Registration Seminar

Deep Learning-Based Early Disease Classification System for Thoracic Radiographs

Under the Supervision of

Dr. Prabina Pattanayak and Dr. Chandrajit Chowdhury

Presented By

Kirti Swagat Mohanty

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Department of Electronics and Communication Engineering,
National Institute of Technology, Silchar

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Introduction

- Pulmonary diseases represent a significant global health burden, affecting millions of people worldwide and contributing substantially to morbidity and mortality rates.
- Early and accurate diagnosis of these conditions is crucial for effective treatment and improved patient outcomes.
- Chest X-rays are indispensable tools in understanding lung health and diagnosing pulmonary diseases, pulmonary diseases, providing clear images of various lung conditions.
- They are budget-friendly and easy to perform, making them widely accessible for initial evaluations in evaluations in medical settings around the world.
- Their ability to reveal crucial information enables early detection and monitoring of lung diseases, diseases, benefiting both patients and healthcare providers.
- Despite their strengths, X-rays can be complex in interpretation, highlighting the need for enhanced enhanced diagnostic support systems.

Image Source: https://www.sleepdrs.com

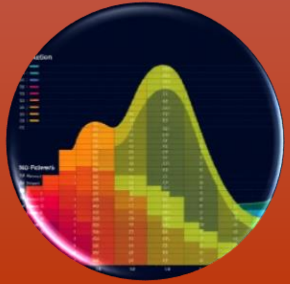
Literature Review

Deep Learning in Chest Radiograph

Siamese Networks and Contrastive Learning

Transfer Learning and Model Adaptation

Multi-Task Learning in Medical Imaging



Dataset Utilization and Model Evaluation

Literature Review

Authors, Year	Findings/ Conclusion
Rajpurkar et al., 2018	• CheXNeXt achieved radiologist-level performance on 11 pathologies. • CheXNeXt performed better than radiologists in detecting atelectasis, with an AUC of 0.862 (95% CI .825–0.895), statistically significantly higher than radiologists' AUC of 0.808 (95% CI 0.777–0.838).
Okolo et al., 2022	• Proposed and evaluated the Input Enhanced Vision Transformer (IEViT), a novel enhanced Vision Transformer model that can achieve improved performance on chest X-ray images associated with various pathologies. • The result shows, the proposed IEViT model outperformedVision Transformer (ViT) for all the data sets and variants examined, achieving an F1-score between 96.39% and 100%, and an improvement over ViT of up to +5.82% in terms of F1-score across the four examined data sets.
Azizi et al., 2021	• Proposed Multi-Instance Contrastive Learning (MICLe) as a generalization of existing contrastive learning approaches to leverage multiple images per medical condition. • MICLe improves the performance of self-supervised models, yielding state-of-the-art results. • self-supervised learning outperforms strong supervised baselines pretrained on ImageNet by 1.1% in mean AUC.

Literature Review

Authors, Year	Findings/ Conclusion
Grill et al., 2020	• Proposed BYOL(Bootstrap Your Own Latent) algorithm for self-supervised learning of image representations. BYOL learns its representation by predicting previous versions of its outputs, without using negative pairs. • Using a ResNet-200 (2x), BYOL reaches a top-1 accuracy of 79:6% which improves over the previous state of the art (76:8%) while using 30% fewer parameters.
Davila et al. 2024	• The Transfer learning (TL) addresses the challenge of scarce large, annotated datasets for various medical domain .Fine-tuning strategies have been proposed to adapt pre-trained models to specific medical contexts, including full fine-tuning, linear probing, selective fine-tuning, and dynamic fine-tuning. • The study provides a comprehensive analysis on the performance of various fine-tuning methods applied to pre-trained models across a spectrum of medical imaging domains. Auto-RGN proves effective in 41.7% of cases, emerging as a useful technique for medical imaging, particularly with ResNet-50 and DenseNet-121
Moeskops at al,. 2016	• Proposed a single CNN to be trained to segment six tissues in MR brain images, the pectoral muscle in MR breast images, and the coronary arteries in cardiac CTA. The CNN therefore learns to identify the imaging modality, the visualised anatomical structures, and the tissue classes. • For each of the three tasks (brain MRI, breast MRI and cardiac CTA), this combined training procedure resulted in a segmentation performance equivalent to that of a CNN trained specifically for that task, demonstrating the high capacity of CNN architectures. • Hence, a single system could be used in clinical practice to automatically perform diverse segmentation tasks without task-specific training.

Literature Review

Authors, Year	Findings/ Conclusion
Kamal et al., 2022	• Proposed Anatomy-XNet, an anatomy-aware attention based thoracic disease classification network that prioritizes the spatial features guided by the pre-identified anatomy regions. • Adopted a semi-supervised learning method by utilizing available small-scale organ-level annotations to locate the anatomy regions in large-scale datasets where the organ-level annotations are absent. • The proposed method sets a new state-of-the-art benchmark by achieving an AUC score of 85.78%, 92.07%, and, 84.04% on three publicly available large-scale CXR datasets–NIH, Stanford CheXpert, and MIMIC-CXR, respectively.

Motivation

Clinical Challenges in Radiograph Interpretation:

- The interpretation of chest radiographs, while fundamental to medical diagnosis, presents a complex set of challenges that impact diagnostic accuracy.
- Foremost among these is the overlapping appearance of different pulmonary conditions, which can create significant ambiguity in interpretation.
- Perhaps most critically, the subtle nature of early disease manifestations requires exceptional attention to detail, as these nuanced indicators often hold crucial diagnostic value.

Resource Constraints in Healthcare:

- The growing global demand for radiological services, coupled with an uneven distribution of qualified radiologists, has created significant reporting backlogs.
- These systemic challenges are exacerbated by increasing patient volumes, highlighting the critical need for reliable automated assistance in radiograph interpretation.

Limitations of Current Deep Learning Approaches:

- The substantial requirement for labeled training data, which is both expensive and time-consuming to obtain in the medical domain. Additionally, these models often struggle with learning subtle discriminative features that are crucial for accurate diagnosis

Problem Statement-1

Designing a Contrastive Learning Based Robust Multi-label Chest Disease Classification System

Research Objective

1. Design a novel attention mechanism that dynamically focuses on multi-scale disease patterns
2. Develop a hierarchical feature fusion strategy for comprehensive disease representation
3. Implement an interpretable decision-making process for clinical validation
4. Create robust evaluation metrics for multi-label classification performance

Contrast Learning

- Contrast Learning, also known as Contrastive Learning, is a self-supervised learning technique that technique that learns data representations by contrasting between similar and dissimilar samples. dissimilar samples.
- The core idea is to bring similar (positive) samples closer together in the feature space while pushing while pushing dissimilar (negative) samples apart.

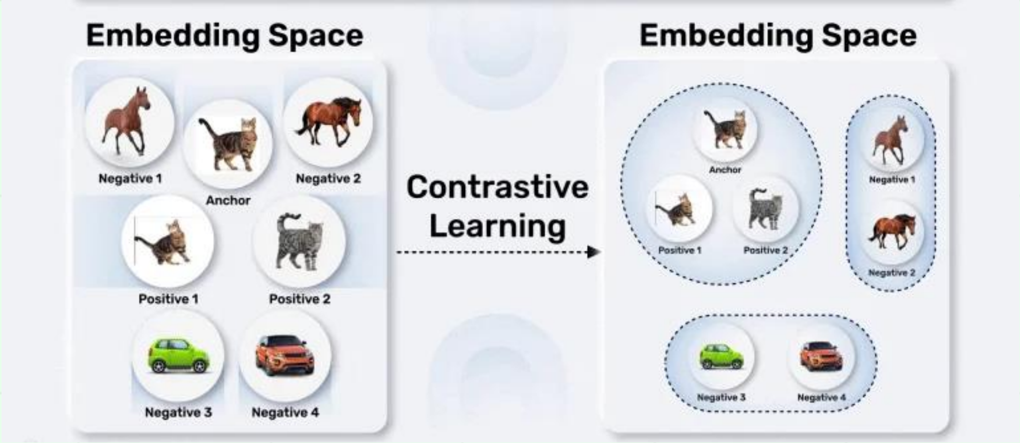


Image: https://learnopencv.com/

How Contrast Learning Works?

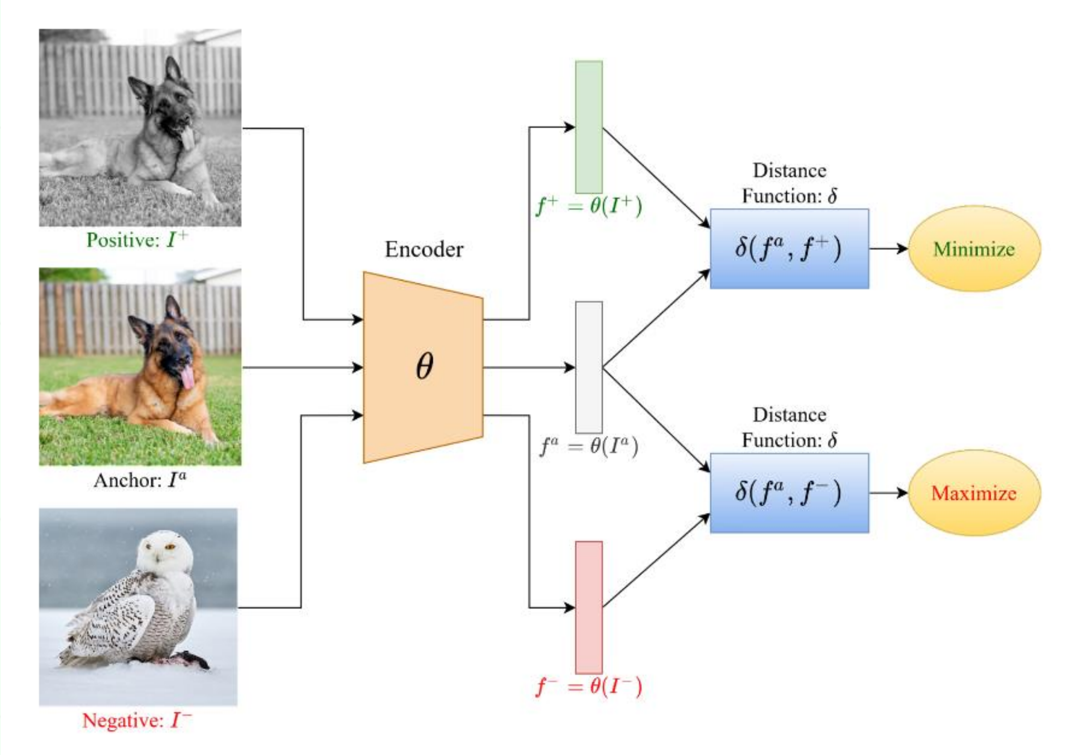


Image: https://www.v7labs.com/

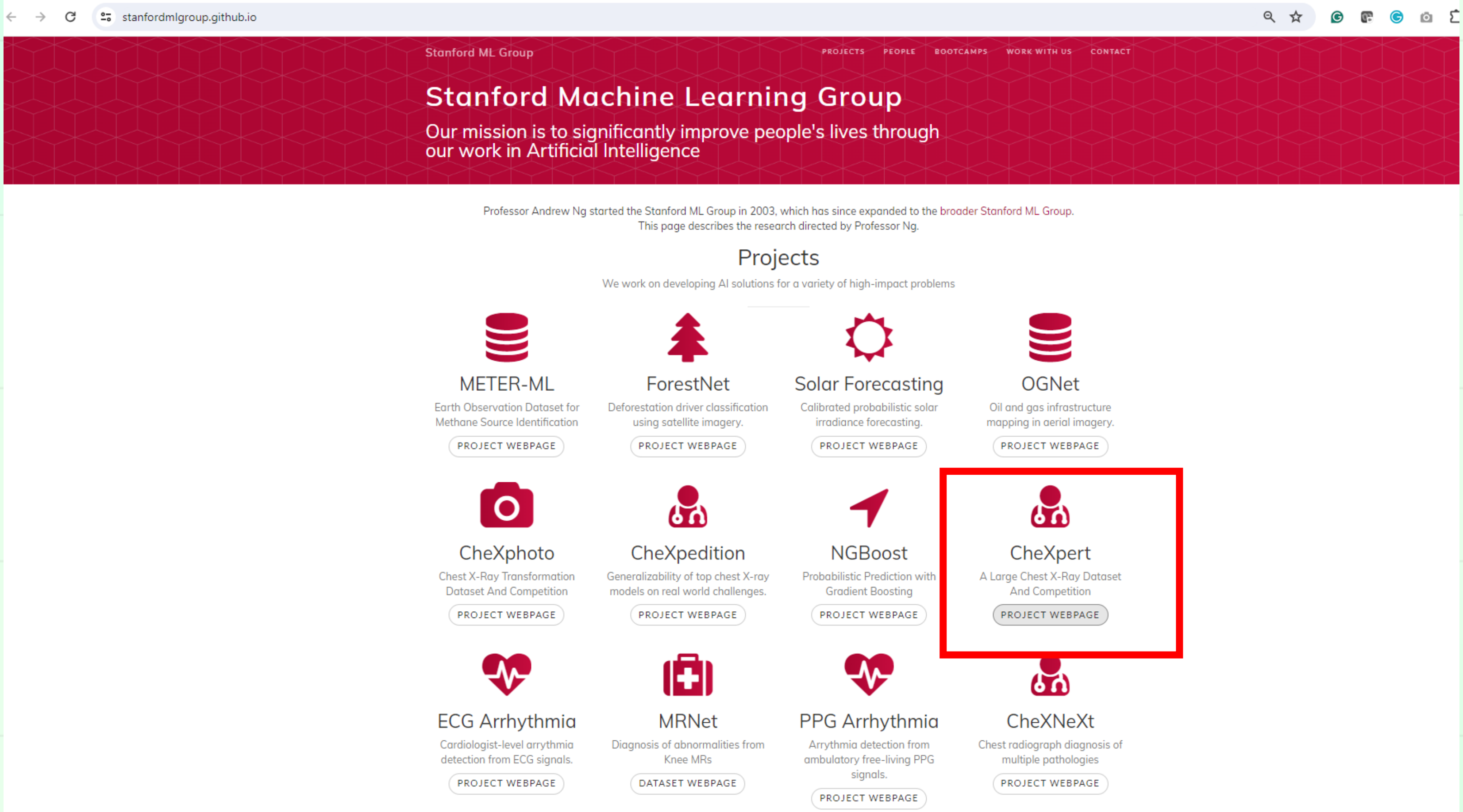
Self-Supervised Learning

- Self-Supervised Learning (SSL) is a Machine Learning paradigm where a model, when fed with fed with unstructured data as input, generates data labels automatically, which are further used in further used in subsequent iterations as ground truths.

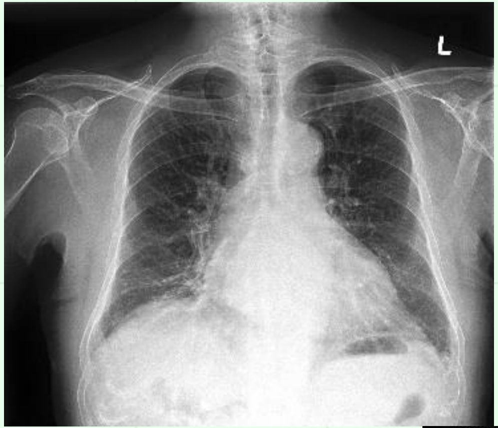
Supervised Learning vs Self-Supervised Learning

- Supervised Learning entails training a model with data that have high-quality manual labels associated labels associated with them to tune the model weights accordingly.
- Self-Supervised Learning also entails training a model with data and their labels, but the labels here are the labels here are generated by the model itself and are not available at the very start.

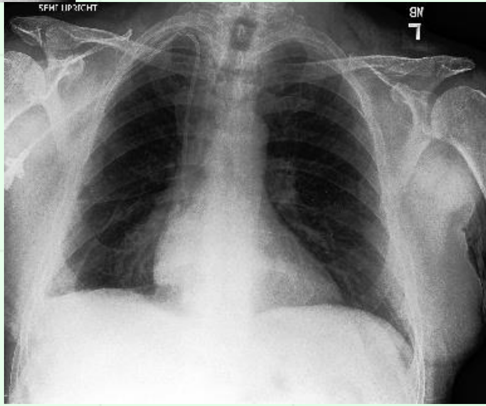
Dataset


stanfordmlgroup.github.io
Stanford ML Group
PROJECTS
PEOPLE
BOOTCAMPS
WORK WITH US
CONTACT
Stanford Machine Learning Group
Our mission is to significantly improve people's lives through our work in Artificial Intelligence
Professor Andrew Ng started the Stanford ML Group in 2003, which has since expanded to the broader Stanford ML Group.
This page describes the research directed by Professor Ng.
Projects
We work on developing AI solutions for a variety of high-impact problems
METER-ML
Earth Observation Dataset for Methane Source Identification
PROJECT WEBPAGE
ForestNet
Deforestation driver classification using satellite imagery.
PROJECT WEBPAGE
Solar Forecasting
Calibrated probabilistic solar irradiance forecasting.
PROJECT WEBPAGE
OGNet
Oil and gas infrastructure mapping in aerial imagery.
PROJECT WEBPAGE
CheXphoto
Chest X-Ray Transformation Dataset And Competition
PROJECT WEBPAGE
CheXpedition
Generalizability of top chest X-ray models on real world challenges.
PROJECT WEBPAGE
NGBoost
Probabilistic Prediction with Gradient Boosting
PROJECT WEBPAGE
CheXpert
A Large Chest X-Ray Dataset And Competition
PROJECT WEBPAGE
ECG Arrhythmia
Cardiologist-level arrythmia detection from ECG signals.
PROJECT WEBPAGE
MRNet
Diagnosis of abnormalities from Knee MRs
DATASET WEBPAGE
PPG Arrhythmia
Arrythmia detection from ambulatory free-living PPG signals.
PROJECT WEBPAGE
CheXNeXt
Chest radiograph diagnosis of multiple pathologies
PROJECT WEBPAGE

Dataset Description



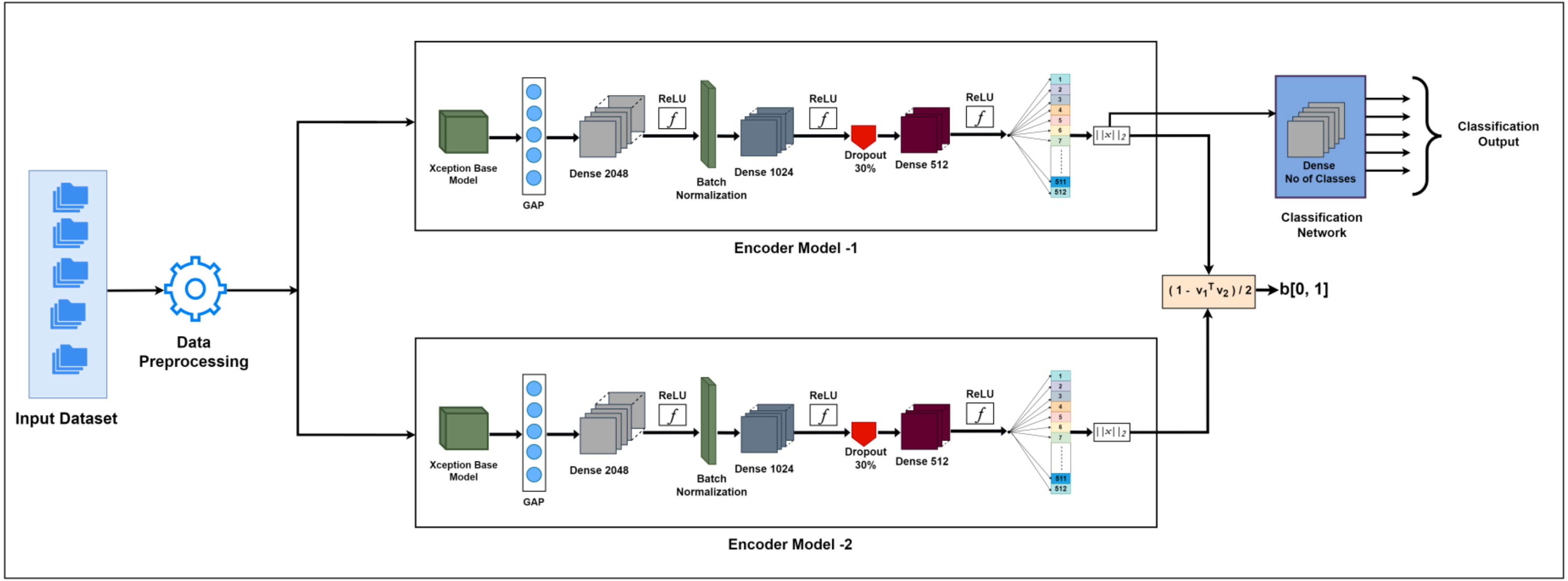
- **Dataset Name**: CheXpert
- **Released by**: Stanford University (Irvin et al., 2019)
- **Collection Period**: October 2002 - July 2017
- **Collection Location**: Stanford Hospital
- **Dataset Size**:
    - Total Images: 224,316 chest X-rays
    - Number of Patients: 65,240
    - Training Set: 223,414 images from 64,740 patients
    - Validation Set: 234 images from 200 patients
    - Test Set: 668 images from 500 patients (ground truth not publicly available)
- **Image Characteristics**:
    - Type: Frontal and Lateral chest radiographs
    - Format: DICOM images converted to PNG
    - Resolution: Variable (upscaled/downscaled to 320×320)
    - Color Space: Grayscale (8-bit)



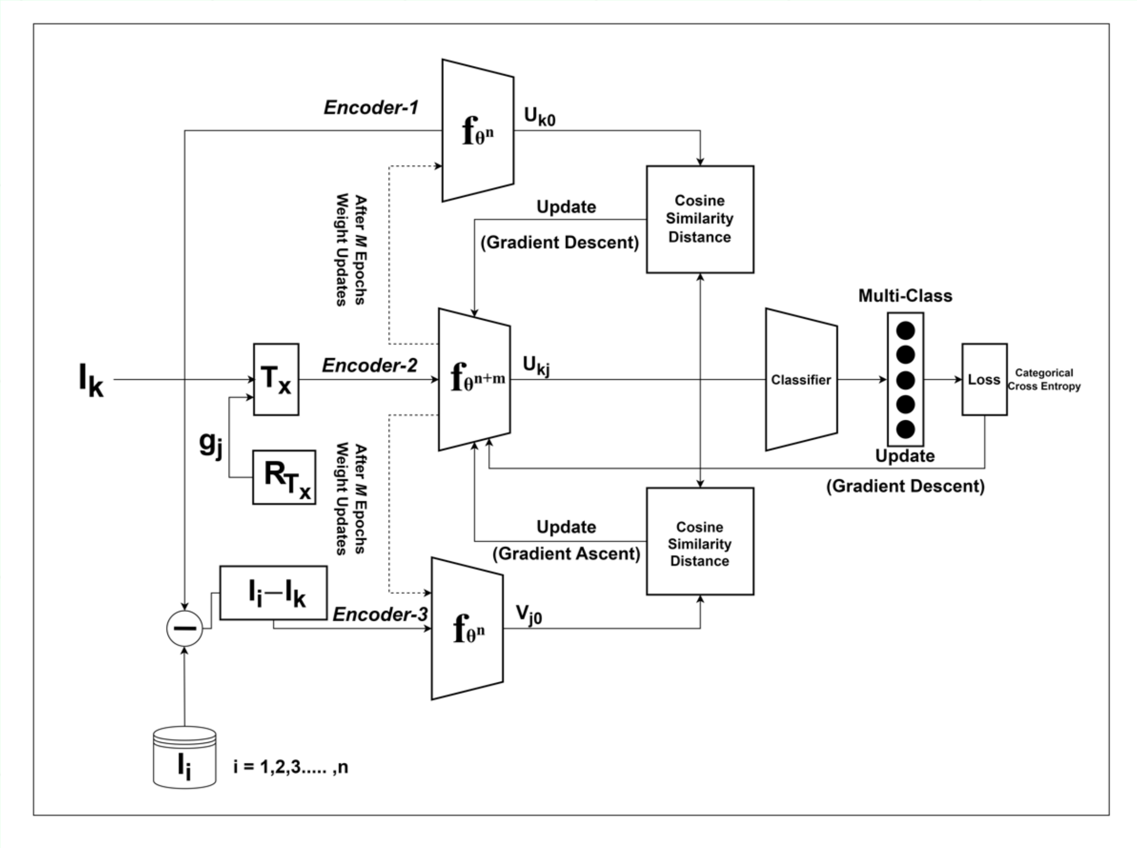
Why CheXpert not Other Dataset?

- Provides more comprehensive representation of pathological variations.
- Implements a unique three-class labeling system (positive, negative, uncertain) that better reflects the reality of clinical of clinical diagnosis.
- Dataset label quality surpasses previous benchmarks through its rule-based labeler.
- Expert-verified validation set ensures higher quality ground truth for model evaluation.
- Standardized preprocessing pipeline ensures consistent image quality across the dataset.
- Well-defined evaluation framework, focusing on five key pathologies (Atelectasis, Cardiomegaly, Consolidation, Edema, and Consolidation, Edema, and Pleural Effusion), enables more meaningful model comparisons and benchmarking. benchmarking.

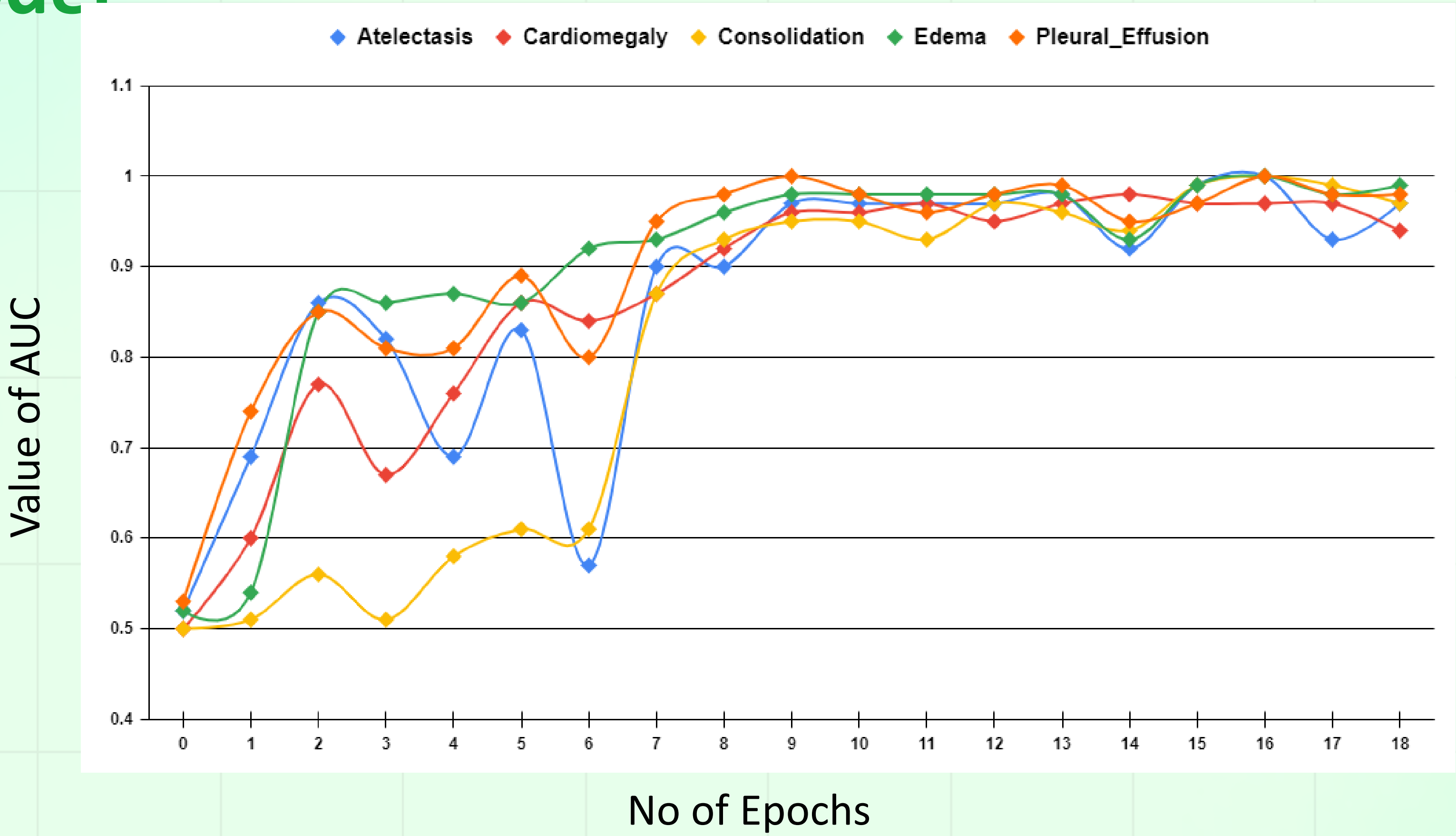
Proposed Architecture



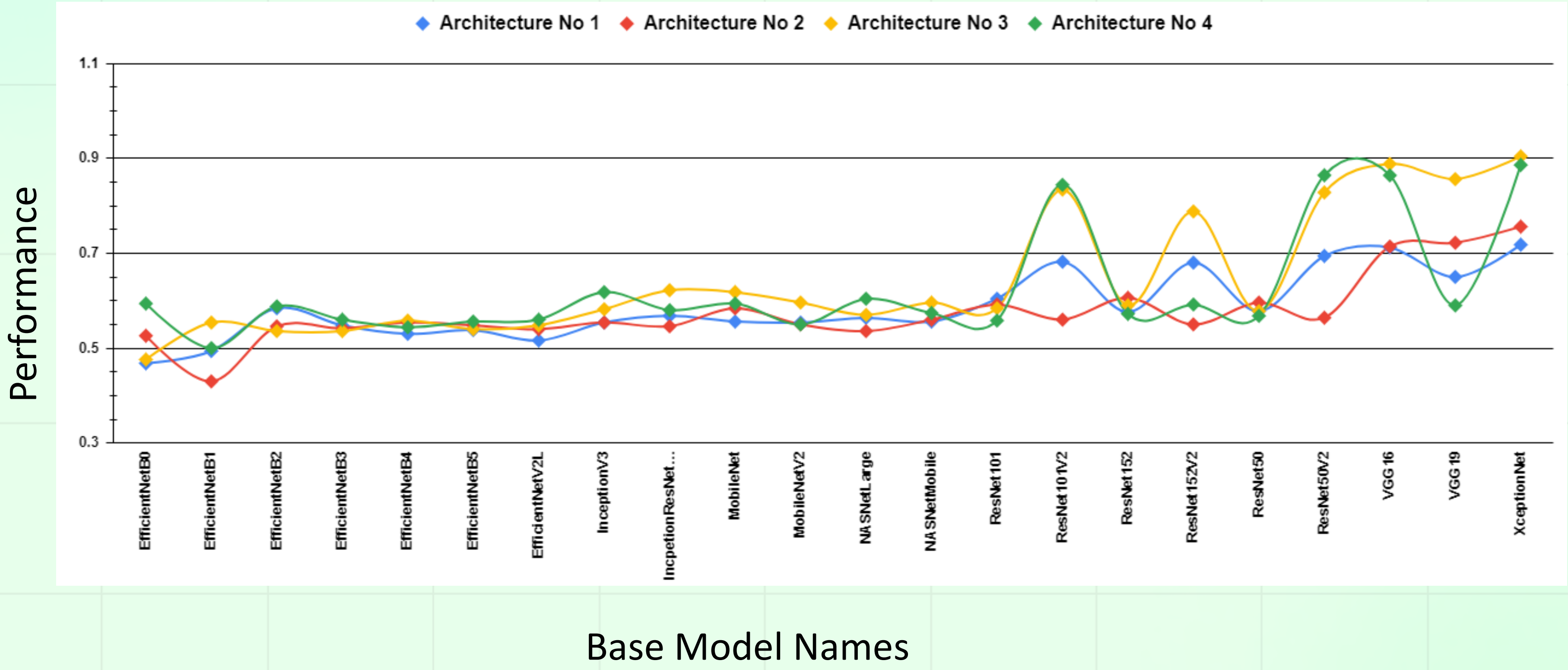
Proposed Training Scheme



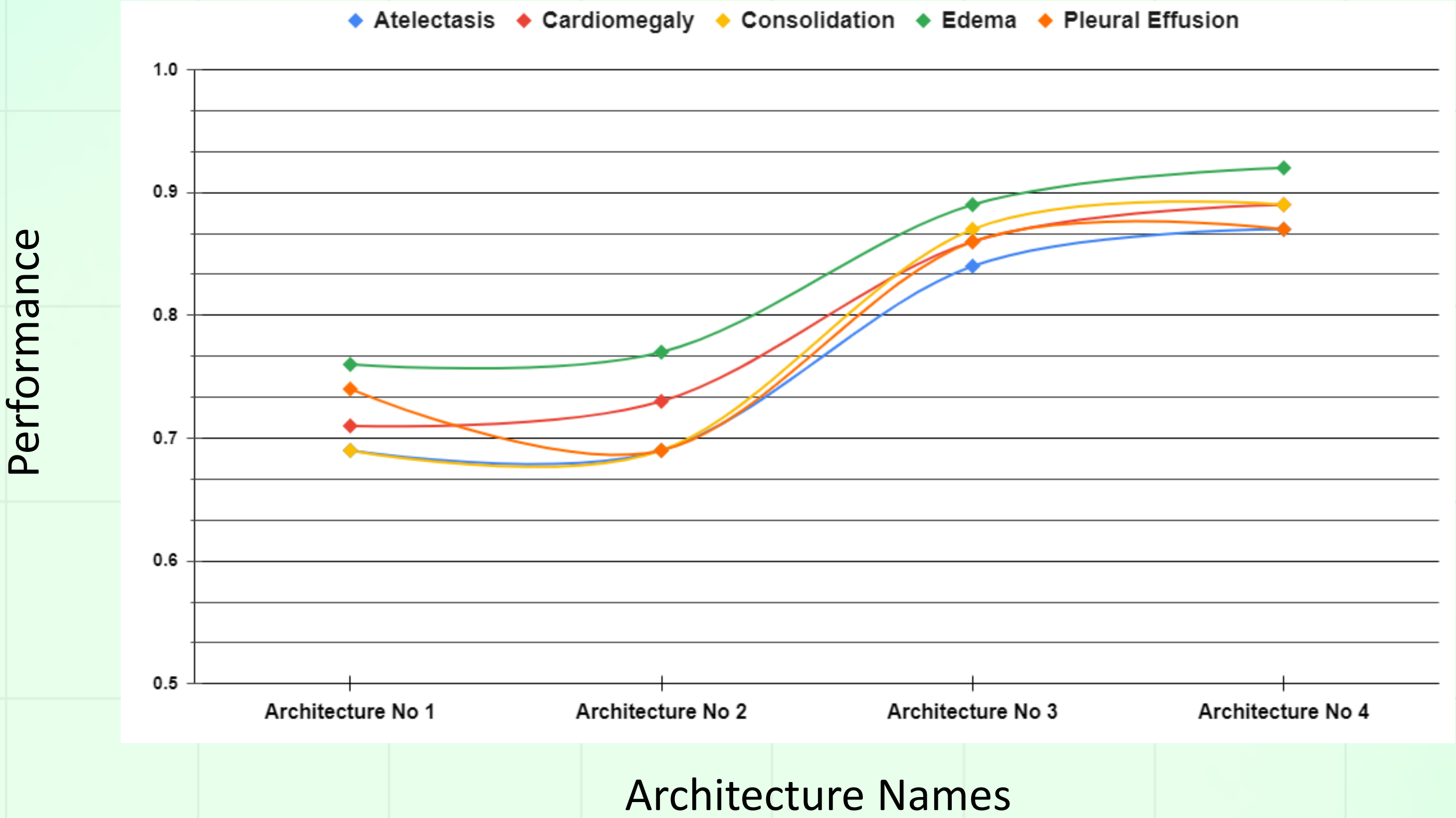
Performance of Avg AUC of Proposed Model Model



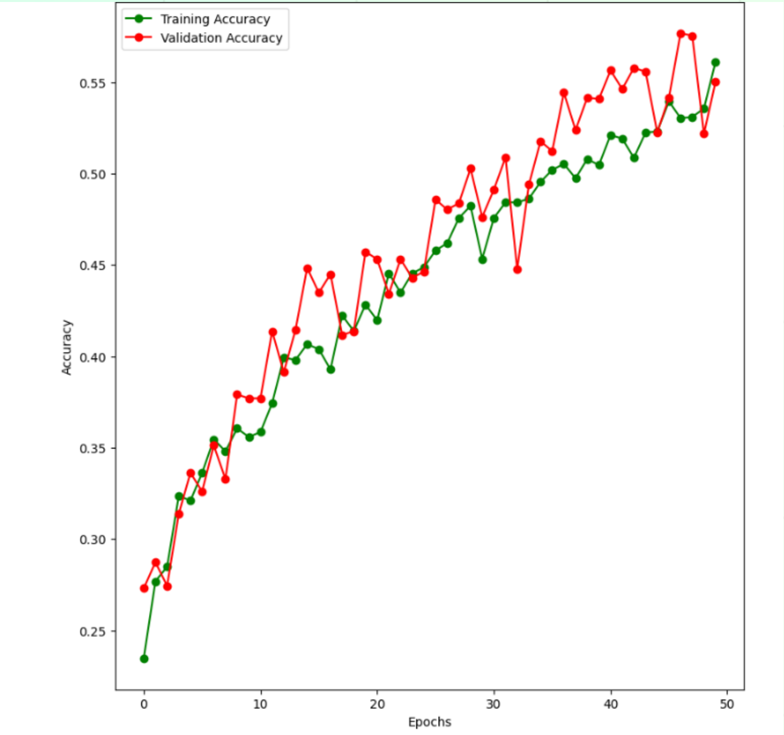
Performance Analysis (Avg. AUC) for Different Different Encoder Architecture

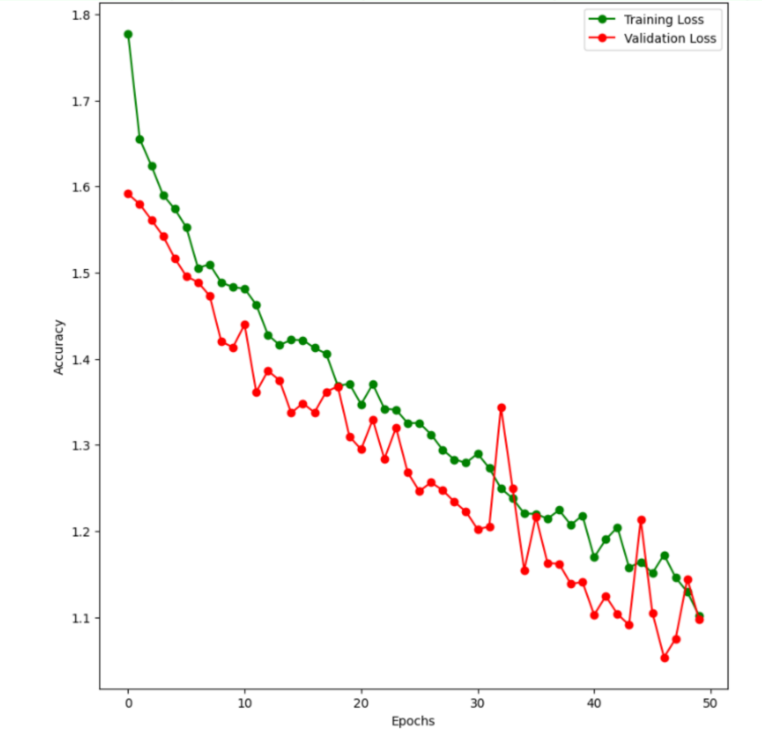


Performance Analysis (Avg. AUC) for Different Encoder Architecture on XceptionNet

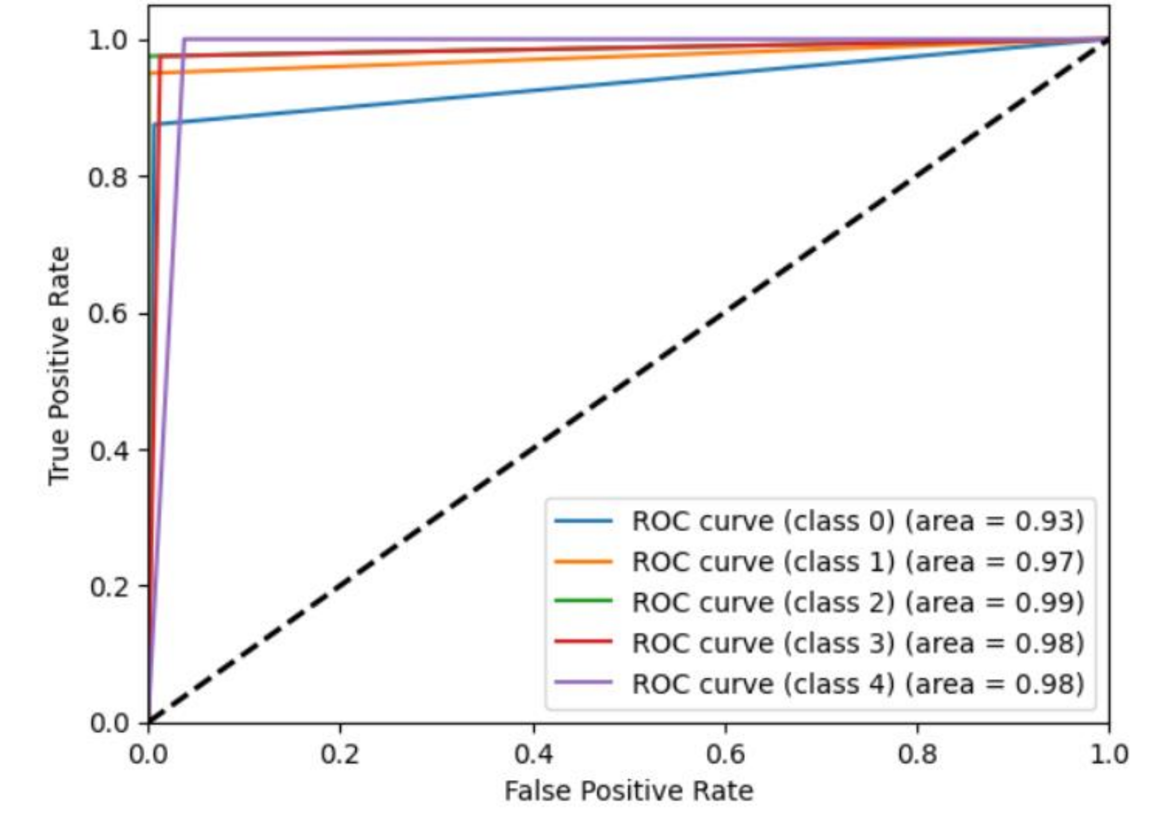


Training & Validation Analysis





SemSSXL: Semi Self-Supervised Xception Learner



Problem Statement-2

Designing a deep-learning based architecture to optimize features from the input image to enhance the classification

Research Questions

- **How the feature abstract affect classification performance?**
- **What is the optimal way to fuse features from transfer learning and encoder streams?**
- **How does the dual-stream architecture compare with single-stream approaches in terms of:**
  - **Classification accuracy**
  - **Feature representation quality**
  - **Model robustness**

Primary Objective:

1. Develop a novel dual-stream architecture combining feature optimization mechanisms with transfer learning.
2. Design an effective feature fusion strategy for various base models such as VGG, Xception, etc. and autoencoder streams.
3. Improve classification accuracy while maintaining model interpretability.

Secondary Objective:

1. Evaluate the contribution of each architectural component.
2. Compare performance with state-of-art architectures.
3. Assess model generalization across different datasets.

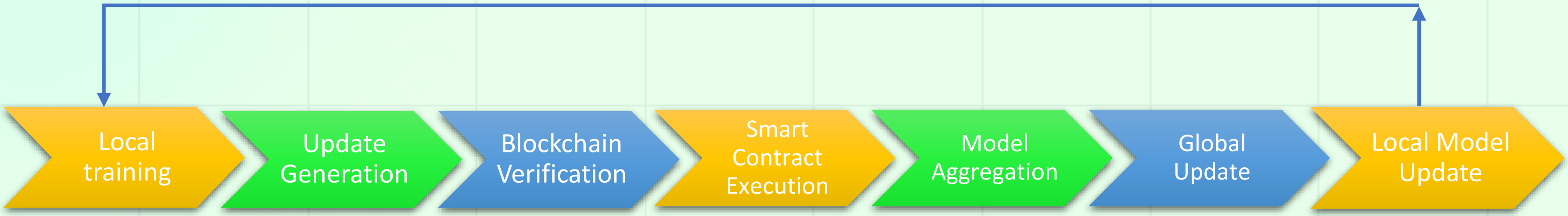
Problem Statement-3

Blockchain-Secured Federated Learning for Privacy-Preserving Multi-label Chest Disease Classification

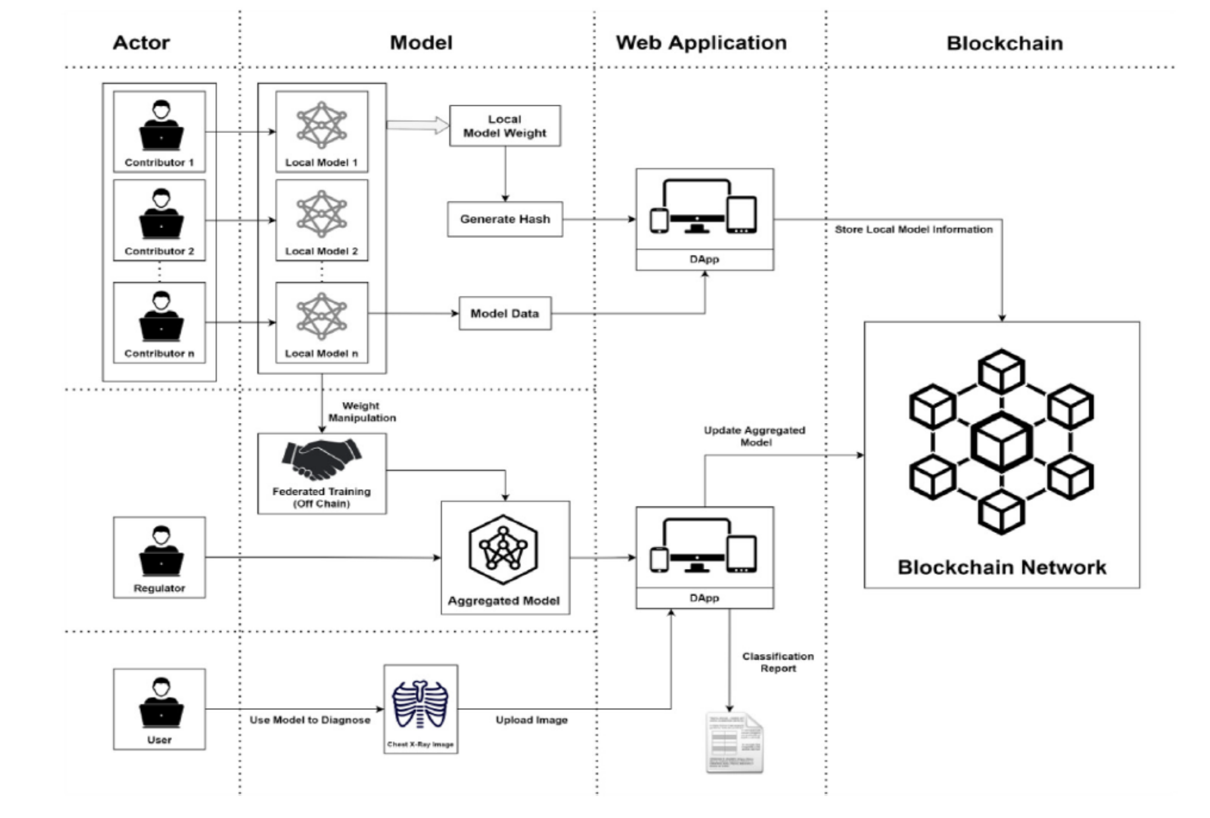
Research Questions

- How to ensure secure model aggregation across institutions?
- What consensus mechanisms are most suitable for medical imaging?
- How to validate model updates without compromising privacy?
- How to handle data heterogeneity across institutions?

Blockchain-Federated Learning Pipeline:



System Architecture



Ref [49]- Blockchain for medical collaboration: A federated learning-based approach for multi-class respiratory disease classification

Implementation Framework

Training Protocol

Local Training Phase	Blockchain Verification	Global Aggregation
• Data preparation • Model initialization • Local optimization • Update generation	• Update Submission • Smart contract execution • Consensus achievement • Reward distribution	• Update collection • Weighted averaging • Model verification • Distribution

Privacy Preservation

Data Privacy	Model Privacy
• Local data retention • Anonymization • Encryption	• Parameter Encryption • Secure Aggregation • Split learning

Evaluation Framework

Performance Metrics

Model Performance	System Metrics	Privacy Metrics
• Classification Accuracy • AUC-ROC Curve	• Communication overhead • Computational cost • Storage requirements	• Information leakage • Attack resistance • Compliance score

Expected Outcomes

Technical Achievements

Secure Framework	Performance Gains
• Privacy preservation • Model integrity • Audit capability • Compliance assurance	• Improved accuracy • Faster convergence • Better generalization • Reduced costs

Clinical Impact

Collaboration Benefits	Implementation Benefits
• Knowledge sharing • Resource Optimization • Larger Datasets • Better Models	• Privacy Compliance • Trust Enhancement • Cost Reduction • Scalability

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Thank You
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