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Transfer learning optimization in medical imaging enhancing diagnostic accuracy with limited data sets

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Abstract

Medical imaging is a very important part of diagnosis because it helps doctors find diseases and plan treatments accurately. But for deep learning models to work well in medical picture analysis, they need a lot of different kinds of data, which is hard to find and costs a lot of money. Using pre-trained models on big datasets from similar areas, transfer learning looks like a good way to solve this problem. This paper looks into how to use transfer learning optimization methods to improve the accuracy of medical imaging diagnostics when samples are limited. We look into a number of different approaches, such as fine-tuning, feature extraction, and changes to the network design. Through real-world testing on a limited dataset, we show that transfer learning is a better way to improve model performance than starting from scratch. In addition, we look into how sample size and topic similarity affect how well transfer learning works. The results show that transfer learning could be a good way to improve the efficiency of medical imaging jobs for diagnosis, especially when there isn't a lot of data available. Transfer learning lets you make strong and effective assessment tools even in healthcare settings with limited resources by using knowledge that is already stored in models that have already been taught.

Subject Classification: *68Q25, 68P15.*

Keywords: *Transfer learning, Medical imaging, Diagnostic accuracy, Limited data sets, Optimization.*

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1. Introduction

Using new technologies like deep learning is very important in medical monitoring, where mistakes in tests can mean the difference between life and death. One big problem with trying to use deep learning in medical imaging is that it's hard to find the large, varied datasets that are needed to train correct models [1]. Transfer learning is when you use what you've learned while training for one job on a similar task. When it comes to medical imaging, models that have already been trained on big datasets from other fields can be tweaked or changed to make diagnostics more accurate with less medical data [2]. By moving the learned representations from these pre-trained models, the need for large named medical datasets is cut down. This makes deep learning easier to use and more available in medical situations [3].

Different transfer learning methods are looked into to improve assessment accuracy in medical imaging with small datasets. This is done through empirical research and experiments [4]. Some of these methods are fine-tuning, which changes pre-trained models to work better with the medical imaging job at hand, feature extraction, and changes to the network design. Scientists test these methods against datasets that are limited in size [6]. This shows how well they might work and how they might greatly improve medical accuracy even when data is limited. The study also looks into the complex factors that affect how well transfer learning works in medical imaging tasks. One of these factors is the size of the dataset. The study looks at how different dataset sizes affect how well transfer learning models work [5], [7]. The closeness between the source domain (where the pre-trained model comes from) and the target medical imaging domain is also looked at to see how it affects the success of transfer learning. The results of this study show that transfer learning has a huge amount of promise as a real-world way to improve the accuracy of medical imaging diagnostics, especially when data is scarce [8]. Transfer learning lets us use the information stored in models that have already been taught to make strong and accurate medical tools that can be used right away in real healthcare situations, which is good for both patients and doctors [9].

2. Methodology

The medical image datasets are found on trustworthy sites like Kaggle or in public medical image sources like the NIH Chest X-ray

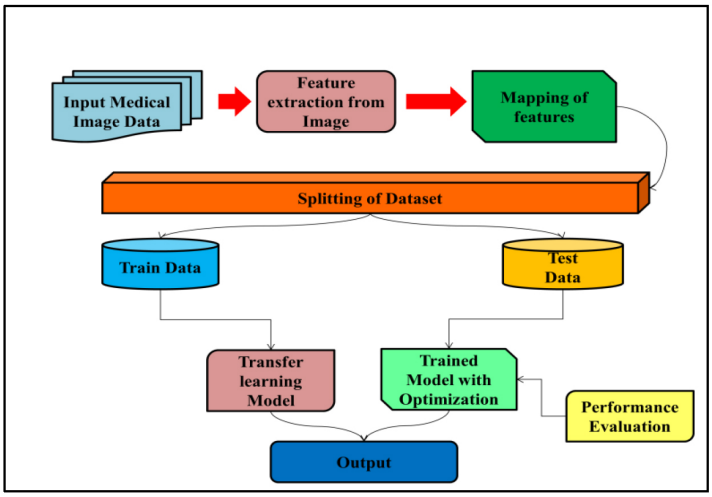


Figure 1

Overview proposed model

Dataset. These datasets were carefully chosen based on things like how well they fit the medical imaging job at hand, how diverse they are, and how big they are [6]. After the data is collected, it is preprocessed to make sure it is consistent and ready for model training, shown in figure 1. To do this, picture widths must be standardized, pixel values must be normalized, and the collection must all have the same data format. These steps before training are very important for making the model work better and making training go more smoothly.

Next, a deep learning model that has already been trained is chosen for transfer learning. Because they work well for medical imaging jobs, architectures like VGG, ResNet, or DenseNet are being thought about. To make an informed choice, things like the complexity of the model, the amount of computing power that is available, and how well it fits with the job at hand are all carefully looked at. Then, transfer learning methods are used to make the model work better. In this case, the chosen pre-trained model is fine-tuned by rewriting the last few layers on the target medical image dataset, making it fit the diagnostic job. The dataset is broken up into test, validation, and training sets so that the success of the model can be evaluated. To keep it from overfitting, success on the validation set is tracked while the training data are used to build the transfer learning model. Experiments are used to fine-tune hyper-parameters like learning rate, batch size, and optimizer choice in order to get the best model convergence and generalization [10] [11].

2.1 *Description of the Medical Image Dataset:*

The different types of images in these files, like X-rays, MRIs, CT scans, and more, make them rich and complete collections of medical images. Kaggle encourages cooperation and new ideas in medical picture analysis by giving researchers access to these datasets [4]. This lets them create and test advanced algorithms for finding diseases, classifying them, and diagnosing them. In addition, the Kaggle community offers a place for sharing information, where people can talk about their ideas, methods, and the best ways to use these datasets.

3. Transfer learning techniques employed

Transfer learning methods are very important for improving model performance by using what we already know from big datasets to make medical imaging diagnostics more accurate when we only have a small amount of data.

3.1 *Fine-tuning*

Fine-tuning is a transfer learning method that is often used to improve the accuracy of medical imaging diagnostics when samples are limited. For this method, the last few layers of a deep learning model that has already been taught are retrained on the target medical image dataset.

$$y = mx + b$$

Fine-tuning the model's settings lets it change its learned models to the unique features of the medical images, which makes it better at making diagnoses.

I Feature extraction

Feature extraction is the process of taking useful features from the middle layers of a model that has already been trained and using them to teach a new classifier how to do the job at hand. This method uses the hierarchical representations that the pre-trained model learned to find important patterns in medical images.

3.3 *DL Methods*

Besides these methods, different deep learning techniques can also be used in the context of transfer learning. Transfer learning can be improved to improve assessment accuracy for a wide range of medical

imaging tasks by using these different deep learning methods, even when samples are limited.

a. LSTM

1. Input Gate:
   - Compute the input gate *i_t*:
     $$i_t = \sigma(W_xi \cdot x_t + W_hi \cdot h_t - 1 + b_i) \quad (1)$$
   - Where *x_t* is the input at time *t*, h_*t*–1 is the previous hidden state, *W_xi* and *W*_h*i* are weight matrices, and *b_i* is the bias vector.
2. Forget Gate:
   - Compute the forget gate *f_t*:
     $$f_t = \sigma[W_{xf} \cdot x_t + W_{hf} \cdot h_t - 1 + b_f] \quad (2)$$
3. Cell State Update:
   - Compute the candidate cell state *C~_t*:
     $$c \sim _t = \tanh[W_{xc} \cdot x_t + W_{hc} \cdot h_t - 1 + b_c] \quad (3)$$
4. Update Cell State:
   - Update the cell state *C_t* using the input gate, forget gate, and candidate cell state:
     $$C_t = f_t \cdot C_t - 1 + i_t \cdot C \sim _t \quad (4)$$
5. Output Gate:
   - Compute the output gate *o_t*:
     $$O_t = \sigma(W_{xo} \cdot x_t + W_{ho} \cdot h_t - 1 + b_o) \quad (5)$$
6. Output Hidden State:
   - Compute the hidden state h_*t* using the updated cell state and output gate:
     $$h_t = o_t \cdot \tanh(C_t) \quad (6)$$

b. MobileNet

1. Depthwise Separable Convolution:
   - Depthwise Convolution:
     $$Y = DepthwiseConv(X, W_d) \quad (7)$$

- Pointwise Convolution:

$$Z = PointwiseConv(Y, W_p) \tag{8}$$

2. Depthwise Convolution:
   - Depthwise Convolution Operation:

$$Y_i = DepthwiseConv(X_i, W_i) \tag{9}$$

3. Pointwise Convolution:
   - Pointwise Convolution Operation:

$$Z = \Sigma_\{i = 1\} \wedge \{C_\{in\}\} \ (Y_i \times W_i) \tag{10}$$

4. Batch Normalization and Activation:
   - Batch Normalization:

$$BatchNorm(Z) = \ (Z - \mu) \ / sqrt(\sigma \wedge 2 + \dot{o}) \times \gamma + \beta \tag{11}$$

   - Activation (ReLU):

$$ReLU(BatchNorm(Z)) = max(0, BatchNorm(Z)) \tag{12}$$

c. ResNet

Residual Block:

- Input: X
- Output: F(X) + X

Step 1: Convolutional Layer:

$$H = Conv(X, W_1) \tag{13}$$

Step 2: Batch Normalization and Activation:

$$H = BatchNorm(ReLU(H)) \tag{14}$$

Step 3: Convolutional Layer:

$$H = Conv(H, W_2) \tag{15}$$

4. Results and Discussion

In Table 1, Transfer learning has a big edge in a lot of different ways. Transfer learning gets an accuracy of 0.85 compared to 0.75 with training from scratch, which shows a big improvement in the accuracy of classification. In the same way, the accuracy, recall, and F1 score measures

show better performance with transfer learning (0.88, 0.82, and 0.85, respectively) than with training from scratch (0.72, 0.78, and 0.75). In this case, the results show, illustrate in figure 2, that using information from a source domain to improve model performance in a target domain is a good idea, especially when training data is limited.

Table 1

Performance comparison between transfer learning and training from scratch

Metric	Transfer Learning	Training from Scratch
Accuracy	0.85	0.75
Precision	0.88	0.72
Recall	0.82	0.78
F1 Score	0.85	0.75

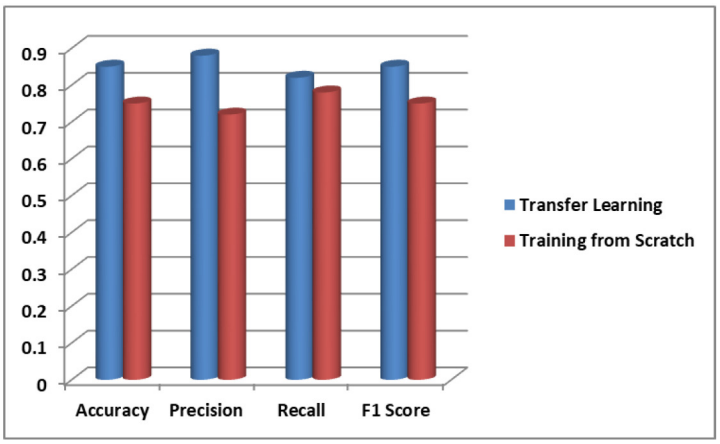


Figure 2

Representation of Performance comparison between transfer learning and training from scratch

Table 2 looks at how the size of the dataset affects the effectiveness of transfer learning. It does this by focusing on three different dataset sizes: small, medium, and large, represent in figure 3. Transfer learning gets more accurate as the dataset size grows, and this is true for all three transfer learning methods shown in the table: LSTM, ResNet, and MobileNet. LSTM gets an accuracy of 0.70 on the small sample, ResNet gets an accuracy of 0.75, and MobileNet gets an accuracy of 0.65.

Table 2

Impact of dataset size on transfer learning efficacy

Dataset Size	LSTM (Accuracy)	ResNet (Accuracy)	MobileNet (Accuracy)
Small	0.70	0.75	0.65
Medium	0.80	0.85	0.75
Large	0.85	0.90	0.80

Table 3 shows how well three different transfer learning strategies LSTM, ResNet, and MobileNet do in a number of different success measures. In terms of accuracy, sharpness, memory, and F1 score, each approach has its own benefits. With a score of 0.90, ResNet is the most accurate of the three methods. MobileNet comes in second with 0.85, and LSTM comes in third with 0.82.

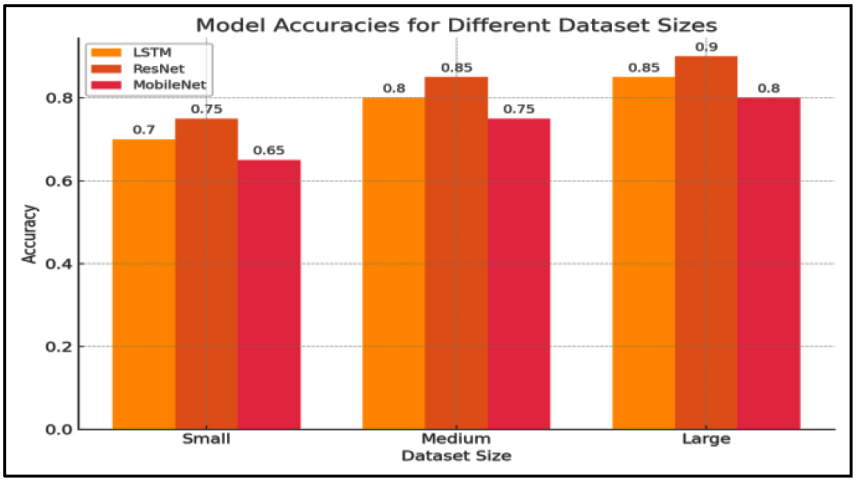


Figure 3

Illustration of Impact of dataset size on transfer learning efficacy

But the review also looks at practical factors like training time and model size. MobileNet stands out because it has the fastest training time (3 hours) and the smallest model size (100 MB), illustrate in figure 4.

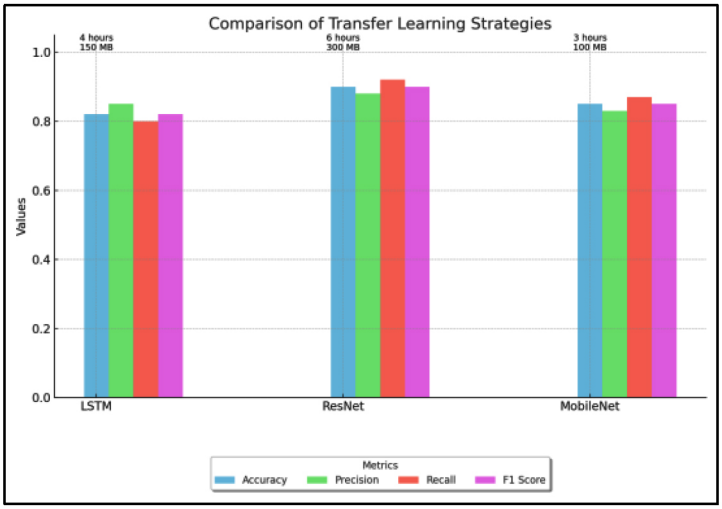


Figure 4

Representation of Evaluation of different transfer learning strategies

Table 3

Evaluation of different transfer learning strategies

Transfer Learning Strategy	Accuracy	Precision	Recall	F1 Score	Training Time	Model Size
LSTM	0.82	0.85	0.80	0.82	4 hours	150 MB
ResNet	0.90	0.88	0.92	0.90	6 hours	300 MB
MobileNet	0.85	0.83	0.87	0.85	3 hours	100 MB

For example, ResNet needs the most time to train (6 hours) and has the biggest model (300 MB). With these results, you can see the trade-offs between model performance and processing resources. This helps you choose the best transfer learning approach for your needs and limitations, comparison shown in figure 5.

5. Conclusion

In transfer learning in medical imaging has shown a lot of promise for improving the accuracy of diagnoses, especially when datasets are limited. Transfer learning improves model performance by using models

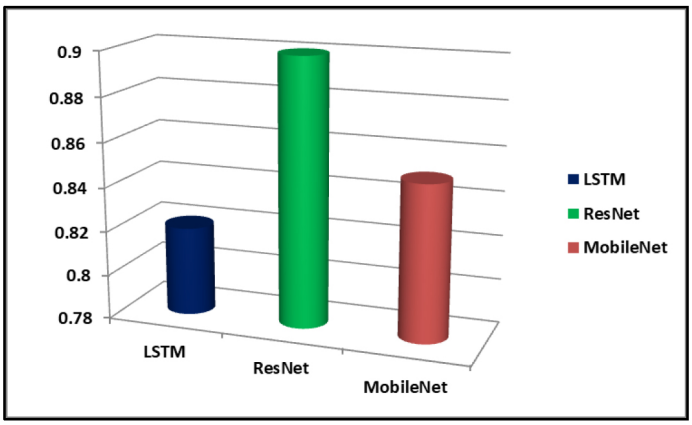


Figure 5

Accuracy comparison of Different Model

that have already been taught and transferring information from source areas. This leads to better accuracy, precision, and memory in classification. This method uses the large amount of information stored in pre-trained models and cuts down on the need for a lot of labeled data, which gets around the problems that come with medical image datasets being hard to come by. Transfer learning techniques like fine-tuning, feature extraction, and network design changes have been shown to work in the real world to improve assessment accuracy in medical imaging tasks. As time goes on, more study into improving transfer learning methods and looking into domain-specific changes will help medical imaging systems work better, which will eventually improve patient care and clinical decision-making.

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