. One of the datasets used for this challenge is the ImageNet dataset [13], which contains over 15 million labeled images. Some CNN models have been very successful in classifying images in the ImageNet dataset into its corresponding categories. These models are briefly explained in the following subsections. A more comprehensive description of each model can be found elsewhere [14].
2.1.2. AlexNet

This CNN model was the winner of ILSVRC2012 [3]. The architecture consists of eight layers. The first layers are convolutional layers followed by a max-pooling layer for data dimension reduction. Rectified linear unit (ReLU) is used for the activation function, which has the fast training advantage over other activation functions [15]. The remaining three layers are fully connected layers [33].

2.1.3. VGGNet

The Visual Geometry Group (VGG) first introduced VGG-16 in ILSVRC2014 followed by VGG-19 as two successful architectures on ImageNet [16]. These models make an improvement over AlexNet by replacing large kernel-sized filters with multiple small kernel-sized filters resulting in 13 and 16 convolution layers for VGG-16 and VGG-19 respectively.

2.1.4. CaffeNet

This CNN model is a slight variation of AlexNet. Unlike AlexNet, CaffeNet does not use data augmentation (section B.3) and places the pooling layer before normalization operation. As a result, CaffeNet slightly improves the computational efficiency of AlexNet, since the data dimension reduction happens before normalization operation [17].

2.1.5. ZFNet

This CNN model was the winner of ILSVRC2013 and is an improved version of AlexNet with similar eight layers architecture [18]. ZFNet introduced the concept of deconvolutional network [19] to tackle the black-box nature of CNN models by showing how CNN learns feature representations. Deconvolutional network maps the learned features into input pixel space, which improves the CNN interpretability.

2.1.6. Inception

GoogLeNet model (also called Inception-V1) attempted at improving the efficiency of VGGNet in terms of memory usage and runtime without reducing accuracy [20]. To achieve this, it eliminated the activation functions of VGGNet that are redundant or zero because of the correlations among them. Therefore, GoogLeNet introduced and added a module called Inception that approximates sparse connections between the activation functions. After Inception-V1 the architecture was further refined in three subsequent versions. Inception-V2 used batch normalization for training [21]. Inception-V3 proposed a factorization method to improve the computational complexity of convolution layers [22]. Inception V-4 introduced a uniform simplified version of the Inception-V3 architecture with more inception modules [23].
2.1.7. ResNet

Adding more layers to CNN models can lead to accuracy saturation and vanishing gradients. Residual Learning, which is the backbone of ResNet CNN, aims at solving this problem [24]. CNN models prior to ResNet learned features at different abstraction levels at the end of each convolution layer. Rather than learning features, ResNet learns residuals, which is the subtraction of learned features from input for each convolution layer. This is done by using a concept called identity shortcut connections (i.e., connecting the input of a layer to x layers after that) [5]. Variations of ResNet use a different number of layers, such as ResNet-34, ResNet-50, and ResNet-101.

2.1.8. Inception-Residual Network

This CNN model combines the strengths of the Inception and ResNet architectures. As mentioned, Inception effectively learns features at different resolutions within the same convolution layer, while ResNet enables the network to a have deeper CNN to learn features that are more complex without losing performance. Inception-Residual Networks combine these strengths in two versions: Inception-ResNet-V1 and Inception-ResNet-V2 [23]. Inception-ResNet-V1 is based on Inception-V3 and Inception-ResNet-V2 is based on Inception-V4.

2.1.9. Xception

Xception stands for extreme inception and is a modified version of the Inception-V3 [25]. This CNN model uses depth wise separable convolution to involve the spatial dimension and channel dimension of the image separately in the training process. Xception has almost the same number of parameters as InceptionV3 with slightly better performance on ImageNet.

2.1.10. DenseNet

In DenseNet [26], each convolution layer receives the output (i.e., feature maps) of all preceding layers as input and passes its own output (i.e., feature maps) to all subsequent layers. Therefore, each layer obtains the collective knowledge of all preceding layers. The resulting CNN model becomes thinner and more compact due to the decreasing number of feature maps. DenseNet has several versions such as DenseNet-121, DenseNet-169, and DenseNet-201.

2.2. Transfer Learning

The most common issue with training CNN models for medical image analysis (i.e., full training from scratch) is lack of large labeled datasets. [27]. TL can help address this limitation by transferring the learned parameters (i.e., network weights) of well-trained CNN models on a large dataset (e.g., ImageNet) to solve medical
image analysis problems. To achieve this, the convolutional layers of a well-trained CNN model are either fine-tuned or frozen (i.e., used as is), while the fully connected layers are trained from scratch on the medical dataset. The idea behind TL is that although medical datasets are different from non-medical datasets, the low-level features (e.g., straight and curved lines that construct images) are universal to most of the image analysis tasks [28]. Therefore, transferred parameters (i.e., weights) may serve as a powerful set of features, which reduce the need for a large dataset as well as the training time and memory cost. There are two transfer learning approaches: feature-extracting and fine-tuning [28].

2.2.1. Feature-extracting

This approach utilizes a well-trained CNN model on a large dataset (e.g., ImageNet) as a feature extractor for the target domain (e.g., medical). More specifically, all convolution layers of the well-trained CNN model are frozen, while fully connected layers are removed. The convolution layers serve as a fixed feature extractor to adapt to a new (medical) task. Extracted features are then fed to a classifier, which can be new fully connected layers or any supervised machine learning method. Finally, only the new classifier is trained during the training process rather than the entire network [8].

2.2.2. Fine-tuning

This approach also utilizes a well-trained CNN model on a large dataset (e.g., ImageNet) as the base and replaces the classifier layers with a new classifier. However, in this method convolution layers of the well-trained CNN model are not frozen and their weights can get updated during the training process. This is done by initializing the weight of the convolution layers with the pre-trained weights of the well-trained CNN model while initializing the classifier layers with random weights. In this method the entire network is trained during the training process [24].

2.3. Data Augmentation

Increasing the size of labeled data usually improves the performance of CNN models. Data augmentation is a method for artificial data generation for training by creating variations of the original dataset [29]. For image data this includes a variety of image manipulation methods such as rotation, translation, scaling, and flipping techniques [30].

The most important consideration for data augmentation is memory and computational constraints. There are two commonly used data augmentation approaches: online and offline. Online data augmentation is performed
on-the-fly during training, while offline data augmentation generates the data beforehand and stores it in memory. The online approach saves memory, but results in slower training time. The offline approach is faster in training, but consumes a large amount of memory.

2.4. Visualization of Convolutional Neural Networks

It is difficult to interpret CNN black-box models and understand their decision-making process. It is useful to crack this process to make sure that the neural network is concentrating on appropriate parts of the image [31]. In addition, this can reveal new domain knowledge. Visualization of the learned features by CNNs is the most common practice to understand and trust the decision making process of these networks [18]. The most commonly used visualization methods are briefly described in this section, while more details could be found elsewhere [32].

2.4.1. Activation Maximization

This method aims at visualizing the most preferred inputs of neurons at each convolution layer. These preferred inputs show what features are learned. The learned features in a specific layer are represented by a synthesized input image that would cause maximal activation of a neuron [33].

2.4.2. Deconvolution

This method finds the patterns in the input image that activate a specific neuron (i.e., feature map) of a convolution layer. These patterns are reconstructed by mapping the neuron’s feature map back to the image pixel space. This process is implemented by a deconvolutional network (DeconvNet) structure, which forward-passes through the original CNN (i.e., inversed computation of a convolution layer) and performs up-sampling (i.e., reversing the down-sampling of a pooling layer) for a given feature map back to the input image [34].

2.4.3. Class Activation Mapping

Class Activation Mapping, also known as heatmap, was proposed by Zhou et al. [35]. Heatmap extracted from class activation mapping techniques is a simple method to determine the discriminative image regions used by a CNN model to classify images. This is done by visualizing the trigger of activation functions of intermediate convolution layers [36].

3. Method

3.1. Overview

Overall, this scoping literature review followed the PRISMA guidelines [37] and the methodological framework for scoping reviews proposed by Arksey et al [38]. We aimed to address the following research questions:
1. For what medical tasks ImageNet based models can be effective? Is the prediction task nominal or numerical? 2. What is the data type? What is the required dataset size for achieving a satisfactory performance? Is there any need for data augmentation? 3. What transfer learning approaches are most prevalent? 4. What ImageNet based models are most prevalent? Is there any other classifier that fully connected layers used for the final classification task? 5. What is the best achieved performance in each study? What is the performance of other well-trained CNN models for this specific task? 6. For which problems researchers have been able to provide interpretation using visualization techniques?

3.2. Literature search

We searched for eligible articles in MEDLINE, IEEE, and the ACM digital library. Since the ImageNet dataset was initially released in 2012, the results were limited to the studies published after June 1st 2012 up to January 2nd, 2020. The search strategies for each database can be found in Table S1 of the online supplement.

3.3. Inclusion and exclusion criteria

We included original research studies focused on classification problems of macroscopic medical images that directly used CNN models well-trained on non-medical images in ImageNet without any manipulation (i.e., methodological improvement, partial transfer of convolution layers of well-trained CNN models, combination of different models). We excluded studies lacking key information for the core study characteristics listed in Table 1.

3.4. Study selection

To assess inclusion eligibility, two reviewers independently evaluated the title and abstract of each retrieved article. The same reviewers independently evaluated the full text of potentially eligible studies. Disagreements were resolved through consensus between the two reviewers. The Cohen’s kappa intrarater agreement was 0.81 for title/abstract screening and 0.86 for full-text screening.

3.5. Data extraction

The following 13 features were extracted from the included studies to answer the research questions listed in Table 1 in terms of problem description, input, process (i.e., methodology), and output.

3.6. Data analysis

Included studies were summarized according to the characteristics laid out in Table 1. We also provided descriptive statistics in graphical format to convey the frequency of use of different modeling approaches according
to medical task, anatomical focus, image type, data size and augmentation method, transfer learning approach, and visualization method.

Table 1: Features extracted from each study.

| Research Question                                                                 | Category | Feature          | Description                                                                 |
|-----------------------------------------------------------------------------------|----------|------------------|-----------------------------------------------------------------------------|
| 1. For what medical tasks ImageNet based models can be effective? Is the prediction task nominal or numerical? | Problem  | Medical task     | Describes the medical goal of transfer learning                             |
|                                                                                   |          | Anatomical focus | Determines the body organ or area involved                                   |
|                                                                                   |          | Classification type | Numeric or nominal and if nominal, how many classes                         |
| 2. What is the data type? What is the required dataset size for achieving a satisfactory performance? Is there any need for data augmentation? | Input    | Image type       | Imaging modality (e.g., x-ray, MRI, ultrasound)                             |
|                                                                                   |          | Dataset size     | Number of cases in the dataset used for training and testing                |
|                                                                                   |          | Augmentation     | Choice of online or offline augmentation and the final size of the dataset used |
| 3. What transfer learning approaches are most prevalent?                           | Process  | Transferred knowledge | Transfer learning approach (i.e., feature-extracting or fine-tuning)       |
| 4. What ImageNet based models are most prevalent? Is there any other classifier that fully connected layers used for the final classification task? |          | CNN model        | The ImageNet based model with the best performance                         |
|                                                                                   |          | Classifier       | Whether a fully connected layer or a different classifier is used for classification |
| 5. What is the best achieved performance in each study? What is the performance of other well-trained CNN models for this specific task? | Output   | Performance      | Highest achieved performance based on the primary outcome                  |
|                                                                                   |          | Benchmark        | Models used as a baseline for comparison                                    |
| 6. For which problems researchers have been able to provide interpretation using visualization techniques? |          | Visualization    | Visualization method used for model interpretation                          |

4. Results

The search resulted in 8,421 studies; after title and abstract review, 689 were selected for full-text and 102 studies met the inclusion criteria described in section 3.2 (Figure 1). A complete list of the included studies and their
characteristics is available in the online supplement (Tables S3 to S10). Table S2 contains a list of abbreviations used in the manuscript. Table 2 classifies studies according to CNN model category and image modality.

![Figure 1: Inclusion flow of the scoping review.](image)

**Table 2:** Distributions of studies over method categories and image types.

| Model Category          | X-ray          | MRI            | Fundus        | Ultrasound    | CT            | Endoscopy     | Skin lesion  | OCT          |
|-------------------------|----------------|----------------|---------------|---------------|---------------|---------------|--------------|--------------|
| Inception               | [27,39–46]     | [47–51]        | [52,53]       | [54–59]       | [60,61]       | [62–65]       | [66]         | [67]         |
| VGGNet                  | [68–73]        | [74–76]        | [77–81]       | [82–84]       | [85–87]       | [88]          | [89–91]      | [92–94]      |
| ResNet                  | [95–97]        | [98–101]       | [102–105]     | [106]         | [107–109]     | [110,111]     | [112]        | [113]        |
| AlexNet                 | [114–118]      | [119–123]      | [124]         | [9,125,126]   | [127]         | [134]         | [128–133]    | [135]        |
| DenseNet                | [128–133]      | [134]          |               |               |               |               | [136]        | [136]        |
| InceptionResNet         | [136]          | [82]           |               |               |               |               | [137]        |              |

Table 3 shows descriptive statistics of the extracted features (see Table 1 for an explanation of extracted features). X-Ray and magnetic resonance imaging (MRI) were the most commonly used types of images with 29% and 17% frequency respectively. Eye, breast and brain were the most studied organs with 18%, 14% and 12% frequency respectively. The most frequently used CNN models overall, irrespective of the body organ or imaging modality, were Inception-V3 (19%), VGG-16 (18%), AlexNet (15%), and ResNet-50 (13%). Over half of the studies (54%) performed some kind of data augmentation. The majority of studies (65%) did not benchmark their CNN model against any other model. While ILSVRC was a 1000 category classification challenge based on ImageNet, most medical TL studies (71%) performed a binary classification.
Table 3: Frequency of study characteristics.

| Anatomical focus | Frequency (%) | CNN Model   | Frequency (%) |
|------------------|---------------|-------------|---------------|
| Eye              | 18            | Inception   | 29            |
| Breast           | 14            | VGGNet      | 26            |
| Brain            | 12            | ResNet      | 19            |
| Lung             | 8             | AlexNet     | 15            |
| Skin             | 7             | DenseNet    | 8             |
| Tooth            | 7             | InceptionResNet | 3         |
| Thyroid          | 6             |             |               |
| Stomach          | 6             |             |               |
| Others           | 24            |             | 17            |
| Transfer Learning Approach | %       | Fundus      | 12            |
| Fine tuning weights | 67       | Ultrasound   | 12            |
| Feature-extracting | 33       | CT          | 11            |
| Visualization    | %             | Endoscopy    | 7             |
| None             | 67            | Skin lesion  | 7             |
| Heatmap          | 23            | OCT         | 6             |
| Deconvolution    | 8             |             |               |
| Activation Maximization | 3       | None        | 46            |
| Final Classifier | %             | Offline      | 47            |
| Fully connected layer | 84       | Online      | 7             |
| Others           | 16            |             |               |
| Benchmark        | %             | Classification Task | % |
| None             | 65            | Binary      | 71            |
| 1                | 13            | Categorical | 25            |
| 2                | 11            | Numeric     | 4             |
| >2               | 11            |             |               |

Figures 2 shows the frequency of studies using specific types of TL CNN models per image type. Inception models were the most frequently used models for studies that analyzed X-Rays (31%), endoscopic images (57%), and ultrasound images (55%). GoogLeNet and AlexNet (29% each) were the most frequent models for MRIs. VGGNet models were the most commonly used for studies analyzing skin lesions (43%), fundus images (42%) and OCT data (50%). Three CNN models were used with similar frequency in CT scan studies.

Figure 3 shows the frequency of studies using specific types of TL CNN models per anatomical site. Various versions of Inception model were the most frequently approach in studies analyzing breast images (50%), while VGGNet was the most frequent in studies involving eye (44%), skin (50%) and tooth (57%) images. AlexNet and DenseNet were the most frequent model in brain (42%) and lung studies (38%).
**Figure 2:** Frequency of studies using specific types of TL CNN models per image type.

**Figure 3:** Frequency of studies using specific types of TL CNN models per anatomical site. Only anatomical sites with at least 5% overall representation in the included studies are shown.
Figure 4 combines Figure 2 and Figure 3 by considering both imaging modality and anatomical site at the same time. GoogLeNet (combined with SVM classifier) was used in 100% of the studies that analyzed breast MRI, while AlexNet was the most commonly used CNN model (36%) for studies that analyzed brain MRI. Inception models (especially Inception-V3) were the most frequent (57%) among the studies that analyzed skeletal system X-Rays (i.e., hip, knee and wrist). AlexNet (50%), DenseNet (60%) and VGGNet (67%) were the most commonly used models for studies that analyzed breast, lung and tooth X-rays respectively. Only a few studies analyzed CT scans with no predominant CNN model.

![Anatomical site and image type](image)

**Figure 4:** Frequency of studies using specific types of TL CNN models per image type and anatomical site. Only anatomical sites and image types with at least 5% overall representation in the included studies are shown.

Figure 5 and Figure 6 show the frequency of transfer learning approaches with and without data augmentation, and per dataset size respectively. Data augmentation was more prevalent among studies that employed fine-tuning TL (72% of fine-tuning TL studies versus 15% of the feature-extracting TL studies). Moreover, among the studies with less than 1,000 images, 22% of the feature extracting TL studies and 77% of fine-tuning TL studies performed data augmentation. Similar patterns were observed among studies with 1,000 to 10,000 images (10% vs. 77%), as well as those with over 10,000 images (0% vs. 55%).
Figure 5: Frequency of transfer learning approaches in studies with and without data augmentation.

Figure 6: Frequency of transfer learning approaches in studies with data augmentation according to different dataset sizes.

Figure 7 shows the frequency of different visualization methods per anatomical site. 33% of the reviewed studies attempted to provide CNN model visualization, mostly through heat maps (67%) (see Table 3). Studies analyzing images of the brain (58%), lung (50%), and tooth (43%) were the ones to most frequently include a visualization approach.

Figure 7: Frequency of different visualization methods per anatomical site. Only sites with at least 5% overall frequency in the included studies are displayed.
5. Discussion

We reviewed TL studies using CNN models well-trained on the ImageNet dataset for medical image analysis. We identified the most prevalent approaches regarding model selection, data augmentation, and visualization according to image modality and anatomical site. Our findings can be used to help guide researchers identify potential optimal approaches to specific medical image analysis problems as well as areas that warrant further research.

5.1. Transfer learning methods

From the imaging modality perspective, Inception models were the most frequently used for studies that analyzed X-Rays, endoscopic images (e.g., [62,64,65]), and ultrasound images (e.g., [55,57,58]), suggesting that wide networks (instead of deep networks) with inception modules benefiting from different kernel sizes may be more effective for these type of images. A few benchmarking studies comparing Inception models against very deep networks for these image types support this hypothesis (e.g., [27,43]). Most studies on skin lesion (43%)[89–91], fundus (42%) [77–81] and OCT images (50%) [92–94] showed that VGGNet obtained adequate performance, suggesting that shallow CNN models with multiple small kernel sizes may be optimal for processing these images. It is possible that small kernel sizes help capture detailed changes in images more accurately. Although a few studies have shown better performance of shallow networks of VGGNet over deeper CNN models (e.g., [90,94]), and small kernel size over large kernel size (e.g., [78,80]), further research is needed with other deeper CNN models to confirm this hypothesis. GoogLeNet and AlexNet were the most prevalent approaches among studies that analyzed MRIs, suggesting that adequate accuracy can be achieved for these types of images without relying on very deep CNN models.

Considering both anatomical site and imaging modality, Inception models (especially Inception-V3) were the most prevalent for analyzing X-Rays of the skeletal system (e.g., hip, knee, wrist) [39–41], suggesting the effectiveness of Inception models for this area. Similarly, GoogLeNet models combined with SVM classifiers were the most prevalent in breast MRI studies [49,50]. The effectiveness of wide networks (e.g., Inception models) for these anatomical sites and imaging modalities is supported by a few benchmarking studies that compared them against very deep networks (e.g., [48]), but more investigation is required.
Most studies on brain MRI images [119–121,123] as well as breast X-Ray [114–116,118] images obtained adequate performance with AlexNet, which may indicate that shallow CNN models with large kernel sizes are optimal for those problems. Similarly, higher prevalence of VGGNet in tooth X-ray studies [68,70,72,73] suggests that shallow CNN models with small kernel sizes may be adequate for this kind of analysis. However, we did not find any benchmarking study focused on the analysis of tooth X-rays; further research with other CNN models is needed to confirm optimal models for the analysis of brain MRI and tooth X-ray. Models based on DenseNet were the most frequently used for studies that analyzed lung X-rays [128,130,131], suggesting that deeper CNN models are optimal for this problem, which is supported by two strong benchmarking studies ([130,131]). Finally, considering that only a few studies analyzed CT scans of different organs (e.g., tooth [60], prostate [126], and brain [9]), little can be concluded about optimal CNN models for these areas.

From the TL approach perspective (i.e., feature extracting or fine-tuning), the majority of studies with less than 1,000 images after data augmentation used a feature extracting TL approach, while the majority of studies with more than 1,000 images applied a fine-tuning TL approach. This finding is congruent with previous research, which showed similar preference patterns [138]. However, only few studies (e.g., [70,91]) applied both feature extracting and fine-tuning TL approaches on the same task, and compared their performance. Therefore, it is not clear whether larger data size (e.g., using data augmentation) or better choice of CNN model is the most important factor in determining accuracy and time and memory requirements.

Finally, for the final classifier, studies that used a fine-tuning TL approach used fully connected layers (as opposed to traditional classifiers) more often than studies that used a feature extracting TL approach (93% versus 68%). This choice may have been influenced by previous findings showing that feature extracting TL studies used smaller datasets compared to fine-tuning TL studies, since training the fully connected layers usually needs larger datasets compared to training traditional classifiers [138].

5.2. Dataset size and data augmentation methods

Data augmentation was more prevalent among studies that employed fine-tuning TL (72%) versus feature-extracting TL (15%). Moreover, in studies with smaller datasets (i.e., less than 1,000 images) most of the feature extracting TL studies did not performed data augmentation (78%) (e.g., [70,120]), while majority of the fine-tuning TL studies performed that (77%) (e.g., [123,127]). On the other hand, among studies with large datasets (i.e., more than 10,000) none of the feature extracting TL studies performed data augmentation, while still over half of the fine-
tuning TL studies performed that (55%) (e.g., [64,104]). Congruent with previous findings [139], this suggests that feature-extracting TL can be done with smaller datasets, but fine-tuning TL requires larger datasets, which can be achieved by either collecting a large dataset (i.e., more labeled data) or using data augmentation.

Very few studies have reported performance results for various data sizes, or with and without data augmentation (e.g., [121]). Therefore, it is not clear to what extent the size of the dataset used in many studies (e.g., [64,133]) was essential to achieve the reported performance. Finding optimal thresholds for dataset size for each approach and medical image analysis problem is an important research gap because large datasets may not always be available. Another research gap is that only image modification (e.g. image rotation, translation) has been used as a method to create new data. Other methods to create high-quality synthetic images, such as generative adversarial network (GAN) [140], warrant investigation.

5.3. Classifier performance and visualization

65% of the reviewed studies did not benchmark their CNN model against any other model, and 13% benchmarked against only one model. In addition, studies comparing the performance of multiple models did not discuss the potential technical reason(s) that explain their findings. Also, there were many problems areas (e.g., CT scans for liver, tooth and brain) that had just one study with one single CNN model. Although all studies achieved adequate performance, we believe that there was possibly room for further performance improvement and/or complexity reduction if a wider range of CNN models had been tried in each study. Therefore, stronger focus on systematic benchmarking through standardized methods is critical to better understand optimal approaches for each specific medical task.

Only 33% of the reviewed studies addressed CNN model visualization, mostly through heat maps (67%). This is an important research gap that warrants attention. CNN model visualization can provide insights on its decision-making process, which is crucial for establishing trust in the medical community [31]. Meaningful integration of CNN models in healthcare practice is highly unlikely, unless medical practitioners can understand, to some extent, its decision-making process. CNN model visualization can also benefit researchers as a diagnostic tool to further improve CNN methods [141,142].

This study had limitations. First, many of the initially selected studies were excluded due to lack of enough information for the review. Standard reporting is critical to improve the reproducibility of research in this area. For
example, studies should include a clear description of the TL approach (i.e., feature-extracting or fine-tuning), including the final dataset size after augmentation, and report the final performance results for all models. Second, there were many problems areas that had just one study with a single CNN model for which we were not able to make any conclusions. Further research is needed to identify optimal methods for those areas. Third, due to the paucity of comparable benchmarking studies, our methodological implications need to be considered with caution. Further research is needed using standardized and replicable benchmarking methods to enhance comparability among studies. Finally, this study was limited to the use of well-trained CNN models on ImageNet in medical TL for image classification. Future reviews should focus on studies applying well-trained CNN models from other domains to medical image classification as well as other medical image tasks such as image segmentation.

6. Conclusion

We systematically reviewed TL studies that employed well-trained CNN models on the non-medical ImageNet dataset for medical image analysis. This study identified the most prevalent tracks of implementation in the literature for data preparation, methodology selection and output evaluation for various medical image analysis tasks. Most prevalent models included wide CNN models using the Inception modules for ultrasound, endoscopy and skeletal system X-rays; shallow CNN models with large kernel size using AlexNet for brain MRIs and breast X-rays; deep CNN models with DenseNet for lung X-rays; and shallow CNN models with small kernel size using VGGNet models for eye (including fundus and OCT images), skin and dental X-rays. Feature-extracting TL was most prevalent with smaller datasets, while fine-tuning TL required larger datasets, sometimes achieved through data augmentation. Fully connected layers for the final classification were also more prevalent with larger datasets. Finally, the majority of studies did not benchmark their CNN models against other models and did not apply visualization techniques to provide insights on the decision-making process of the CNN model.

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| Database         | Search query                                                                 |
|------------------|------------------------------------------------------------------------------|
| MEDLINE          | ("transfer learning"[All Fields] OR "deep learning"[All Fields] OR “convolutional neural network”[All Fields] OR "convolutional neural networks"[All Fields]) AND ( "MRI"[All Fields] OR “MRIs”[All Fields] OR “Magnetic resonance images”[All Fields] OR “Magnetic resonance image”[All Fields] OR “MR image”[All Fields] OR “MR images”[All Fields] OR “CT”[All Fields] OR “CTs”[All Fields] OR “computed tomographic image”[All Fields] OR “computed tomographic images”[All Fields] OR “computed tomography image”[All Fields] OR “computed tomography images”[All Fields] OR “computed tomographic scan”[All Fields] OR “computed tomographic scans”[All Fields] OR “computed tomography scan”[All Fields] OR “computed tomography scans”[All Fields] OR “ultrasound”[All Fields] OR “mammographic images”[All Fields] OR “mammographic image”[All Fields] OR “mammography images”[All Fields] OR “mammography image”[All Fields] OR “mammogram”[All Fields] OR “mammograms”[All Fields] OR “mammography image”[All Fields] OR “mammography images”[All Fields] OR “skin lesion”[All Fields] OR “skin lesions”[All Fields] OR “Endoscopic images”[All Fields] OR “Endoscopic image”[All Fields] OR “Endoscopy image”[All Fields] OR “Endoscopy images”[All Fields] OR “radiograph”[All Fields] OR “radiographs”[All Fields] OR “radiographic image”[All Fields] OR “radiographic images”[All Fields] OR “radiography image”[All Fields] OR “radiography images”[All Fields] OR “x-ray”[All Fields] OR “x-rays”[All Fields] OR “fundus image”[All Fields] OR “fundus images”[All Fields] OR “optical coherence tomography image”[All Fields] OR “optical coherence tomography images”[All Fields] OR “OCT image”[All Fields] OR “OCT images”[All Fields] OR “cephalogram”[All Fields] OR “cephalograms”[All Fields] OR “cephalometric image”[All Fields] OR “cephalometric images”[All Fields] OR “dermoscopic images”[All Fields] OR “dermoscopic image”[All Fields] OR “dermoscopy image”[All Fields] OR “dermoscopy images”[All Fields] |
| IEEE             | ("transfer learning" OR "deep learning" OR "convolutional neural network" OR "convolutional neural networks") AND ( "MRI" OR "MRIs" OR "Magnetic resonance images" OR "Magnetic resonance image" OR "MR image" OR "MR images" OR "CT" OR "CTs" OR "computed tomographic image" OR "computed tomographic images" OR "computed tomography image" OR "computed tomography images" OR "computed tomographic scan" OR "computed tomographic scans" OR "ultrasound" OR "mammographic images" OR "mammographic image" OR "mammograms" OR "mammography image" OR "mammography images" OR "skin lesion" OR "skin lesions" OR "endoscopic images" OR "endoscopic image" OR "endoscopy images" OR "endoscopy image") |
| ACM digital library | ("transfer learning" OR "deep learning" OR "convolutional neural network" OR "convolutional neural networks") AND ( "MRI" OR "MRIs" OR "Magnetic resonance images" OR "Magnetic resonance image" OR "MR image" OR "MR images" OR "CT" OR "CTs" OR "computed tomographic image" OR "computed tomographic images" OR "computed tomography image" OR "computed tomography images" OR "computed tomographic scan" OR "computed tomographic scans" OR "ultrasound" OR "mammographic images" OR "mammographic image" OR "mammograms" OR "mammography image" OR "mammography images" OR "skin lesion" OR "skin lesions" OR "endoscopic images" OR "endoscopic image" OR "endoscopy images" OR "endoscopy image" OR "radiograph" OR "radiographs" OR "radiographic image" OR "radiographic images" OR "radiography image" OR "radiography images" OR "x-ray" OR "x-rays" OR "fundus image" OR "fundus images" OR "optical coherence tomography image" OR "optical coherence tomography images" OR "OCT image" OR "OCT images" OR "cephalogram" OR "cephalograms" OR "cephalometric image" OR "cephalometric images" OR "dermoscopic images" OR "dermoscopic image" OR "dermoscopy image" OR "dermoscopy images" OR "dermoscopy image") |
### Table S2: List of abbreviations.

| Abbreviation | Full                     | Abbreviation | Full                     |
|--------------|--------------------------|--------------|--------------------------|
| TraT         | Transformation Type      | HM           | Heatmap                  |
| ClassT       | Classification Task      | Ag           | Augmentation              |
| FinalC       | Final Classifier         | Acc          | Accuracy                  |
| Vis          | Visualization Method     | Sen          | Sensitivity               |
| FE           | Feature Extraction       | RF           | Random Forest             |
| FC           | Fully Connected Layer    | DC           | Deconvolution             |
| SVM          | Support Vector Machine   | DiceC        | Dice Coefficient          |
| AM           | Activation Maximization  | FT           | Fine-tuning               |
| LDA          | Linear Discriminant Analysis | AnantF        | Anatomical focus          |
| MRI          | Magnetic resonance imaging | CT           | Computed tomography       |
| OCT          | Optical coherence tomography | X-ray        | X-ray                     |

### Table S3: CT scan image studies and the extracted features according to Table 1.

| Paper et al. | AnantF | Medical task | Method | Data Size | Ag Data Size | Performance | TraT | ClassT | FinalC | Benchmark | Vis |
|--------------|--------|--------------|--------|-----------|--------------|-------------|-------|--------|--------|-----------|-----|
| Dawud et al. 2019[9] | Brain | Brain haemorrhage classification | AlexNet | 2,104 | 12,635 | Acc=93.48% | FT | Binary | SVM | DC |
| Peng et al. 2020[108] | Liver | Transarterial chemoembolization prediction | ResNet-50 | 1,687 | 8,435 | Acc>82.8% | FT | 4 classes | FC |
| Shin et al. 2016[138] | Lung | Interstitial lung disease classification | AlexNet | 905 | 10,860 | Acc=90.2% | FT | 6 classes | FC |
| Da Nóbrega et al. 2018[109] | Lung | Lung nodule classification | ResNet-50 | 7,371 | | AUC=0.93 | FE | Binary | SVM | |
| Nishio et al. 2018[85] | Lung | Lung nodule classification | VGG-16 | 1,236 | | Acc=68.0% | FT | 3 classes | FC |
| Lee et al. 2019[107] | Thyroid | Cervical lymph node metastasis diagnosis | ResNet-50 | 995 | | Acc=90.4% | FE | Binary | FC | Inception-V3 | HM |
| Santin et al. 2019[87] | Thyroid | Abnormalities of thyroid cartilage detection | VGG-16 | 515 | 2,575 | AUC=0.72 | FT | Binary | FC |
| Chowdhury et al. 2019[61] | Osteomeatal complex | Osteomeatal complex inflammation classification | Inception-V3 | 956 | | Acc=85% | FE | Binary | FC |
| Kajikawa et al. 2018[126] | Prostate | Dosimetric eligibility prediction | AlexNet | 480 | | Acc=70% | FT | Binary | FC | HM |
| Lee et al. 2019[60] | Tooth | Cystic lesions classification | Inception-V3 | 2,126 | 212,600 | AUC>0.847 | FT | Binary | FC |
| Belharbi et al. 2017[86] | Vertebra | Spotting L3 slice | VGG-16 | 642 | | MAE=1.91 | FT | Numeric | FC | GoogLeNet, VGG-19, AlexNet |
Table S4: MRI scan image studies and the extracted features according to Table 1.

| Paper          | AnantF | Medical task                                         | Method | Data Size | Ag Data Size | Performance | TraT | ClassT | FinalC | Benchmark | Vis |
|----------------|--------|------------------------------------------------------|--------|-----------|--------------|-------------|------|--------|--------|-----------|-----|
| Langner et al. 2019[75] | Body   | Morphological indicators of aging identification     | VGG-16 | 23,905    | MAE=2.49     | FE          | Numeric FC |
| Zhang et al. 2019[119]     | Brain  | Visual response prediction                           | AlexNet| 1,750     | Acc=98.6%    | FE          | Binary FC |
| Maqsood et al. 2019[120]   | Brain  | Alzheimer's disease stages classification            | AlexNet| 382       | Acc=92.85%   | FE          | 4 classes FC |
| Wang et al. 2019[121]      | Brain  | Alcoholism classification                            | AlexNet| 379       | Acc=97.42    | FT          | Binary FC |
| Afzal et al. 2019[123]     | Brain  | Alzheimer's stage detection                          | AlexNet| 218       | Acc=98.44%   | FT          | Binary FC |
| Deepak and Ameer 2019[47]  | Brain  | Brain tumor classification                           | GoogLeNet| 3,064     | Acc=98%      | FT          | 3 classes KNN |
| Yang et al. 2019[51]       | Brain  | Glioma grading                                      | GoogLeNet| 113       | Acc=0.867    | FT          | Binary FC | AlexNet |
| Talo et al. 2019[99]       | Brain  | Brain disease detection                              | ResNet-50| 1,074     | Acc=95.23%   | FT          | 5 classes FC | AlexNet, ResNet-18, ResNet-34 |
| Gao et al. 2019[100]       | Brain  | Behavior tasks decoding                              | ResNet-34| 965       | Acc=75.0%    | FE          | Binary FC | Inception-V3, AlexNet |
| Korfiasis et al. 2017[98]  | Brain  | Methylation of the O6-methylguanine methyltransferase (MGMT) gene status prediction | ResNet-50| 10,468    | Acc=94.9%    | FE          | 3 classes FC | ResNet-18, ResNet-34 |
| Swati et al. 2019[74]      | Brain  | Brain tumor detection                                | VGG-19 | 3,064     | Prec=96.13   | FT          | Binary FC | DC |
| Khan et al. 2019[76]       | Brain  | Alzheimer’s disease diagnosis                        | VGG-19 | 3,200     | Acc>92.0%    | FT          | Binary FC | HM |
| Zhu et al. 2019[50]        | Breast | Occult invasive disease prediction                   | GoogLeNet| 131       | AUC=0.70     | FE          | Binary SVM |
| Zhu et al. 2019[49]        | Breast | Radiogenomic associations in breast cancer detection | GoogLeNet| 275       | AUC=0.65     | FE          | Binary SVM | VGG-16 |
| Dallora et al. 2019[48]    | Knee   | Age assessment                                       | GoogLeNet| 402       | MAE=0.98     | FT          | Numeric FC | ResNet-50 |
| Yuan et al. 2019[122]      | Prostate| Prostate cancer classification                       | AlexNet| 221       | Acc=86.92%   | FT          | Binary FC |
| Zhong et al. 2019[101]     | Prostate| Prostate cancer classification                       | ResNet-50| 169       | AUC=0.726    | FT          | Binary FC |
Table S5: Ultrasound image studies and the extracted features according to Table 1.

| Paper               | AnantF | Medical task                        | Method      | Data Size | Ag Data Size | Performance       | TraT   | ClassT | FinalC | Benchmark          | Vis |
|---------------------|--------|------------------------------------|-------------|-----------|--------------|-------------------|--------|--------|--------|--------------------|-----|
| Cheng et al. 2016[83] | Abdomen | Abdominal ultrasound image classification | VGG-16 | 5,518     |              | Acc=77.9%         | FE     |        |        | CaffeNet           |     |
| Cao et al. 2019[134] | Breast | Breast lesion detection             | DenseNet-161 | 1,043     |              | Acc>80.0%         | FE     | Binary |        | AlexNet, ZFNet, VGG-16, ResNet-50, GoogLeNet |     |
| Xiao et al. 2018[54] | Breast | Breast masses classification         | Inception-V3 | 2,058     | 6,174        | Acc=85.13%        | FT     | Binary |        | ResNet-50, Xception |     |
| Fujioka et al. 2019[59] | Breast | Breast mass lesion classification   | GoogLeNet   | 947        |              | Acc=92.5%         | FE     | Binary |        |                   |     |
| Byra et al. 2019[82] | Breast | Breast mass classification          | VGG-19      | 882       | 5,292        | Acc=92.5%         | FT     | Binary |        |                   |     |
| Kuo et al. 2019[106] | Kidney | Chronic kidney disease (CKD) prediction | ResNet-101 | 4,505     | 37,696       | Acc=85.6%         | FT     | Binary |        |                   |     |
| Xue et al. 2020[56]  | Liver  | Liver fibrosis grading              | Inception-V3 | 2,330     | 6,990        | AUC=0.977         | FT     | Binary |        |                   |     |
| Byra et al. 2018[139] | Liver  | Liver steatosis assessment          | Inception-ResNet-V2 | 550     |              | AUC=92.5%         | FT     | Binary |        |                   |     |
| Song et al. 2019[55] | Thyroid| Thyroid nodules diagnosis           | Inception-V3 | 1,358     |              | Sen=95.2%         | FE     | Binary |        |                   |     |
| Chi et al. 2017[57]  | Thyroid| Thyroid nodule classification       | GoogLeNet   | 428       | 3,852        | Acc=98.2%         | FT     | Binary |        |                   |     |
| Guan et al. 2019[58] | Thyroid| Thyroid nodule classification       | Inception-V3 | 2,836     |              | Sen=93.3%         | FT     | Binary |        |                   |     |
| Qin et al. 2019[84]  | Thyroid| Thyroid nodules classification      | VGG-16      | 233       | 1,156        | Acc=86.21%        | FE     | Binary |        |                   |     |

Table S6: Skin Lesion image studies and the extracted features according to Table 1.

| Paper               | Medical task                      | Method      | Data Size | Ag Data Size | Performance       | TraT   | ClassT | FinalC | Benchmark          | Vis |
|---------------------|-----------------------------------|-------------|-----------|--------------|-------------------|--------|--------|--------|--------------------|-----|
| Hosny et al. 2019[127] | Skin lesions classification      | AlexNet     | 206       | 14,832       | Acc>95.91%        | FT     | 3 classes |        | AlexNet, VGG-16, VGG-19 |     |
| Cui et al. 2019[66]  | Melanoma diagnosis               | Inception-V3 | 2,200     |              | Acc=93.74%        | FE     | Binary |        |                   |     |
| Binol et al. 2019[137] | Rosacea identification            | Inception-ResNet-V2 | 10,922   | Online      | DiceC=89.8%       | FT     | Binary |        | ResNet-101         |     |
| Kassani et al. 2019[112] | Melanoma detection               | ResNet-50   | 9,887     | 34,577       | Acc=92.0%         | FT     | 7 classes |        | Xception, VGG-16, VGG-19 | DC |
| Lopez et al. 2017[91] | Skin lesion classification        | VGG-16      | 1,279     | 7,782        | Acc=81.3%         | FT     | Binary |        |                   |     |
| Kwasigroch et al. 2017[90] | Skin lesion classification       | VGG-19      | 1,803     | 6,498        | Acc=80.7%         | FT     | Binary |        | ResNet-50          |     |
| Yu et al. 2018[89]   | Melanoma detection               | VGG-16      | 724       | 940          | Acc=83.5%         | FT     | Binary |        |                   |     |
**Table S7**: Fundus image studies and the extracted features according to Table 1.

| Paper                  | Medical task                  | Method       | Data Size | A & Ag Data Size | Performance | TraT   | ClassT | FinalC | Benchmark                  | Vis |
|------------------------|-------------------------------|--------------|-----------|------------------|-------------|--------|--------|--------|----------------------------|-----|
| Li et al. 2016[124]    | Glaucoma diagnosis            | AlexNet      | 650       | 650              | AUC=0.83    | FE     | Binary | FC     | VGG-19, VGG-16, GoogLeNet  |     |
| Li et al. 2019[52]     | Diabetic retinopathy detection| Inception-V3 | 8,816     |                  | Acc=93.49%  | FT     | 5 classes | FC                       |     |
| Arcadu et al. 2019[53] | Optical coherence tomography  | Inception-V3 | 30,371    |                  | AUC=0.97    | FT     | Binary | FC     |                           |     |
| Lu et al. 2019[102]    | Optic disc laterality detection | ResNet-152  | 576       |                  | Acc=97.2%   | FT     | Binary | FC     |                           |     |
| Hemelings et al. 2019[103] | Glaucoma detection           | ResNet-50    | 1,775     | 7,038            | AUC=0.995   | FT     | Binary | FC     |                           |     |
| Christopher et al. 2018[104] | Glaucomatous optic neuropathy | ResNet-50    | 14,822    | 148,220          | AUC=0.91    | FT     | Binary | FC     | VGG-16, Inception-V3      | HM  |
| Li et al. 2019[105]    | Cataract diagnosis            | ResNet-50    | 8,030     |                  | Acc=87.7%   | FE     | 4 classes | FC                       | ResNet-18 | HM  |
| Gómez-Valverde et al. 2019[77] | Glaucoma detection          | VGG-19       | 2,313     | Online           | AUC=0.94    | FT     | Binary | FC     | GoogLeNet, ResNet-50      |     |
| Choi et al. 2017[78]   | Retinal disease detection     | VGG-19       | 279       | 10,000           | Acc=72.8%   | FE     | 10 classes | RF                       | AlexNet         |
| Li et al. 2018[79]     | Diabetic retinopathy         | VGG-19       | 1,014     | 15,210           | Acc>92.01%  | FT     | 4 classes | FC                       | AlexNet, VGG-16, VGG-19 |     |
| Zhang et al. 2019[80]  | Retinopathy of prematurity screening | VGG-16     | 382,922   |                  | Acc=99.88%  | FT     | Binary | FC     | AlexNet, GoogLeNet        |     |
| Nagasato et al. 2019[81] | Branch retinal vein detection | VGG-16        | 466       | 8,388            | AUC=0.97    | FT     | Binary | FC     |                           |     |

**Table S8**: OCT image studies and the extracted features according to Table 1.

| Paper                  | Medical task                  | Method       | Data Size | A & Ag Data Size | Performance | TraT   | ClassT | FinalC | Benchmark                  | Vis |
|------------------------|-------------------------------|--------------|-----------|------------------|-------------|--------|--------|--------|----------------------------|-----|
| Islam et al. 2019[135] | Diabetic retinopathy         | DenseNet-201 | 109,309   |                  | Acc=97.0%   | FT     | 4 classes | FC                       |     |
| Kermany et al. 2018[67] | diabetic retinopathy classification | Inception-V3 | 207,130   |                  | Acc=96.6%   | FE     | 4 classes | FC                       |     |
| Lu et al. 2018[113]    | diabetic retinopathy         | ResNet-101   | 25,134    |                  | Acc>84.8%   | FE     | Binary | FC     |                           |     |
| An et al. 2019[92]     | Glaucoma diagnosis            | VGG-19       | 347       | 1,041            | AUC=0.94    | FT     | Binary | RF     |                           |     |
| Feng et al. 2019[93]   | Retinal disorders detection  | VGG-16       | 109,312   |                  | Acc=98.6%   | FT     | 4 classes | FC                       |     |
| Kaveri et al. 2019[94] | Glaucoma detection            | VGG-16       | 737       |                  | AUC>0.93    | FE     | Binary | RF     | Inception-V3, ResNet-18   | HM  |
| Paper                  | AnantF | Medical task                               | Method   | Data Size | Ag Data Size | Performance | TraT  | ClassT | FinalC | Benchmark  | Vis |
|-----------------------|--------|-------------------------------------------|----------|-----------|--------------|-------------|--------|--------|--------|------------|-----|
| Huynh et al. 2016[14] | Breast | Mammographic tumor classification          | AlexNet  | 607       | AUC=0.81     | FE          | Binary | SVM    |        |            |     |
| Zhang et al. 2018[15] | Breast | Mammogram and tomosynthesis image classification | AlexNet  | 3,290     | 26,320       | AUC=0.72    | FT     | Binary | FC     |            |     |
| Li et al. 2017[16]   | Breast | breast cancer risk assessment              | AlexNet  | 456       | AUC=0.82     | FE          | Binary | SVM    |        |            |     |
| Ragab et al. 2019[18] | Breast | Breast cancer detection                    | AlexNet  | 1,318     | 5,272        | Acc=87.2%   | FT     | Binary | SVM    |            |     |
| Jiang et al. 2017[43] | Breast | Breast cancer risk assessment              | AlexNet  | 736       | 2,944        | AUC=0.88    | FT     | Binary | FC     | AlexNet    |     |
| Mednikov et al. 2018[44] | Breast | Breast cancer detection                    | Inception-V3 | 410 | 100,000 | AUC=0.91 | FT | Binary | FC |            |     |
| Arefan et al. 2020[45] | Breast | Breast cancer risk prediction              | GoogLeNet | 678 |        | AUC=0.73 | FT | Binary | LDA |            | HM |
| Yi et al. 2019[95]   | Breast | Breast mass lesion classification          | ResNet-50 | 3,034 | Online | AUC=0.93 | FT | Binary | FC |            | HM |
| Pan et al. 2019[132] | Chest  | Abnormality detection in chest radiographs | DenseNet-121 | 17,202 | Online | AUC=0.90 | FT | Binary | FC |            |     |
| Dunnmon et al. 2019[133] | Chest  | Abnormality detection in chest radiographs | DenseNet-121 | 216,431 | Acc=0.91 | FE | Binary | FC | AlexNet, ResNet-18 | HM |
| Rajkomar et al. 2017[46] | Chest  | Abnormality detection in chest radiographs | GoogLeNet | 1,505 | 159,530 | Acc=99.7% | FT | Binary | FC |            |     |
| Zhou et al. 2019[27]  | Heart  | Cardiomegaly classification                | Inception-V3 | 108,948 |        | AUC=0.86 | FE | 8 classes | FC | ResNet-50, Xception | DC |
| Yu et al. 2019[41]   | Hip    | Hip fracture detection                     | Inception-V3 | 617 |        | Acc>90.9% | FE | 4 classes | FC |            | HM |
| Abidin et al. 2018[39] | Knee  | Chondrocyte patterns classification        | Inception-V3 | 842 |        | AUC>0.95 | FE | Binary | SVM | CaffeNet |     |
| Yi et al. 2019[96]   | Knee   | Knee arthroplasty classification           | ResNet-18 | 158 | 1,274 | AUC=1.0  | FT | Binary | FC |            | HM |
| Abbas et al. 2018[117] | Lung   | Manifestation of tuberculosis identification | AlexNet  | 138 | 60,000 | AUC=0.99 | FT | Binary | FC |            |     |
| Gozes et al. 2019[128] | Lung   | Tuberculosis detection                     | DenseNet-121 | 112,000 | Online | AUC=0.965 | FT | Binary | FC |            |     |
| Nguyen et al. 2019[130] | Lung   | Tuberculosis detection                     | DenseNet-121 | 18,686 | 112,120 | AUC=0.89 | FT | 14 classes | FC | VGG-16, VGG-19, ResNet-50, Inception-ResNet-V2 | HM |
| Varshni et al. 2019[131] | Lung   | Pneumonia detection                        | DenseNet-169 | 2,862 |        | AUC=0.80 | FE | Binary | SVM | VGG-16, VGG-19, ResNet-50, Xception |     |
### Table S9 (Continued): X-Ray image studies and the extracted features according to Table 1.

| Paper                          | AnantF | Medical task                          | Method      | Data Size | Ag Data Size | Performance     | TraT | ClassT | FinalC | Benchmark | Vis |
|-------------------------------|--------|---------------------------------------|-------------|-----------|--------------|-----------------|------|--------|--------|-----------|-----|
| Ahsan et al. 2019[69]         | Lung   | Tuberculosis detection                | VGG-16      | 1,324     | Online       | Acc>78.3%       | FT   | Binary | FC     | HM        |     |
| Yi et al. 2019[97]            |        | Skeletal system                       | ResNet-18   | 250       | 7,500        | AUC=1.0         | FT   | 5 classes | FC     | HM        |     |
| HJ et al. 2020[129]           | Tooth  | Skeletal classification               | DenseNet-121| 5,890     | 50,000       | Acc>90%         | FT   | 3 classes | FC     | HM        |     |
| Lee et al. 2018[42]           | Tooth  | Dental caries diagnosis               | Inception-V3| 3,000     | 30,000       | Acc>82.0%       | FT   | 4 classes | FC     |           |     |
| Poedjiasto et al. 2018[68]    | Tooth  | Jaw tumor diagnosis                   | VGG-16      | 500       | 1,000        | Acc=83.0%       | FT   | Binary | FC     | HM        |     |
| Lee et al. 2020[72]           | Tooth  | Osteoporosis in dental panoramic radiographs classification | VGG-16 | 680 | | Acc=84.0% | FT | Binary | FC | HM | |
| Prajapati et al. 2017[70]     | Tooth  | Dental diseases classification        | VGG-16      | 250       | | Acc=88.5% | FE | 3 classes | FC | | |
| Lee et al. 2018[73]           | Tooth  | Periodontally compromised teeth diagnosis | VGG-19 | 1,740 | 104,400 | Acc>76.7% | FT | Binary | FC | | |
| Kim et al. 2018[40]           | Wrist  | Fracture detection                    | Inception-V3| 1,389     | 11,112       | AUC=0.954       | FT   | Binary | FC     |           |     |
| Han et al. 2018[136]          | Wrist  | Bone age assessment                   | Inception-V3| 12,611    | | MAE=15.16 | FE | Numeric | SVR | | |
| Yune et al. 2019[71]          | Wrist  | Gender classification                 | VGG-16      | 10,318    | | Acc=95.9% | FT | Binary | FC | HM | |

### Table S10: Endoscopy image studies and the extracted features according to Table 1.

| Paper                          | AnantF | Medical task                          | Method      | Data Size | Ag Data Size | Performance     | TraT | ClassT | FinalC | Benchmark | Vis |
|-------------------------------|--------|---------------------------------------|-------------|-----------|--------------|-----------------|------|--------|--------|-----------|-----|
| Wimmer et al. 2017[88]        | Stomach| Celiac disease diagnosis              | VGG-16      | 1,661     | Online       | Acc=90.5%       | FT   | Binary | FC     | VGG-16, Inception-V3, VGG-19 |     |
| Liu et al. 2018[62]           | Stomach| Gastric cancer diagnosis              | Inception-V3| 2,331     | 16,317       | Acc=98.5%       | FT   | Binary | FC     | VGG-16, Inception-V3, VGG-19 | AM  |
| Sakai et al. 2018[64]         | Stomach| Gastric cancer diagnosis              | GoogLeNet   | 29,037    | 348,943      | AUC=0.95        | FT   | Binary | FC     | VGG-16, Inception-V3, VGG-19 |     |
| Li et al. 2020[65]            | Stomach| Early gastric cancer diagnosis        | Inception-V3| 2,088     | 20,000       | Acc=90.9%       | FT   | Binary | FC     | Inception-V3, VGG-16 |     |
| Lee et al. 2019[110]          | Stomach| Gastric cancer detection              | ResNet-50   | 787       | | AUC=0.97 | FT | 3 classes | FC | Inception-V3, VGG-16 |     |
| Zhu et al. 2019[111]          | Stomach| Invasion depth of gastric cancer diagnosis | ResNet-50  | 993       | | Acc=89.16% | FE | Binary | FC | | |
| Li et al. 2017[63]            | Gastrointestinal tract | Gastrointestinal bleeding Detection | Inception-V3 | 2,890     | 5,410        | Acc=98.62%      | FE   | Binary | FC | | |