

MAJOR PROJECT

**AI-Driven Chest X-ray Analysis for
Automated Disease Detection**

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PROBLEM OVERVIEW

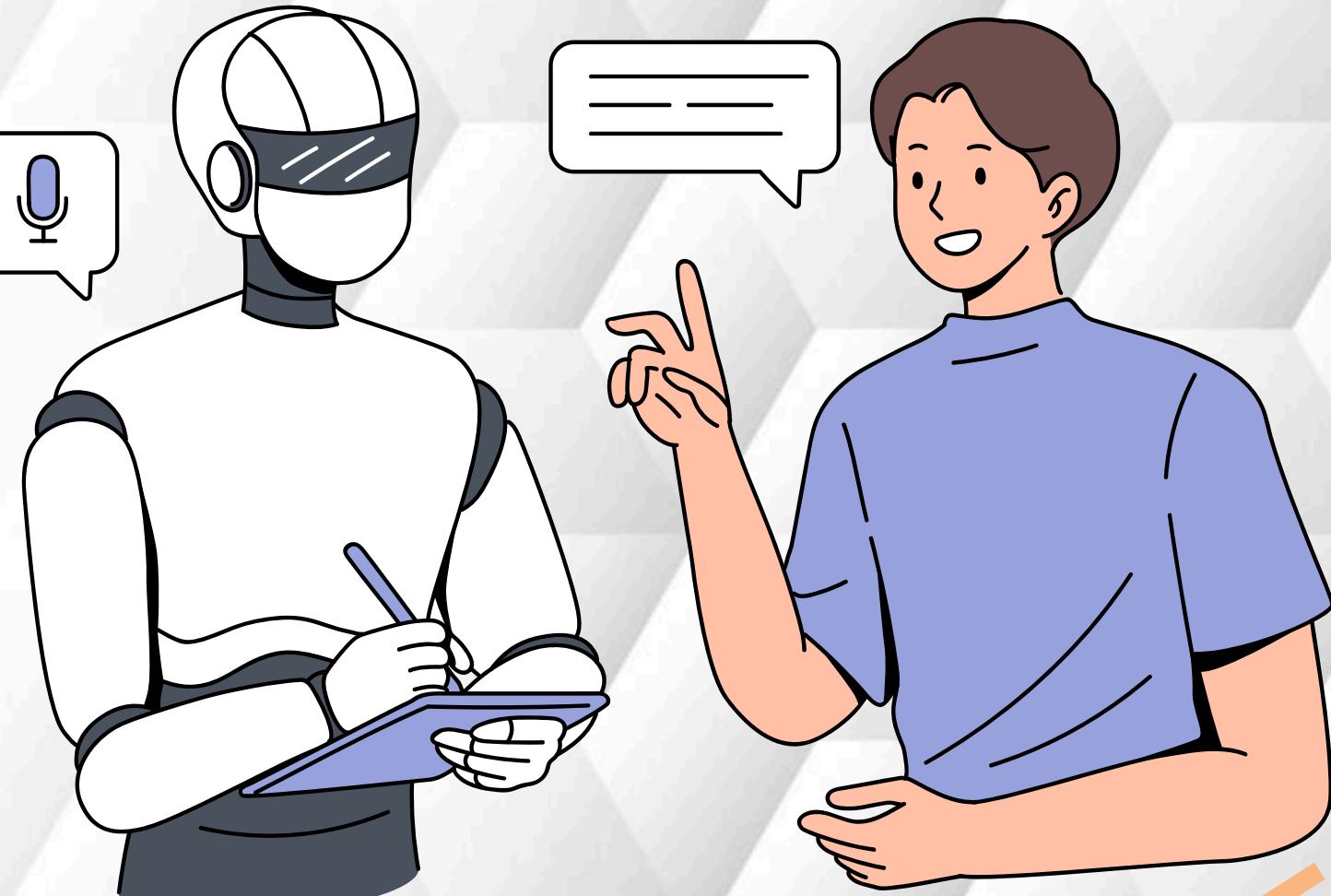
- Diagnosing lung conditions such as atelectasis, consolidation, and pneumothorax through X-ray imaging is challenging due to the complexities involved in interpretation and the high patient loads faced by healthcare facilities.
- This project aims to automate the detection of these conditions and generate preliminary reports, facilitating quicker and more accurate diagnoses for healthcare professionals.





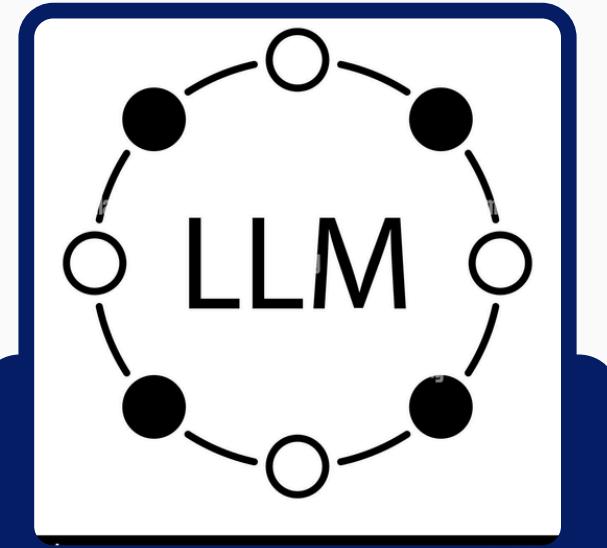
SCOPE OF THE PROJECT

- **Disease Classification:** Deep learning model identifies lung diseases from X-rays.
- **Report Generation:** RAG model provides diagnosis and treatment suggestions.
- **User Interface:** Simple platform for uploading X-rays and receiving results.





TECH STACK



LLM

An LLM processes and generates human-like text based on input data.



Tensorflow

Used for building and training deep learning models for image processing



Flask

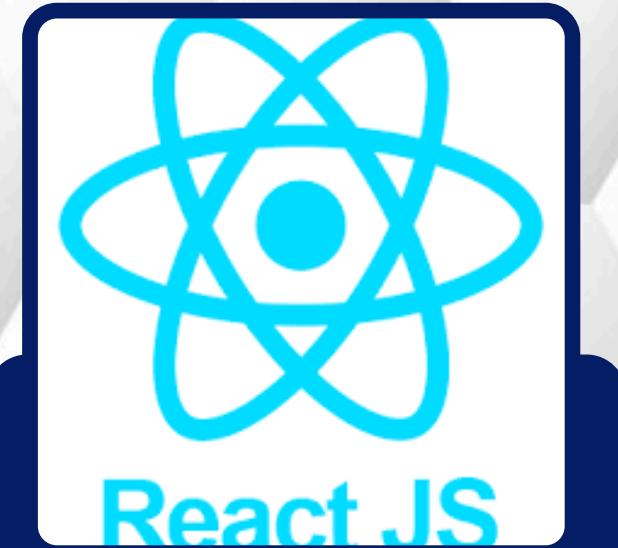
Flask is a lightweight web framework for Python for building backend-web applications.



Chroma

ChromaDB

ChromaDB is a vector database for querying high-dimensional embeddings.



React.Js

React is a JS library for building user interfaces with a component-based architecture.



Dataset

Field	Description
Image Index	File name
Finding Labels	Disease type (class label)
#Follow-up	Follow-up number
Patient ID	Unique patient identifier
Patient Age	Age of the patient
Patient Gender	Gender of the patient
View Position	X-ray orientation
OriginalImageWidth	
OriginalImageHeight	Image height (pixels)
OriginalImagePixelSpacing_x	Pixel spacing (X-axis)
OriginalImagePixelSpacing_y	Pixel spacing (Y-axis)

	Image Index	Finding Labels	Follow-up #	Patient ID	Patient Age	Patient Gender	View Position	OriginalImage[Width]	Height]	OriginalImagePixelSpacing[x	y]	Unnamed: 11
0	00000001_000.png	Cardiomegaly	0	1	58	M	PA	2682	2749	0.143	0.143	NaN
1	00000001_001.png	Cardiomegaly Emphysema	1	1	58	M	PA	2894	2729	0.143	0.143	NaN
2	00000001_002.png	Cardiomegaly Effusion	2	1	58	M	PA	2500	2048	0.168	0.168	NaN
3	00000002_000.png	No Finding	0	2	81	M	PA	2500	2048	0.171	0.171	NaN
4	00000003_000.png	Hernia	0	3	81	F	PA	2582	2991	0.143	0.143	NaN

and exit points

- The dataset contains X-ray images with metadata such as patient details (ID, age, gender) and image properties (dimensions, pixel spacing).
- Labels include lung disease types, follow-up information, and X-ray orientation, supporting classification tasks.



Preprocessed Dataset

- Column Consolidation:** Original image width and height are merged into a single column for better handling of image properties.
- Data Cleaning:** Missing or irrelevant entries (e.g., NaN values) are handled, and consistent labels for diseases are applied across the dataset.
- Pixel Spacing Adjustments:** Original image pixel spacing for X and Y axes is retained for accurate scaling during analysis.
- Path Field Inclusion:** File paths for each X-ray image are included to link the data to the corresponding images for easy access during training.

Image Index	Finding Labels	Follow-up #	Patient ID	Patient Age	Patient Gender	View Position	OriginalImage[Width Height]
601	00020826_009.png	Consolidation	9	20826	22	M	AP 3056 2544
211	00000583_001.png		1	583	38	F	PA 2500 2048
843	00005566_004.png	Atelectasis Infiltration	4	5566	85	M	PA 2500 2048



Handling Class Imbalance

- **Definition:** Data augmentation is a technique to increase the diversity of a training dataset by applying various transformations to existing images.
- **Purpose:** It helps improve model generalization and reduces overfitting by exposing the model to a wider range of data variations.
- **Common Techniques:** Includes transformations like flipping, rotation, shifting, zooming, and normalization.
- **Keras Implementation:** Use ImageDataGenerator for real-time augmentation during training, allowing parameters like horizontal flip, rotation range, and zoom range to be easily set.

```
from keras.preprocessing.image import ImageDataGenerator  
IMG_SIZE = (128, 128)  
core_idg = ImageDataGenerator(samplewise_center=True,  
                             samplewise_std_normalization=True,  
                             horizontal_flip=True,  
                             vertical_flip=False,  
                             height_shift_range=0.05,  
                             width_shift_range=0.1,  
                             rotation_range=5,  
                             shear_range=0.1,  
                             fill_mode='reflect',  
                             zoom_range=0.15)
```



Models and Results

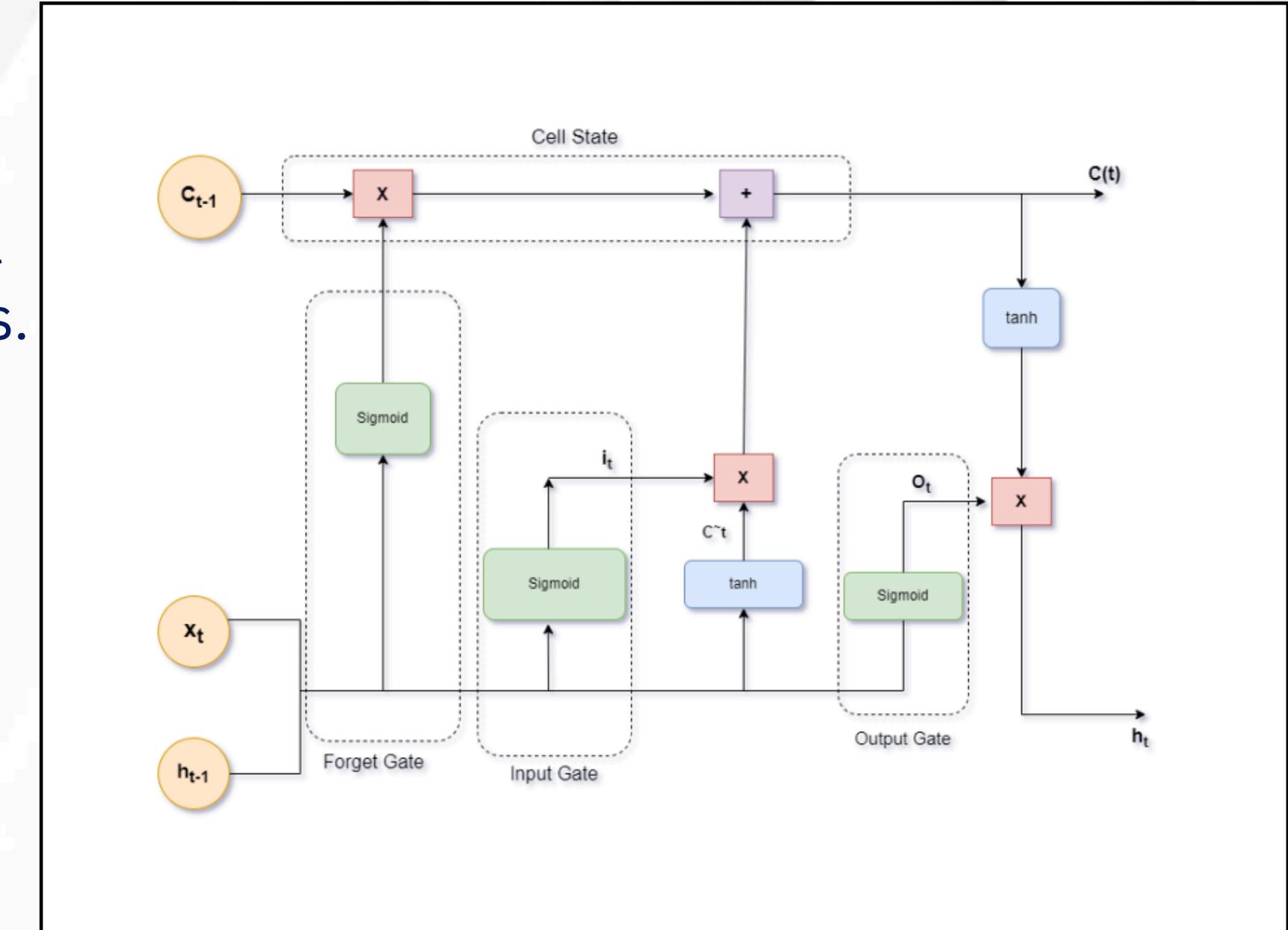
Model	Number of Parameters	Accuracy Score	Average ROC-AUC Score
mobilenet	3.3 Million	0.88	0.68
densenet	8 Million	0.85	0.72
Resnet-50	25 Million	0.9	0.74
VGG-16	138 Million	0.91	0.76
VGG-19	144 Million	0.92	0.75
efficientnet	66 Million	0.9	0.73
inception	24 Million	0.89	0.72



FINDINGS OF LITERATURE REVIEW

1. Long Short Term Memory

- Purpose:** Captures relationships between different medical conditions in chest X-rays.
- Feature Extraction:** Images are processed by a DenseNet encoder to extract relevant features.
- Prediction:** An LSTM decoder predicts the presence or absence of multiple diseases sequentially, one label at a time, based on previous label predictions.
- Dependency Modeling:** Helps model dependencies between conditions (e.g., if one disease is present, another might be likely).

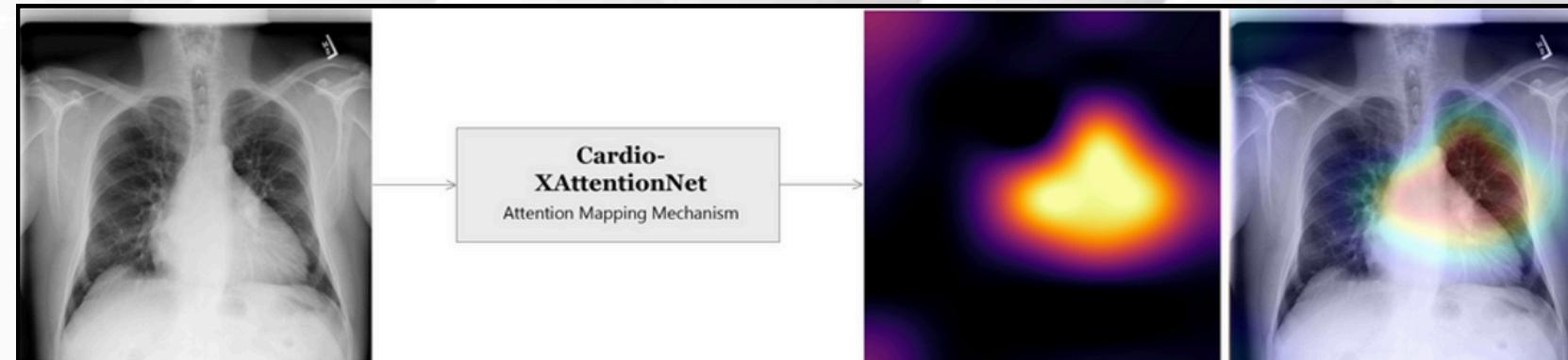




FINDINGS OF LITERATURE REVIEW

2. Class Activation Maps

- **Technique:** Class Activation Maps (CAM), specifically Grad-CAM, enhance interpretability of deep learning models for chest X-ray analysis.
- **Feature Processing:** A convolutional neural network (CNN) extracts features from the images.
- **Heatmap Visualization:** Grad-CAM generates heatmaps to highlight areas of abnormalities, aiding in localization of conditions like pneumonia.
- **Trustworthiness:** Provides visual explanations that enhance model trustworthiness and help validate predictions against expert assessments.

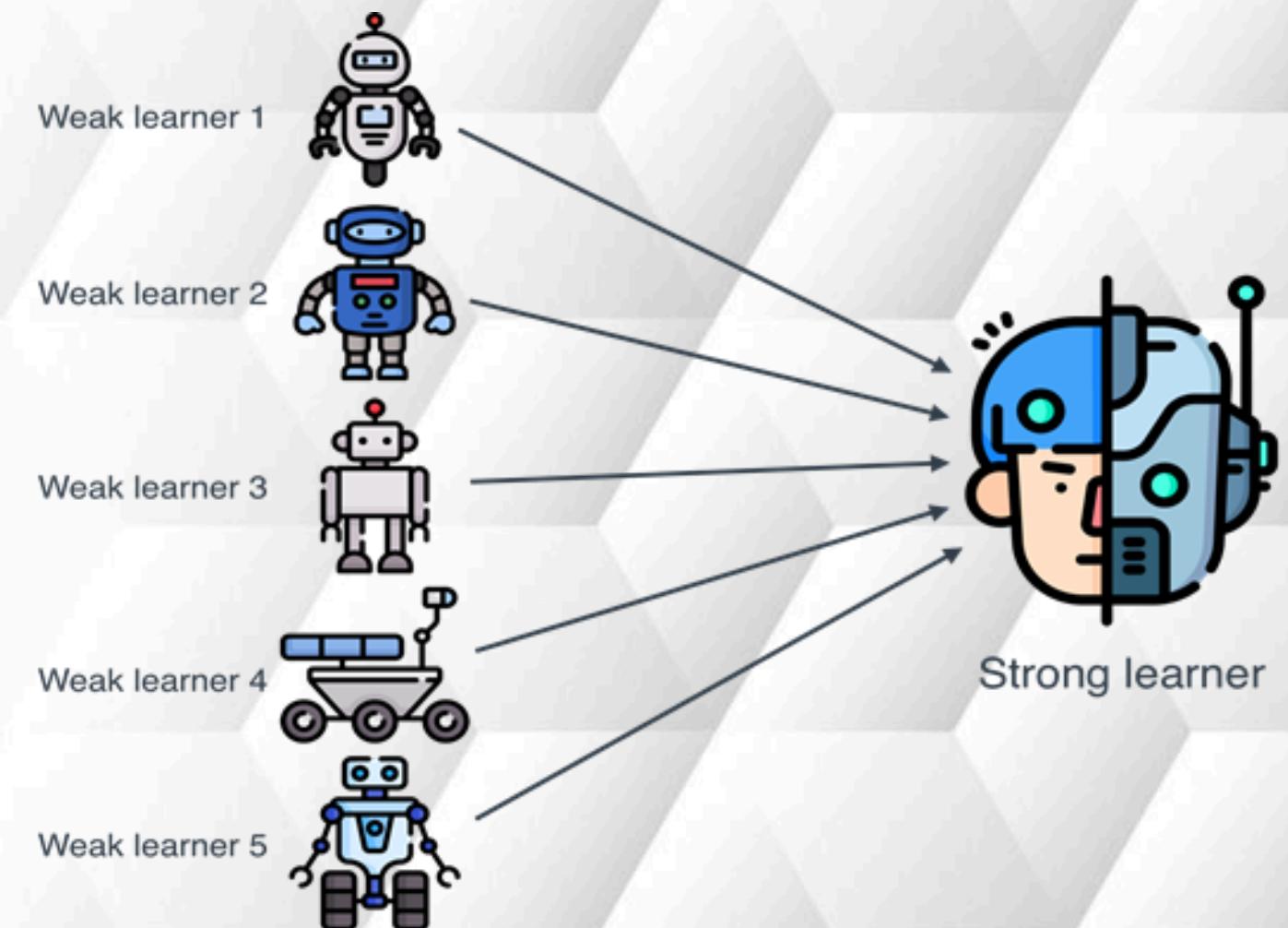




FINDINGS OF LITERATURE REVIEW

3. Ensemble Method

- **Purpose:** Improves accuracy of chest X-ray classification and disease localization by combining multiple pre-trained models.
- **Feature Extraction:** Uses deep learning models like ResNet, VGG, and AlexNet to extract relevant image features for disease detection.
- **Prediction:** Each model predicts the presence of multiple thoracic diseases, and their outputs are combined for better classification.
- **Localization:** Uses activation maps and pooling to generate heatmaps and localize disease areas in the X-ray images.





*Thank
You*