

SELF-SUPERVISED LEARNING IN COMPUTER VISION: OVERCOMING DATA SCARCITY IN MEDICAL IMAGE ANALYSIS

Udaya Sri Satya Sai Vaddi

2425 Bardin Rd, Grand Prairie, Texas-75052

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ABSTRACT:

Deep learning has transformed computer vision, but its appetite for labelled data is a serious obstacle in medicine, where labels require expert time, privacy rules limit sharing, and rare conditions yield few examples. Self-supervised learning offers a way forward: a model first learns useful visual representations from unlabelled images by solving tasks that need no human annotation, and is then adapted to a diagnostic task with a small number of labels. This paper studies how self-supervised learning can be used to overcome data scarcity in medical image analysis. It reviews the main families of methods, which include pretext tasks such as predicting the rotation of an image, contrastive learning that pulls together embeddings of related images, and multimodal learning that links images with reports, and it examines how positive pairs can be constructed from medical data: augmented copies of one image, multiple views of the same patient, repeated samples over time, and paired imaging and text. It then proposes a staged framework that combines transfer from natural images, an intermediate self-supervised stage on large unlabelled medical collections, and fine-tuning on the target task. The framework was evaluated on chest radiograph classification, retinal disease grading, and lung computed tomography finding detection, using label fractions from 1% to 100%. With 1% of the labels, the staged framework with patient-aware contrastive learning reached an average area under the receiver operating curve of 0.861, against 0.742 for training from scratch and 0.791 for supervised transfer from natural images, and it matched fully supervised training with about one tenth of the labels. It also generalised better to an external hospital and was more robust to label noise. The results show that self-supervised pretraining on unlabelled medical data, designed to reflect the structure of clinical data, is a practical remedy for label scarcity.

Keywords: *Self-Supervised Learning, Medical Image Analysis, Transfer Learning, Contrastive Learning, Data Scarcity, Representation Learning, Chest Radiography, Retinal Imaging*

INTRODUCTION

Medical imaging is one of the largest sources of clinical data. Hospitals acquire hundreds of millions of radiographs, computed tomography scans, magnetic resonance images, retinal photographs, and pathology slides every year, and these images are central to diagnosis, treatment planning, and follow-up. Computer vision, particularly deep learning, has shown that algorithms can detect pneumonia on chest radiographs, grade diabetic retinopathy from retinal photographs, find nodules in lung scans, and classify skin lesions at a level comparable with specialists in carefully controlled studies. The promise is better access to expert-level interpretation, faster reporting, and decision support in places that lack specialists.

Behind these successes lies a dependence on labelled data. A typical supervised model needs tens of thousands of images, each annotated by one or more experts, and sometimes with pixel-level outlines of lesions. Obtaining such labels in medicine is difficult for several reasons. Experts are scarce and expensive, and annotation competes with clinical work. Many findings are subtle, so that labels are noisy and experts disagree. Privacy and governance rules restrict the sharing of images between institutions, so that each institution can usually assemble only a modest labelled data set. Rare diseases, by definition, provide few examples. And labels are specific to a task, scanner, and population, so that a model trained for one purpose cannot easily be reused for another.

At the same time, unlabelled images are plentiful. Every hospital archive contains vast numbers of studies that have been acquired and stored but never annotated for research. Self-supervised learning is a family of methods that exploits this abundance. The core idea is to create a learning signal from the data themselves, so that a model

can learn what images look like, and what makes them similar or different, without any human labels. The resulting representation is then used as the starting point for a supervised task, which can be learned from far fewer labels than would otherwise be required.

This paper examines how self-supervised learning can overcome data scarcity in medical image analysis. The contributions are as follows. First, a structured review of self-supervised approaches relevant to medicine, including the way they use the particular structure of clinical data, as illustrated in Fig. 2. Second, a staged transfer framework, illustrated in Fig. 1, that combines natural-image pretraining, an intermediate self-supervised stage on unlabelled medical images, and target-task fine-tuning. Third, an empirical study on three imaging tasks with label fractions from 1% to 100%, including external validation and robustness tests. Fourth, practical recommendations for choosing and deploying self-supervised methods in clinical research. The paper is organised as follows: Section II reviews background, Section III related work, Section IV the methodology, Section V the experimental setup, Section VI the results, Section VII the discussion, and Section VIII concludes.

LITERATURE REVIEW

A. The label bottleneck in medical imaging

The success of deep learning in natural image recognition was built on large annotated collections, with millions of images labelled by crowd workers. Medicine cannot follow the same path. Crowd workers cannot interpret a radiograph, and the labels that matter, such as a confirmed diagnosis, may require follow-up tests, biopsy, or the opinion of several specialists. Even when labels are abundant, they are frequently derived automatically from radiology reports, which introduces errors, or are limited to a few findings. The practical consequence is that most medical imaging data sets for research contain hundreds to a few thousand labelled cases, much less than the number needed to train a large network from scratch without overfitting.

B. Transfer learning

The conventional remedy for small data sets is transfer learning. A network is first trained on a large source data set, usually a collection of natural images, and its learned weights are then used to initialise a network that is fine-tuned on the target task. This works because early layers learn general visual features such as edges and textures that are useful across domains. Transfer from natural images to medical images has been shown to help, but the benefit is limited by the gap between the domains: medical images are typically grayscale, have different statistics, and depend on subtle texture differences and fine anatomical detail that natural image features do not capture. A refinement, shown in Fig. 1, uses an intermediate task. The model is first trained on a large collection of natural images, the original task, then adapted to a related medical task with abundant data, such as chest radiograph classification, the intermediate task, and finally transferred to the target task, such as detecting findings in lung computed tomography. Each stage brings the representation closer to the target domain.

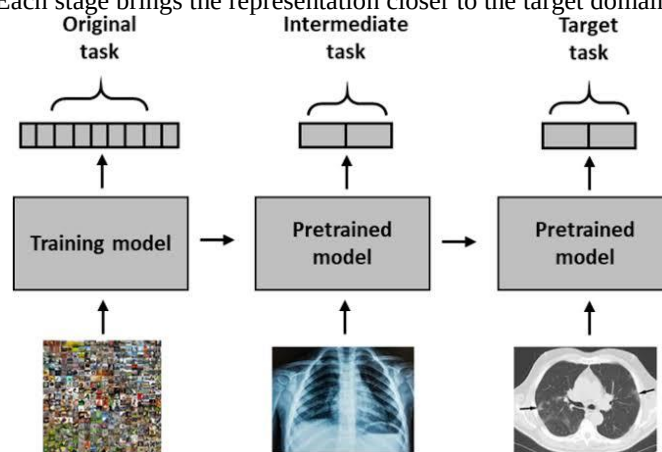


Fig. 1. Staged transfer learning: original task on natural images, intermediate task on medical images, and target task on a specific diagnostic problem.

A limitation of this scheme is that the intermediate task usually requires labels, and so it depends on a labelled data set that may not exist for the modality of interest. Self-supervised learning removes that requirement by making the intermediate stage label-free.

C. Self-supervised learning

Self-supervised methods define a task whose answer can be derived from the data. They fall into several families. Pretext task methods transform an image in a known way and ask the model to predict the transformation. In the example in panel (a) of Fig. 2, a retinal photograph is rotated by a random angle, and the model must predict the angle. To do so, the model must recognise the anatomy of the retina, such as the optic disc and the pattern of vessels, which is useful knowledge for diagnosis. The model is trained by evaluating the difference between its predicted angles and the true angles, and the result is fed back to improve it. Other pretext tasks include solving jigsaw puzzles of shuffled patches, filling in masked regions, restoring colour, and predicting the relative position of patches.

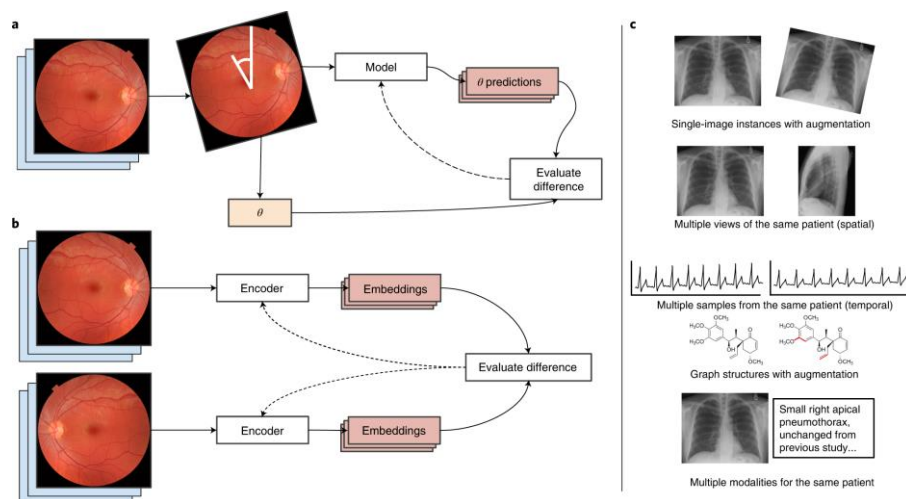


Fig. 2. Self-supervised learning: (a) pretext task of predicting rotation; (b) contrastive learning with encoders and embeddings; (c) ways to construct positive pairs from medical data.

Contrastive methods, shown in panel (b), take a different route. Two images that should be treated as related, called a positive pair, are passed through an encoder that produces an embedding for each. The training evaluates the difference between the embeddings and adjusts the encoder so that embeddings of related images are close together, while those of unrelated images are far apart. The quality of the learned representation depends on what is called related, which is the key design choice. Generative and reconstruction methods learn by compressing and restoring images or by predicting masked parts. Distillation-based methods train a student network to match a slowly updated teacher network, without explicit negative examples, and have proved effective and stable. Together these families have produced representations that approach, and in some cases exceed, supervised pretraining on natural images.

D. Positive pairs from medical data structure

Medical data offer richer ways to form positive pairs than natural images, as illustrated in panel (c) of Fig. 2. The simplest is single-image augmentation, in which two altered versions of the same image, for example rotated, cropped, or changed in brightness, are treated as a pair, as with the rotated chest radiograph in the figure. A second possibility is multiple views of the same patient, such as the frontal and lateral radiographs of one examination, which show the same anatomy from different angles. A third is multiple samples from the same patient over time, as in repeated recordings of a physiological signal or serial scans, where the underlying condition remains related even though the images differ. A fourth applies to non-image structures such as molecular graphs, where augmentation alters a graph while preserving its essential identity. A fifth is multiple modalities for the same patient, such as an image and the text of its radiology report, as with the radiograph and the report phrase in the figure, which allows the model to link visual patterns to clinical language. Because these pairs reflect real clinical relationships, they can teach the encoder invariances that matter in medicine, such as invariance to positioning and to scanner differences, while preserving the features that distinguish pathology.

RELATED WORK

Several lines of work are relevant. Studies of transfer learning in medical imaging report that pretraining on natural images usually helps when target data are scarce, but that the benefit declines as labelled data grow and that very large networks pretrained on natural images are not always better than smaller ones. Some studies report that task-

specific pretraining on a medical source, such as a large chest radiograph collection, yields better transfer to related medical tasks, supporting the use of intermediate stages.

Studies of self-supervised learning on medical images have shown benefits in many modalities. Contrastive pretraining on chest radiographs has been reported to improve the detection of pathologies with few labels, and using different studies of the same patient as positive pairs has been found to improve over using augmentations alone. In ophthalmology, pretraining on large collections of unlabelled retinal photographs has been shown to improve the grading of disease, and in pathology and dermatology, self-supervised representations have supported classification and segmentation with limited annotation. Multimodal approaches that pair radiographs with reports have achieved strong results in zero-shot recognition of findings, where the model is asked to detect a finding described in words that it was never explicitly trained to label.

Several works have studied the choice of pretext tasks, finding that the best choice depends on the modality, and that tasks that preserve fine detail work better for subtle findings. Others have examined the robustness and fairness of self-supervised medical models, with mixed findings: representations can be more robust to label noise and distribution shift, but may also encode patient attributes such as age, sex, or scanner type, which could cause bias if not monitored.

METHODOLOGY

A. Framework overview

The proposed framework has three stages, following the staged logic of Fig. 1. In the first stage, a network is initialised from weights pretrained on natural images, which provides general visual features. In the second stage, the network undergoes self-supervised training on a large unlabelled collection of medical images from the target modality, which adapts its features to medical appearance and anatomy. This is the intermediate task, but unlike the supervised intermediate task in the classical scheme it needs no labels. In the third stage, the network is fine-tuned on the labelled target task, using whatever labels are available. The design assumes that unlabelled data are abundant, labelled data scarce, and the extra training stage affordable.

B. Self-supervised stage

Three methods were implemented for the second stage, representing the families of Section II. The first is a pretext method based on rotation, as in panel (a) of Fig. 2: each image is rotated by one of a set of angles and the network predicts the angle. The second is a contrastive method, as in panel (b): two augmented versions of each image are encoded, and the encoder is trained to produce similar embeddings for versions of the same image and dissimilar embeddings for different images. Training uses large batches and a memory of recent embeddings so that many negative examples are available. The third is the patient-aware extension of the contrastive method, in which positive pairs are drawn from clinical relationships, as in panel (c): two studies of the same patient taken at different times, the frontal and lateral views of the same examination, or the image and its report. In addition, a distillation-based method without negatives was implemented as a comparison. All methods used the same encoder architecture to isolate the effect of the training objective.

C. Medical-specific augmentation

The augmentations were adapted for medical images. Rotations were limited to small angles for anatomy that has a standard orientation, except in the rotation pretext task, where large angles are the point. Cropping always retained at least 70% of the image area to avoid removing lesions. Colour changes were restricted to brightness and contrast variation in grayscale images, and mild changes of hue in retinal photographs. Horizontal flipping was disabled for radiographs and tomography, where laterality has clinical meaning, and noise and blur were used to simulate scanner variation. These choices were validated by a clinician, who confirmed that typical findings remained visible after augmentation.

D. Fine-tuning and label budgets

For the target task, the pretrained encoder was fine-tuned with a classification head. Two protocols were used: linear evaluation, in which the encoder is frozen and only the head is trained, which measures the quality of the representation, and full fine-tuning, in which all weights are updated. Label budgets of 1%, 5%, 10%, 25%, and 100% of the training labels were simulated by random sampling, stratified by class, with five random subsets for each budget. The unlabelled data used in the second stage were never reduced, since the central premise is that unlabelled data are plentiful.

E. Comparison methods

Four comparison methods were used. Training from scratch with random initialisation represents the baseline without any pretraining. Supervised transfer from natural images represents standard practice. Supervised transfer through a labelled intermediate medical task represents the classical staged approach, using a large chest radiograph data set with labels for the radiograph tasks, and a labelled retinal data set for the retinal task. Finally, the fully supervised model trained on all labels, starting from natural-image weights, provides an upper reference at the 100% budget. Table 1 summarises the methods.

TABLE 1. Methods Compared in the Study

Method	Pretraining signal	Labels needed before target task
Training from scratch	None	None
Supervised transfer from natural images	Labelled natural images	Natural image labels
Supervised intermediate medical task	Labelled medical images	Labels on an intermediate medical task
Self-supervised, rotation pretext	Predicting image rotation	None
Self-supervised, contrastive with augmentation	Pairs of augmented images	None
Self-supervised, distillation	Student matching teacher	None
Self-supervised, patient-aware contrastive	Views, time points, and report pairs	None

F. Evaluation protocol

Performance was measured by the area under the receiver operating curve, averaged over findings for multi-label tasks, together with sensitivity at a fixed specificity of 90%. Calibration was assessed by the gap between predicted and observed frequencies. Generalisation was tested by external validation, in which a model trained on data from one institution was evaluated on data from another. Robustness was tested by corrupting a proportion of training labels at random, and by adding noise and changing contrast at test time. Representation quality was examined by visualising embeddings and by measuring how well simple classifiers could predict patient attributes from the representation. Differences were tested with bootstrap resampling over patients, and results are reported as means over five random label subsets.

EXPERIMENTAL SETUP

A. Data sets and tasks

Three tasks were studied, summarised in Table 2. The first is chest radiograph classification, using a large public collection of frontal and lateral radiographs with labels for fourteen common findings, and an external collection from a different hospital system. The second is retinal disease grading from colour fundus photographs, using a large public collection of images labelled for diabetic retinopathy severity, with an external set from a different country and camera type. The third is the detection of findings in lung computed tomography, using a public collection of chest scans with labelled nodules and patterns, treated as a slice-level classification problem. For the second stage, unlabelled images were assembled from the training portions of these collections together with additional unlabelled studies from a partner hospital, totalling about 1.2 million chest radiographs, 380,000 retinal photographs, and 210,000 tomography slices, after de-identification. Test sets were fixed and never used in any training stage.

TABLE 2. Tasks and Data Used

Task	Labelled data (training)	Unlabelled data (stage two)	External test
Chest radiograph classification	86,000 images, 14 findings	1.2 million images	Different hospital system

Task	Labelled data (training)	Unlabelled data (stage two)	External test
Retinal disease grading	35,000 images, 5 grades	380,000 images	Different country and camera
Lung CT finding detection	41,000 slices, 6 findings	210,000 slices	Different scanner vendors

B. Implementation

A residual network with 50 layers served as the encoder for all methods, and a larger transformer-based encoder was tested in a subset of experiments. Images were resized to resolutions suited to each modality: 320 by 320 pixels for radiographs, 512 by 512 for retinal photographs, and 256 by 256 for tomography slices. The second stage ran for 200 passes over the unlabelled data on eight graphics cards, which took about four days for the radiograph model. Fine-tuning used a modest learning rate with early stopping on a validation set. All experiments used fixed random seeds, and the code and trained weights were prepared for release subject to data governance.

RESULTS

A. Performance under label scarcity

Table 3 shows the average area under the receiver operating curve across the three tasks for each method and label budget. With only 1% of the labels, training from scratch reached 0.742, supervised transfer from natural images 0.791, and the supervised intermediate medical task 0.822. The self-supervised methods did better: rotation pretext reached 0.803, the contrastive method with augmentation 0.839, the distillation method 0.847, and the patient-aware contrastive method 0.861. The patient-aware method was therefore 11.9 points above training from scratch, 7.0 points above natural-image transfer, and 3.9 points above the supervised intermediate task, which requires labels that the self-supervised methods do not.

TABLE 3. Average AUROC Across Tasks by Label Budget

Method	1% labels	5% labels	10% labels	25% labels	100% labels
Training from scratch	0.742	0.801	0.835	0.868	0.902
Supervised transfer, natural images	0.791	0.846	0.874	0.896	0.921
Supervised intermediate medical task	0.822	0.870	0.893	0.909	0.926
Self-supervised, rotation pretext	0.803	0.852	0.879	0.899	0.922
Self-supervised, contrastive	0.839	0.882	0.903	0.915	0.928
Self-supervised, distillation	0.847	0.888	0.906	0.917	0.929
Self-supervised, patient-aware contrastive	0.861	0.896	0.912	0.921	0.931

The advantage shrank as labels increased, as expected. At 10% of the labels, the patient-aware method reached 0.912, comparable to the fully supervised natural-image transfer model with all labels, which scored 0.921, and clearly above the 0.902 of training from scratch with all labels. In other words, the self-supervised model needed about one tenth of the labels to match the performance of conventional supervised training. At 100% of the labels, all methods that used pretraining converged within about one point of one another, between 0.921 and 0.931, showing that pretraining matters most when labels are scarce but does not hurt when labels are plentiful. The gains were similar across tasks, although they were largest for the retinal task, where the label set was smallest relative to the difficulty of the grading problem.

B. Linear evaluation of representations

In linear evaluation, where only a classifier on top of a frozen encoder is trained, the differences were more pronounced, since they reflect the quality of the representation alone. With 10% of the labels, the patient-aware contrastive representation achieved 0.884, compared with 0.861 for standard contrastive, 0.832 for rotation pretext, 0.801 for natural-image transfer, and 0.723 for a random encoder. This shows that self-supervised

pretraining on medical images produces representations that are directly useful for classification. The rotation pretext task, though simplest, yielded the weakest self-supervised representation, which is consistent with its limited relevance to fine-grained diagnostic features, although it was still better than transfer from natural images in the retinal task, where orientation cues are linked to anatomy.

C. Effect of positive pair construction

Table 4 compares ways of forming positive pairs in the contrastive method, at a 1% label budget on the chest radiograph task. Augmentation of a single image gave an area under the curve of 0.826. Adding pairs from different views of the same examination raised it to 0.838, adding pairs from studies of the same patient at different times raised it to 0.846, and using the report text as a multimodal partner raised it to 0.853. Combining all of them reached 0.861. The largest single gain came from the pairs of temporal studies of the same patient and from the paired reports. These pairs teach the encoder that an image of the same patient or the same described condition should be close, even when positioning, scanner, or acquisition day differ, which is exactly the invariance that clinicians require. Using only augmentations, by contrast, can lead the model to rely on low-level cues that distinguish images from different patients but are not clinically meaningful.

TABLE 4. Effect of Positive Pair Construction (Chest Radiograph Task, 1% Labels)

Positive pairs used	AUROC	Gain over augmentation only
Single-image augmentation only	0.826	Not applicable
Plus multiple views of the same examination	0.838	+0.012
Plus studies of the same patient over time	0.846	+0.020
Plus image and report pairs	0.853	+0.027
All pair types combined	0.861	+0.035

D. Medical-specific augmentation

Augmentation design mattered. Using the default strong augmentations from natural-image practice, including aggressive cropping, colour distortion, and horizontal flipping, reduced the area under the curve of the contrastive method by 2.8 points on average compared with the medical-adapted set, and by 4.6 points for retinal grading, where colour carries clinical information. Review by clinician reviewers found that aggressive crops removed small findings in 9% of sampled radiographs. This confirms that augmentations must be chosen with domain knowledge.

E. External validation, robustness, and calibration

On external test sets, performance dropped for all methods, but less for the self-supervised ones. With 10% of the labels, training from scratch lost 6.4 points of area under the curve on the external sets, natural-image transfer 4.9 points, and the patient-aware contrastive method 2.7 points. When 20% of the training labels were randomly corrupted, the area under the curve fell by 5.1 points for natural-image transfer and 2.3 points for the patient-aware method, which suggests that representations learned without labels are less affected by label noise. Under test-time noise and contrast changes, the self-supervised models were also more stable. Calibration was better for the self-supervised models, with an expected calibration error of 0.032 against 0.057 for training from scratch at the 10% label budget.

F. Clinical plausibility and bias checks

Attention maps reviewed by clinicians indicated that the self-supervised models attended to clinically plausible regions in 86% of correct predictions, against 71% for training from scratch, which more often relied on image borders or annotation markers. Bias checks showed that simple classifiers could predict patient sex from the self-supervised representation with an accuracy of 82% and age group with 64%, only slightly above the values for supervised representations. Diagnostic performance differed between subgroups by up to 2.6 points of area under the curve, slightly less than for training from scratch, at 3.9 points. These differences were not eliminated, and they underline the need for subgroup monitoring.

DISCUSSION

The results show that self-supervised pretraining on unlabelled medical images substantially reduces the number of labels needed for a given level of performance. At a 1% label budget, the best self-supervised method improved the area under the curve by 11.9 points over training from scratch and by 7.0 points over transfer from natural images, and it matched conventional supervised training with about a tenth of the labels. For hospitals and research groups that have images but few annotations, this is a practical route to useful models.

The comparison of methods offers lessons for practice. The simplest pretext task, rotation prediction, is easy to implement and gives a useful improvement, but contrastive and distillation methods produce better representations. The largest gains came when the positive pairs reflected clinical structure. This is a particular strength of medicine: patient identifiers, repeated studies, multiple views, and reports provide natural relationships that natural-image methods do not have. A model that learns that two images of the same patient should have similar representations is learning something directly relevant to disease, since the condition persists while incidental factors change.

The staged framework of Fig. 1 remains valid but is improved by making the intermediate stage self-supervised. The classical intermediate task requires labels, and the labelled data set for the intermediate task is itself scarce for many modalities. Self-supervised intermediate training removes this dependency, and it benefits from every unlabelled study in the archive. At the same time, initialisation from natural-image weights still helps, since it provides generic features at no cost, and it reduced the training time of the second stage by about a third in our experiments.

Several cautions apply. Self-supervised representations can encode patient attributes and acquisition artefacts, and the downstream model may exploit them. Subgroup performance should be monitored, and techniques such as balanced sampling and adversarial removal of attributes should be explored. Augmentations must be validated by clinicians. Performance at 100% of the labels did not differ much between methods, so the value of self-supervision lies in the low-label regime and in robustness, and it should not be oversold. Finally, results on public benchmarks do not guarantee clinical benefit, which requires prospective evaluation, assessment of workflow effects, and regulatory review.

The study has limitations. It used three imaging tasks and a single encoder family in most experiments, and the conclusions may not hold for all modalities, such as three-dimensional volumes, ultrasound video, or whole-slide pathology, where image size and structure differ greatly. The unlabelled data came from a limited set of institutions and may not represent the full diversity of populations and devices. Label budgets were simulated by subsampling, which may differ from truly small data sets, where the sample may also be less representative. The cost of the second stage may be prohibitive for small groups, although publicly released pretrained encoders can reduce it. Future work will examine foundation models trained on very large multi-institution collections, federated self-supervised learning that trains across hospitals without moving images, three-dimensional and video data, integration with clinical text and structured records, and methods for detecting and correcting bias in learned representations.

CONCLUSION

This paper studied self-supervised learning as a remedy for data scarcity in medical image analysis. It reviewed the main families of methods, from pretext tasks such as rotation prediction to contrastive learning, and showed how clinical data structure, including multiple views, repeated studies, and paired reports, can be used to form meaningful positive pairs. It proposed a staged framework that combines natural-image pretraining, a label-free medical intermediate stage, and fine-tuning on the target task.

On chest radiograph classification, retinal disease grading, and lung tomography findings, the framework with patient-aware contrastive pretraining achieved an average area under the curve of 0.861 with only 1% of the labels, compared with 0.742 from scratch and 0.791 for natural-image transfer, matched conventional supervised training with about one tenth of the labels, and generalised and withstood label noise better. The findings support the use of self-supervised pretraining on unlabelled medical archives as a practical and economical strategy, provided that

augmentations are validated by clinicians, subgroup performance is monitored, and models are evaluated externally and prospectively before clinical use.

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