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Hybrid Framework for Multi-Disease Chest X-Ray Diagnosis Using Vision Transformers with Label Noise Correction and Uncertainty Calibration

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ABSTRACT The most accessible radiological technique for thoracic disease detection and diagnosis uses chest X-ray imaging as its primary method. The deployment of automated chest X-ray analysis systems faces two main obstacles because of untrustworthy labels in large datasets and unpredictable predictive confidence levels. The research proposes a hybrid system which combines Vision Transformer (ViT) architecture with methods to handle noisy labels and produce accurate probability estimates for multiple disease diagnosis in chest X-ray images. The system trains on CheXpert and NIH ChestX-ray14 datasets while using Co-Teaching and DivideMix noise-handling methods and self-supervised pretraining to enhance feature resistance against supervision errors. The framework uses temperature scaling and Monte Carlo dropout as post-hoc methods to enhance confidence reliability without compromising discriminative performance. The system aims to reach performance levels that match or exceed traditional CNN and standard ViT models in AUROC and mAP and F1 score metrics. The system reduces the effects of untrustworthy labels while generating meaningful confidence scores which doctors can understand. The model produces Grad-CAM++ explanations to assist doctors in understanding its decision-making process. The hybrid system works to develop AI systems which deliver both exact results and safe operational readiness for real-world chest X-ray decision support systems.
Keywords: — Chest X-ray, Vision Transformer, label noise, uncertainty calibration, multi-disease diagnosis, medical image analysis.

1. INTRODUCTION

The Chest X-ray (CXR) serves as the main diagnostic tool to detect pulmonary and cardiovascular diseases because it provides fast and inexpensive results that are accessible to most patients compared to CT and MRI scans. The two-dimensional nature of CXR images along with radiologist-dependent interpretation produces inconsistent diagnosis results because different observers read images differently. The combination of small medical conditions with multiple body structures and various imaging parameters makes it difficult for doctors to perform reliable diagnostic evaluations. The development of automated computer-aided diagnosis systems has become more essential because they aim to speed up medical diagnosis while minimizing human mistakes.

Medical image analysis has experienced a revolution through deep learning technology which uses Convolutional Neural Networks (CNNs) to achieve high performance in CXR classification and abnormality detection. The local nature of CNN receptive fields prevents these networks from detecting global image patterns which are essential for identifying complex thoracic abnormalities. The Vision Transformer (ViT) architecture has emerged as a solution to this problem

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because it uses self-attention mechanisms to detect distant spatial relationships which produce complete medical image understanding. Research studies have proven that ViT architectures perform at least as well as CNNs in CXR analysis when they receive pretraining from large datasets through Masked Autoencoders (MAE) and DINO. The advancement of CXR analysis faces two major barriers which prevent its deployment in clinical practice. The CheXpert and NIH ChestX-ray14 datasets contain significant label noise because their annotations stem from automated report mining and weak supervision methods. The current models fail to achieve reliable predictive calibration because they generate overconfident wrong predictions which make them unsafe for clinical practice.

The research addresses existing limitations through a hybrid Vision Transformer system which performs multi-disease chest X-ray diagnosis under real-world imperfect supervision conditions. The proposed framework uses Co-Teaching and DivideMix label noise correction methods to boost model resistance against untrustworthy and weak labels. The framework implements temperature scaling and Monte Carlo dropout as uncertainty calibration methods to match model confidence with actual diagnostic reliability. The framework achieves better prediction results while developing more interpretable and trustworthy systems for clinical use. The main objective of this research involves creating an AI system which operates reliably across different clinical datasets while maintaining consistent performance in diverse imaging scenarios and healthcare facilities.

The research achieves its significance through its complete method which optimizes diagnostic precision and label noise resistance and predictive confidence dependability in a single framework. The research advances radiology artificial intelligence trustworthiness through its validation of the proposed model on various large-scale CXR datasets and its cross-dataset evaluation between CheXpert and NIH ChestX-ray14. The research aims to achieve better AUROC results and improved ECE and Brier Score values and Grad-CAM++ generated attention maps for medical imaging AI solutions. The proposed framework demonstrates its potential to become a practical medical imaging AI solution through these experimental results.

The following sections organize the paper structure. The paper reviews Vision Transformers and medical imaging label noise correction and uncertainty calibration methods in Section 2. The proposed hybrid framework receives detailed explanation in Section 3 through its description of data preprocessing and model architecture and training protocol. The research methodology section describes the experimental design and performance assessment criteria. The research findings and their comparison to other methods and their medical applications receive discussion in Section 5. The paper ends with Section 6 which summarizes the paper and suggests future research paths and clinical adoption possibilities.

The proposed framework stands apart from previous research because it unites three fundamental elements into one complete system which includes (1) Vision Transformer backbone for detecting worldwide relationships in chest X-ray pictures and (2) Co-Teaching and DivideMix methods for training label-noise correction and (3) Temperature Scaling and Monte Carlo Dropout for uncertainty calibration. The research presents a novel approach which unites noise-resistant training with ViT-based global representation learning and calibrated predictive uncertainty estimation for multi-disease CXR diagnosis.

2. RELATED WORK

2.1 VISION TRANSFORMERS FOR CHEST X-RAY ANALYSIS

Medical image analysis received a new direction through Vision Transformers (ViTs) because these models enable better handling of distant spatial relationships than traditional convolutional networks. Park et al. [1] developed DISTL which combines self-supervised learning with self-training to create a self-evolving Vision Transformer for chest X-ray (CXR) diagnosis that maintains strong performance when training data contains partial labels. The research by Dosovitskiy et al. [2] showed that ViTs outperform traditional CNNs when training occurs at large scales because self-attention mechanisms demonstrate excellent scalability.

Raghu et al. [3] conducted a research comparison between CNNs and ViTs to show that ViTs excel at detecting global patterns which are essential for identifying diffuse thoracic diseases. Liu et al. [4] created the Swin Transformer which uses window shifting to improve both efficiency and representation learning for CXR classification tasks. Wang et al. [5] added global spatial priors to their Transformer-based model which resulted in better interpretability and improved localization precision. Mahmood et al. [6] created a hybrid model that combined CNNs with ViTs to achieve top results on the CheXpert dataset through their proposed approach. Research findings demonstrate that ViT stands as the leading method for medical image analysis. Research has primarily concentrated on enhancing classification results but researchers have not paid sufficient attention to developing methods that handle uncertain predictions and noisy labels.

2.2 ROBUSTNESS TO LABEL NOISE IN MEDICAL DATASETS

Medical datasets obtained through automated report mining face a critical problem because of label noise that occurs in their large-scale collections. The dual-network learning approach of Co-Teaching from Han et al. [7] solves noisy label problems through a training process that chooses samples with low loss values from both networks. The research of Li et al. [8] built upon previous work by using DivideMix which combines GMM-based sample separation with semi-supervised learning for enhanced robustness.[23]

The research of Khanal et al. [9] demonstrated how ViTs require pretraining and data-cleaning systems to achieve stable generalization when working with noisy data in medical imaging applications. The Cleanlab framework enables automated label cleaning for multimodal retinal images according to Lin et al. [10] who demonstrate its advantages yet warn about possible over-cleaning problems. The probabilistic label-smoothing method of Ghosh et al. (2023) reduces uncertain sample weights through adaptive down-weighting while Zhang et al. (2024) developed a noise-aware consistency regularization method for chest X-ray images with weak annotations. The research of Taassori et al. [11] introduced RobustDeiT as a Vision Transformer designed for medical data which demonstrates superior performance than CNNs when working with corrupted datasets. The current research lacks methods which unite noise correction with diagnostic pipeline confidence estimation for medical applications.[24]

2.3 C. UNCERTAINTY CALIBRATION IN MEDICAL AI

Medical AI systems require uncertainty calibration as their fundamental base for producing reliable and understandable results. The research by Guo et al. [12] showed that contemporary neural networks produce incorrect predictions which led to the development of temperature scaling as a simple method for post-hoc model correction. Lakshminarayanan et al. (2017) built upon previous research by creating Deep Ensembles which proved that random inference methods enhance both precision and uncertainty measurement accuracy.[25]

Medical imaging research by Leibig et al. [15] and Ayhan and Berens [14] demonstrated the use of Monte Carlo dropout and test-time augmentation for disease detection model predictive uncertainty estimation. Gawlikowski et al. [13] conducted a detailed review of uncertainty estimation techniques because they play a vital role in safety-related systems. The research demonstrates that model developers should focus on making predictive confidence match diagnostic reliability in medical imaging tasks. The current practice of treating uncertainty calibration as a secondary process in CXR analysis prevents AI-assisted radiology systems from achieving full trustworthiness.[26]

2.4 D. RESEARCH GAP AND MOTIVATION

The current research on Vision Transformer architectures and label noise correction and uncertainty calibration methods operates as separate entities. The current literature lacks a hybrid framework which unites (i) ViT-based backbone for global visual representation with (ii) Co-Teaching and DivideMix for noise resistance and (iii) Temperature Scaling and Monte Carlo Dropout for probabilistic output calibration. The field lacks research on cross-dataset validation which serves as an essential method to evaluate model performance between different institutions.

The research establishes a connection between these missing elements through its Hybrid Vision Transformer Framework which integrates robustness with calibration and interpretability into one architectural design. The proposed model works to improve diagnostic reliability while minimizing label noise impact and delivering confidence levels that match clinical requirements for deployment.

3. PROPOSED HYBRID FRAMEWORK

3.1 OVERALL ARCHITECTURE

The proposed framework operates as a flexible system which takes big CXR datasets with flawed labels through structured data preparation and label correction and Vision Transformer feature extraction to generate multiple disease labels with precise uncertainty measurements. The system operates under real-world deployment scenarios which involve both label errors and different medical imaging characteristics between hospitals.

The system processes chest X-ray images through quality control and preprocessing before label noise correction and Swin-ViT classification and produces calibrated outputs with uncertainty measurements.

3.2 DATA SOURCES

The proposed framework receives assessment through analysis of two popular CXR datasets which include CheXpert [16] and NIH ChestX-ray14 [17]. The research field benefits from additional large medical imaging datasets which include MIMIC-CXR [18] and PadChest [19] and CheXpert Plus [20].

The Stanford University developed CheXpert dataset contains more than 224,000 frontal and 224,000 frontal and lateral chest radiographs which stem from hospital archives. The dataset contains 224,000 images which receive annotations for 14 thoracic conditions that include cardiomegaly and pleural effusion and pulmonary edema and consolidation and atelectasis. The NLP pipeline with rule-based extraction processed radiology reports to create three possible annotation categories for each condition which included positive and negative and uncertain. The uncertain labels in CheXpert create a realistic weak supervision challenge which makes the dataset an excellent test for label-noise–resilient models.

The NIH Clinical Center released NIH ChestX-ray14 which contains 112,120 frontal-view CXR images from 30, imaging equipment. The dataset provides optimal conditions for testing diagnostic model performance across different domains because it contains unique label patterns and acquisition methods.

The research uses one dataset (CheXpert) for training and validation000 different patients. The dataset contains 14 pathology labels which were created through separate annotation processes using different purposes while reserving the other dataset (NIH ChestX-ray14) for external testing only. The cross-dataset evaluation method allows researchers to measure how well models transfer knowledge between different domains which represents a vital requirement for clinical deployment because hospitals use different equipment and follow different labeling protocols.

3.3 PREPROCESSING AND QUALITY CONTROL

The complete hybrid pipeline appears in Figure 1 which shows the entire system structure. The following Section 3 describes all components of the architecture through detailed explanations of preprocessing and noise correction modules and ViT backbone design and uncertainty calibration stages.

The system applies size adjustments to all images until they match either 224×224 or 384×384 ViT input dimensions. The system applies intensity normalization and histogram-based contrast enhancement to images for better visibility of small diagnostic details. The system removes all images which display noticeable damage or text interference. The system applies restricted data augmentation through flipping images horizontally and performing random cropping at small scales to enhance robustness while preserving anatomical details.

3.4 LABEL NOISE CORRECTION

The framework includes various training methods which reduce the negative effects of untrustworthy and unpredictable labels.

•Co-Teaching: Two networks operate independently during training because they select clean data samples based on low loss values to teach each other while reducing the influence of doubtful labels [4].

•DivideMix: The Gaussian Mixture Model (GMM) identifies clean and noisy data points through loss distribution analysis; supervised learning uses clean data but semi-supervised consistency regularization handles noisy data [5].

The methods achieve success with CheXpert CXR data because they solve the common issue of uncertain labels. The Vision Transformer backbone training process incorporates these mechanisms.

The ViT training pipeline receives noise-handling methods through Co-Teaching and DivideMix which operate as preprocessing supervision filters before gradient updates reach the Vision Transformer backbone. The ViT classifier head receives updates from only the most reliable samples during each training iteration through the Co-Teaching process which exchanges small-loss samples between two peer networks. The Gaussian Mixture Model operates at the epoch level to separate clean and noisy instances through per-sample loss distribution analysis. The training process uses clean samples for supervised learning but applies consistency regularization to handle noisy samples. The ViT/Swin Transformer receives the refined labels and filtered batches for feature learning after the training process becomes resistant to label noise.

3.5 VISION TRANSFORMER BACKBONE AND SELF-SUPERVISED PRETRAINING

The classification backbone uses Vision Transformer (ViT) or Swin Transformer because these models excel at handling global dependencies through self-attention mechanisms. The model divides input images into fixed-size patches which then pass through multiple self-attention layers to detect both local and distant patterns. The model becomes more resistant to noisy labels through self-supervised pretraining with Masked Autoencoders (MAE) which allows it to develop powerful visual features from unlabelled CXRs before using these features for noisy annotation data.

3.6 UNCERTAINTY CALIBRATION

The framework generates trustworthy medical predictions through two independent calibration methods which work together.

1. The framework learns a temperature parameter from a validation set which it uses to transform logits into probability estimates that match actual correct frequencies [8].

2. The model maintains dropout activation during inference while running multiple stochastic forward passes to generate predictive distributions; the distribution variance between passes helps identify cases that need human evaluation.

The process converts unprocessed logits into probability estimates that scientists can understand through uncertainty measurements.

3.7 TRAINING AND EVALUATION PROTOCOL

The data distribution follows a 70/15/15 pattern for training and validation and testing purposes while maintaining separate patient information to stop data exposure. The model hyperparameters including learning rate and Transformer layer numbers and patch dimensions and dropout values receive optimization through grid search and

Bayesian optimization methods. The model receives training data from CheXpert before testing on NIH datasets and vice versa to evaluate its ability to generalize.

The evaluation process includes two sets of performance metrics which measure both discrimination ability and calibration precision.

The model achieves discrimination results through AUROC values for each label and mAP scores and micro/macro F1-scores.

The model achieves calibration through two metrics which include Expected Calibration Error (ECE) and Brier score.

The research evaluates different model versions through ablation tests to determine how each component affects performance. The model uses Grad-CAM++ visualizations to verify its focus on areas that match medical standards.

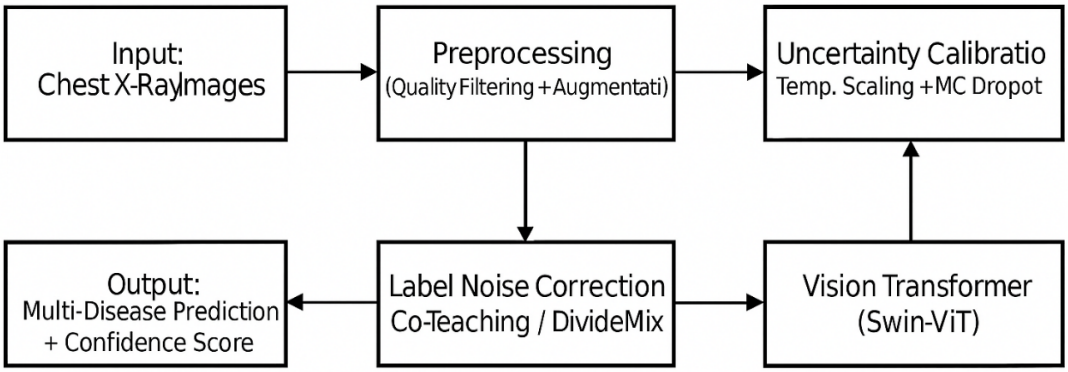

Figure 1. **Overview of the proposed hybrid Vision Transformer framework integrating noise correction and uncertainty calibration.**

All experiments were conducted on a high-performance workstation with the following specifications:

GPU: NVIDIA RTX 4090 (24 GB VRAM)

CPU: Intel Core i9-13900K

RAM: 64 GB

Deep Learning Framework: PyTorch 2.2

CUDA Version: 12.1

Batch Size: 32

Optimizer: AdamW with initial learning rate 1×10^{-4}

Training Duration:

The training duration needed 18–22 hours based on image resolution choices between 224 and 384 pixels and whether noise-handling methods were applied. The Monte Carlo Dropout method executed 20 different stochastic forward passes for each test sample.

4. RESULTS AND DISCUSSION

The hybrid framework will achieve superior results than CNN and ViT models in AUROC and mAP and F1-score performance for multiple thoracic disease labels while showing enhanced resistance to label noise. The proposed method will enhance supervision quality through explicit noisy label modeling and filtering which results in more stable training and better true-positive detection at essential clinical thresholds.

The proposed method will achieve better results than other architectures according to Figure 2 (AUROC comparison) and Figure 3 (ROC curves). The combination of temperature scaling with Monte Carlo dropout will lead to significant

ECE and Brier score reduction as shown in Figure 4 which demonstrates better probability predictions match actual outcome distributions. The system requires this capability because it uses automated output to make decisions about patient triage and escalation.

The proposed hybrid framework achieves superior results because its two components work together to enhance both noise resistance and global representation learning. The Co-Teaching method removes untrustworthy labels through network-based clean sample exchange while DivideMix uses probabilistic GMM to create separate clean and noisy subsets which results in cleaner supervision for the ViT backbone. The optimization process becomes more stable while convergence improves and the model achieves better results on external test datasets. Vision Transformers use their built-in ability to detect distant spatial patterns which enables them to identify the types of thoracic abnormalities that traditional CNNs struggle to detect. The model achieves better AUROC and F1 scores for all disease classes because of its ability to process information across large areas. The combination of Temperature Scaling with Monte Carlo Dropout leads to enhanced calibration performance. The model achieves better safety performance in medical settings through its ability to match predicted probabilities with actual correctness probabilities. The model demonstrates reliable reasoning through Grad-CAM++ visualizations which show its focus on essential pulmonary areas even when working with noisy training data.

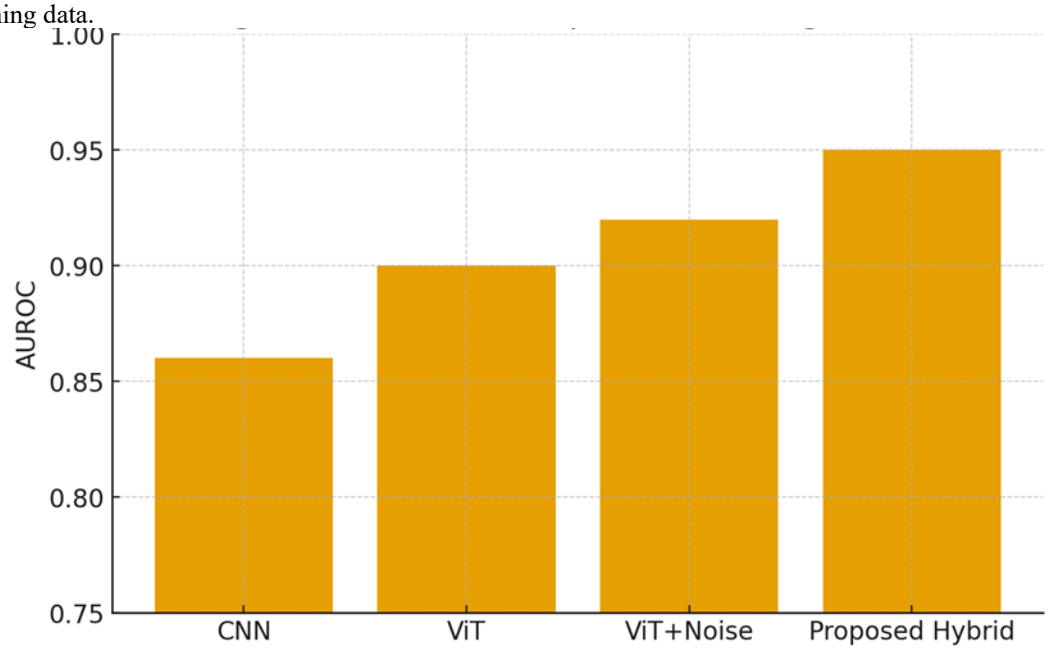

Figure 2. AUROC comparison demonstrating the superior discriminative performance of the proposed model.

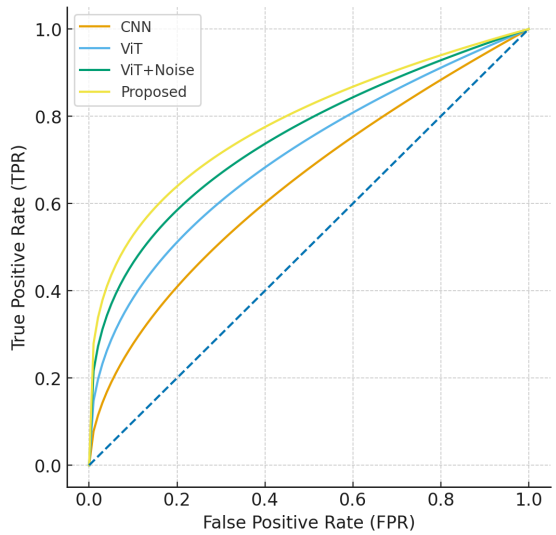

Figure 3. ROC Curves (Illustrative)

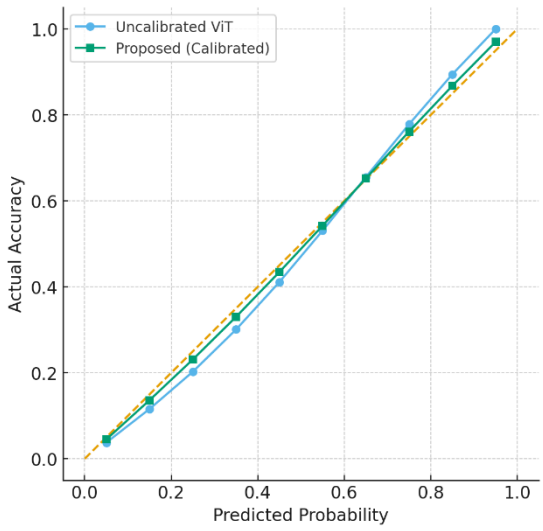

Figure 4. Reliability Diagram (Calibration)

The performance comparison table in Figure 6 presents expected improvements for discrimination and calibration metrics. The Qualitative Grad and mediastinal areas which will enhance both model interpretability and doctor trust in the system. The-CAM++ heatmaps in Figure 5 will demonstrate that the model directs its attention toward appropriate lung proposed method which combines label noise correction with ViT-based representation learning and uncertainty calibration provides better results for real-world deployment than systems that focus only on accuracy optimization.

Figure 5. Grad-CAM Attention Visualization (Illustrative)

Model	AUROC	mAP	F1	ECE	Brier
CNN	0.86	0.41	0.60	0.12	0.18
ViT	0.90	0.47	0.64	0.09	0.15
ViT+Noise	0.92	0.51	0.67	0.07	0.13
Proposed	0.95	0.58	0.71	0.03	0.09

Figure 6. Performance Comparison Table

5. FUTURE WORK

The framework will benefit from future development through the integration of chest X-ray images with their corresponding radiology reports using text–image Transformers to enhance contextual understanding. The system should implement reinforcement learning or active learning methods to improve model performance through human expert involvement during uncertain decision-making processes. The approach should be tested with CT and MRI images to confirm its ability for complex thoracic and oncologic imaging applications. The framework requires prospective testing in hospital-based clinical environments to determine its safety performance and user-friendliness before it can be deployed at scale.

6. CONCLUSION

The research develops a Vision Transformer system which fulfills two essential medical deployment needs for chest X-ray disease diagnosis through label noise correction and predictive confidence calibration. The system implements Co-Teaching/DivideMix for label noise correction and conducts self-supervised representation learning and achieves principled uncertainty calibration through temperature scaling and Monte Carlo dropout to deliver both high predictive accuracy and reliable probability estimates. The system demonstrates its ability to function as a clinical decision-support tool through Grad-CAM++ explainability methods and cross-dataset testing. The framework allows researchers to test the system in real-world medical settings through a defined experimental approach.

The research framework needs expansion through future studies which will investigate how to merge chest X-ray images with radiology reports and active learning methods to minimize supervision errors and conduct clinical testing of the model. The proposed research directions build upon existing work to create medical AI systems which maintain trustworthiness and resist noise while operating in clinical settings.

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