McMaster University | ENGINEERING Computing & Software

CHESTLENS AI

Supervisor

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Project Motivation

- Currently, radiologists manually analyze chest X-ray images, which is time-consuming and has a possibility of errors.
- To help mitigate this issue, we implemented an AI model to identify six common findings on chest X-rays: Atelectasis, Cardiomegaly, Consolidation, Edema, No Finding, and Pleural Effusion.
- The main objective of using an AI model is to help radiologists detect negative results and pinpoint the presence and location of diseases through visual mapping.

Stakeholders

- Primary stakeholders are radiologists who diagnose and treat injuries and diseases using X-rays. The application aids them in identifying diseases and their locations on chest X-ray images through disease predictions and visual mapping.
- Indirect stakeholders include radiographers, hospital administrative staff, and patients, as the AI model's findings influence the patient's treatment journey based on chest X-ray results.

Expected Benefits

- The AI model can be used by radiologists to help confirm or identify any abnormalities, injuries, and diseases present in X-ray images.
- Having the assistance of an AI model will save radiologists time and save hospitals money and resources since the analysis process will be sped up and a diagnosis can be given to patients faster.

Tools & Resources Used

- Frontend: HTML, CSS, JavaScript, and Flask.
- Backend: PyTorch, TorchXrayVision, GradCam, and the MIMIC dataset.
  - ➢ The model training was done on the s3090a faculty server with, GPU: 2 x RTX 3090, CPU: Xeon w5-2455X @ 3.2 GHz, RAM: 128GB.

Key Testing Terms For The Graph & Table

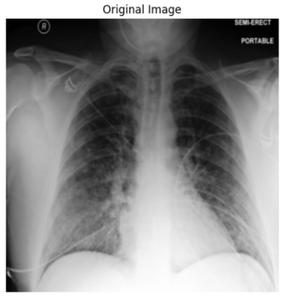
- **ROC:** This chart shows how well a model can tell the difference between two groups (like ”present" and "not present") by displaying its accuracy under various conditions.
- **AUC:** Measures the area under the ROC curve and it shows a model's ability to differentiate between categories. A higher value indicates a better performance.
- **Best Threshold:** This represents the optimal point for balancing true and false positives, enhancing model accuracy.
- **Precision:** This measures the accuracy of the model in correctly identifying "positive" cases, focusing on whether the model's "yes" answers are actually correct.
- **Recall:** This assesses the model's ability to capture all the "positive" cases, emphasizing the importance of not overlooking any "yes" instances.
- **F1 Score:** A metric that merges precision and recall, providing a single value that reflects the model's effectiveness in accurately identifying positives without missing any.

Single Image Test Results

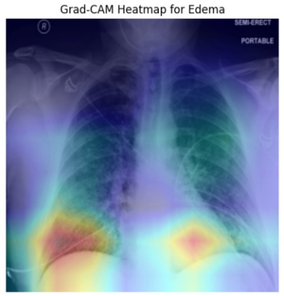
Disease	Model Output	Model Prediction	True Labels
Atelectasis	0.0307247	0	0
Cardiomegaly	0.120689	0	0
Consolidation	0.0190844	0	0
Edema	0.311531	1	1
No Finding	0.330405	0	0
Pleural Effusion	0.00501246	0	0

Our model calculates a score for each disease and compares this score with a specific threshold for each disease: if the score is above the threshold, it predicts that the disease is present (1); if below, it predicts absence (0). This process's effectiveness is shown in the table, where the model correctly identified Edema, matching its predictions with the true labels.

Original Image

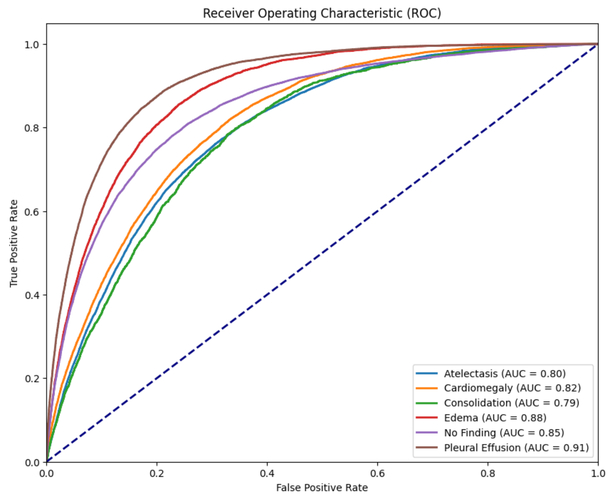


Grad-CAM Heatmap for Edema



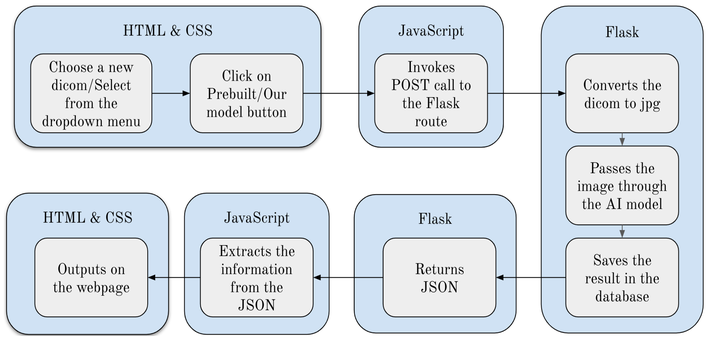
For each disease, an image with highlighting is produced. The highlighting for Edema is shown above and represents the areas of interest. The highlighting produced is verified by checking to see if it matches the areas of interest stated in the corresponding doctor's notes.

Model Testing Results

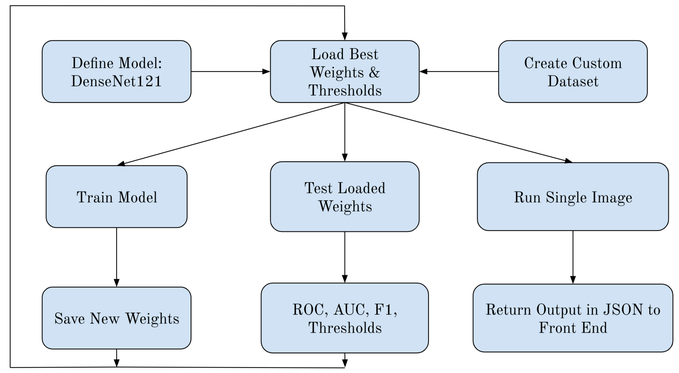


	Atelectasis	Cardiomegaly	Consolidation	Edema	No Finding	Pleural Effusion
AUC	0.7969	0.8154	0.7893	0.8831	0.8483	0.9110
Best Threshold	0.1711	0.1580	0.0385	0.0980	0.3500	0.1623
Precision	0.3395	0.3372	0.0837	0.2730	0.6581	0.5287
Recall	0.7731	0.8180	0.7979	0.8564	0.8095	0.8859
F1 Score	0.4718	0.4777	0.1515	0.4140	0.7260	0.6622

Frontend Workflow



Backend Workflow

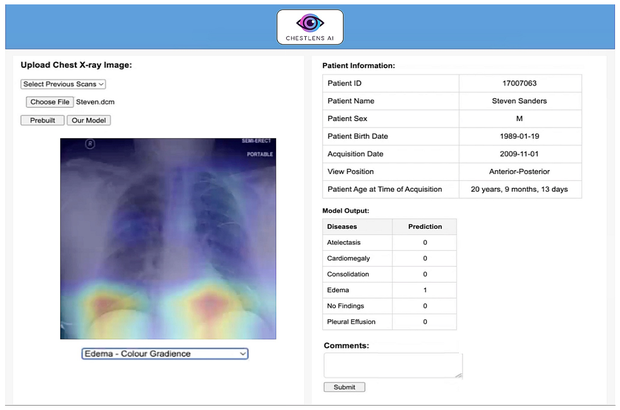


Frontend Website

This image shows our login page that users see when first accessing our frontend website.

S.No.	Patient ID	Name	More Info
1	00000003	Leno Branch	View
2	00000004	Kathrin Kassiopia	View
3	17007063	Steven Sanders	View

Upon entering the correct credentials, doctors will access a page displaying their patients, with the option to click "view" for each patient's file.



When selecting a patient file, doctors can view past scans via a dropdown menu, analyze images with prebuilt or custom models using designated buttons, and upload new scans for processing. Results and patient details appear alongside the image, with disease-specific highlighting available via a dropdown. Doctors can also add notes in the comment box.