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AI-Enhanced Chest X-Ray Interpretation System with Comprehensive Clinical Report Generation

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Abstract- The demand for speedy and precise diagnostic instruments has increased due to the growth in healthcare demand worldwide. Among the most prominent imaging modalities for diagnosing ailments including lung cancer, pneumonia, and tuberculosis is a chest X-ray. However, the manual X-ray interpretation process is time-consuming, error-prone, and limited by the radiologists with the necessary qualifications. The purpose of this project is to construct an automated system that employs deep learning to evaluate chest X-rays and produce full, intelligible diagnostic reports. Convolutional neural networks (CNNs) are used in this technique to identify abnormalities in chest X-rays and convert the data into a structured report. The solution's speed, effectiveness, and dependability solve the problems with traditional diagnostic workflows.

I. INTRODUCTION

MedRad Innovators is a cutting-edge web-based platform that make use of computer vision and deep learning techniques to transform the medical radiology industry. The platform's primary goal is to diagnose 15 distinct chest illnesses from chest X-ray pictures including Cardiomegaly, Consolidation, Edema, Effusion, Emphysema, Fibrosis, Hernia, Infiltration, Mass, No Finding, Nodule, Pleural Thickening, Pneumonia, Pneumothorax, and Atelectasis. The system utilize a refined ResNet-18 deep learning model for image processing and is constructed with Django, a powerful Python-based web platform. The capability of MedRad Innovators to produce a heatmap overlay that emphasizes the region of interest (ROI) in the X-ray pictures. Radiologists can comprehend the model's decision-making process thanks to this heatmap's visual interpretability, allowing radiologists to understand the model's decision-making process. The platform also displays diagnostic probabilities for each condition, aiding medical professionals in making informed decisions.

II. LITERATURE REVIEW

A.K. Gupta et al. (2023) described a technique for identifying anomalies that combines CNNs and transfer learning with a pre-trained ResNet50 model.
A refined ResNet50 model was also employed by Wang et al. (2022), who achieved high anomaly detection accuracy (94.5%) despite limitations brought on by a short dataset.
CNNs were used to detect lung nodules by R.R. Singh et al. (2023), with encouraging precision and recall results.

III. PROBLEM STATEMENT

Radiologists face challenges in manually diagnosing chest X-rays due to the significant workload, the risk of human error, and a shortage of necessary resources of access to specialists, particularly in rural locations. The growing patient population causes delays in diagnosis, and weariness may lead to incorrect diagnoses, which could have detrimental effects. An AI-powered system that automates the procedure can be created to get around these obstacles. In order to ensure prompt and precise care, this system would be available to healthcare providers in both urban and rural areas, highlight significant regions in X-ray pictures for radiologists, and deliver rapid and accurate diagnoses.

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IV. PROPOSED SYSTEM

MedRad Innovators aims to tackle the limitations of existing systems by prioritizing key aspects such as cost-effectiveness, ease of understanding, adaptability, and user accessibility. The solution is inexpensive for healthcare providers and was developed with open-source tools like Django and PyTorch, guaranteeing wider adoption. By highlighting areas of interest with a heatmap overlay, it improves interpretability and makes the model's predictions simpler to comprehend. Additionally, the system is quite adaptable, which enables it to be tailored for certain datasets or medical settings. Furthermore, its web-based platform guarantees browser accessibility, allowing healthcare providers in both urban and rural locations to take advantage of the system

V. METHODOLOGY

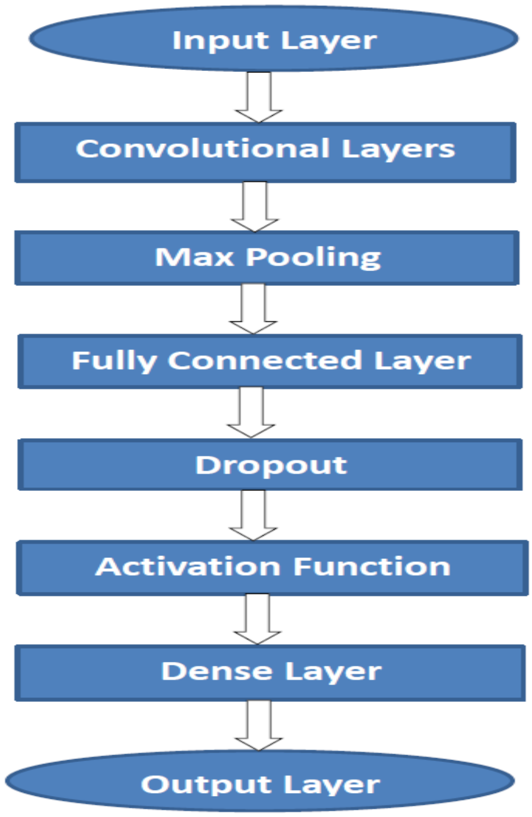

Fig 1: Methodology

The methodology consists of the following way :

1. Input Layer: Accepts chest X-ray images with dimensions of 312x312 pixels, which undergo normalization and preprocessing prior to being introduced into the model.
2. Convolutional Layer: Uses filters to identify patterns like edges, textures, and shapes in the images.
3. Max Pooling: Lowers the feature maps' spatial dimensions, increasing computing effectiveness and minimizing overfitting.
4. Fully Connected Layer: outputs probabilities for each of the 15 chest situations after combining the information that the convolutional layers have collected.
5. Dropout: Encourages the model to acquire more robust features by randomly removing units during training, preventing overfitting.
6. Activation Function: Softmax is employed in the output layer to generate probabilities, and ReLU is utilized in hidden layers to add non-linearity.
7. Dense Layer: The extracted features are mapped to the next layer via the dense layers.
8. Output Layer: Produces the final probabilities for all of the 15 chest conditions.

VI. EXPERIMENTAL RESULT

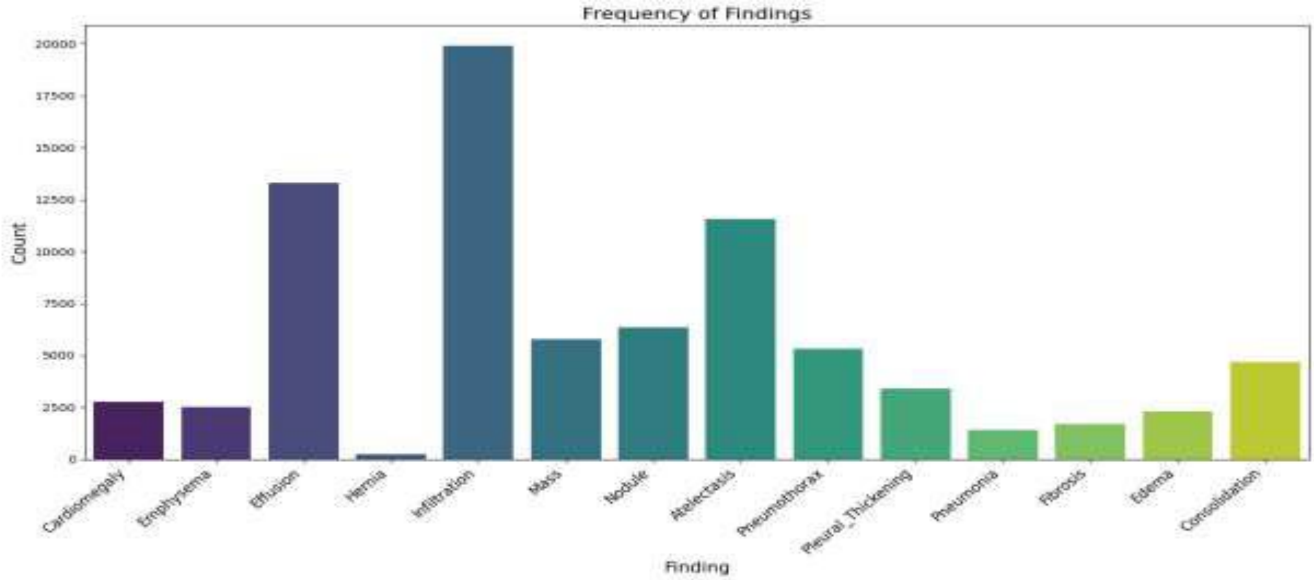

Fig 2: Frequency of findings

The frequency of various findings in a dataset of (presumably) chest X-ray reports is displayed in this bar chart. This is a summary:

- Horizontal X-axis: Finding: Enumerates the different findings, including emphysema, diffusion, cardiomegaly, etc. These are probably anomalies or findings from the X-ray pictures.
- Y-axis (Vertical): Count: Indicates how frequently each finding occurs in the dataset. The more common the finding, the higher the bar.

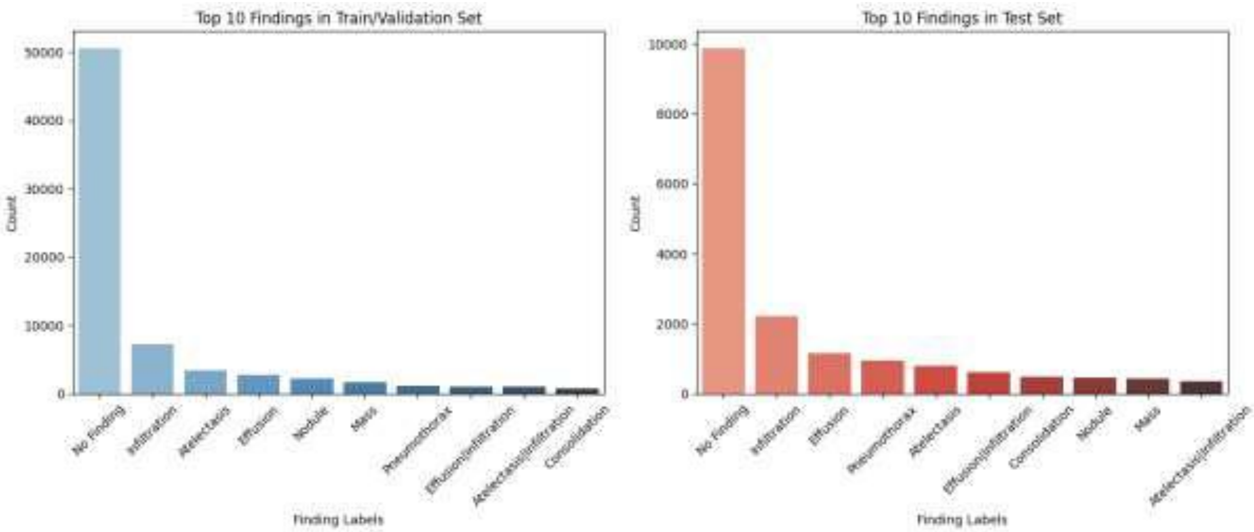

Fig 3: Finding Labels

The dataset is divided into three segments:

- Training Set (70%): The model is trained using this set.
- Validation Set (15%): Used to track overfitting and adjust hyperparameters.
- The test set (15%) is used to assess how well the model performs on data that hasn't been seen yet.

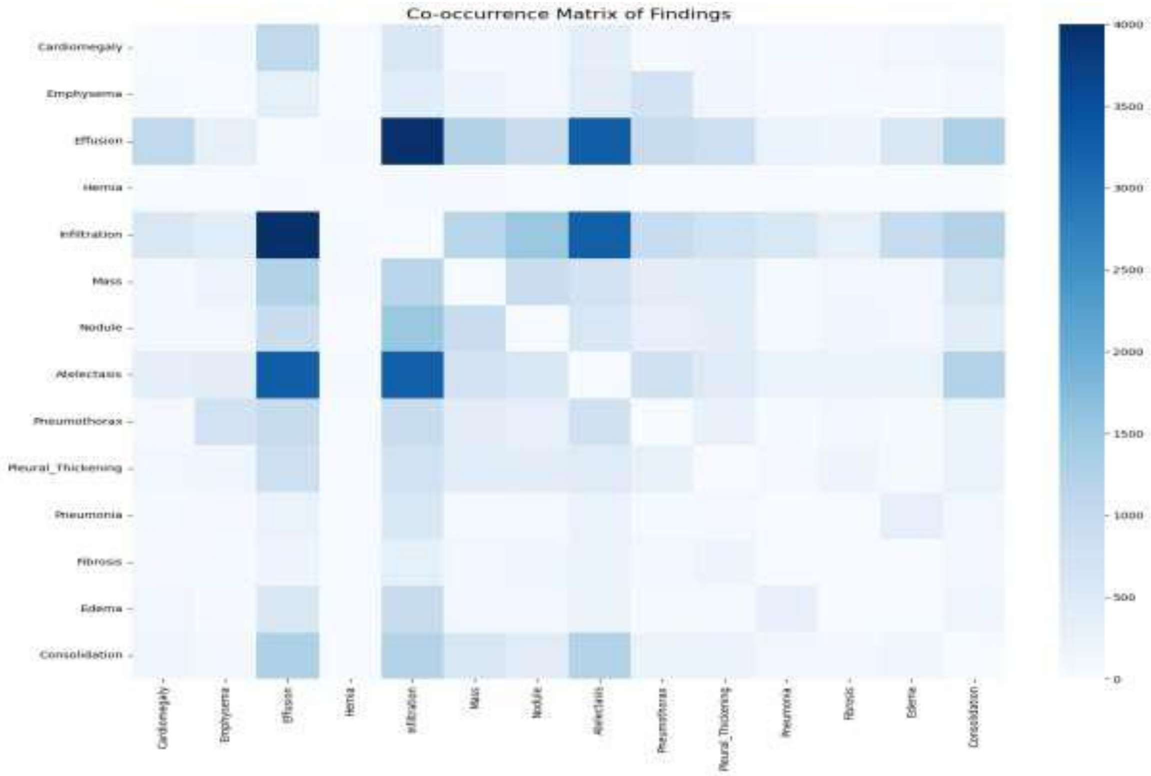

Fig 4: Co-occurrence Matrix of Findings

This heatmap visualization of a co-occurrence matrix illustrates the connections between several data, most likely from chest X-ray records.

- X-axis (Horizontal): Findings: This displays the various findings, such as effusion, emphysema, and cardiomyopathy. The same results are listed on the
- Y-axis (Vertical): Findings.

VII. CONCLUSION

Using deep learning techniques, the MedRad Innovators project successfully created a web-based platform for diagnosing chest X-ray pictures. 15 distinct chest conditions, such as atelectasis, cardiomegaly, diffusion, emphysema, nodule, pleural thickening, pneumonia, and pneumothorax etc.. can be diagnosed by the system using a refined ResNet-18 model.

VIII. REFERENCES

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