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DATA 606 Capstone in Data Science

Title: Multimodal Patient Prognosis System: Integrating EHR, Clinical Notes, and Chest X-Rays for Enhanced ICU Outcome Prediction

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INTRODUCTION

What: A system that predicts patient outcomes (mortality) by combining three data types: Structured EHR, Clinical Notes (NLP), and Chest X-rays (CV).

Why: Early intervention saves lives and gives better treatment sollutions. Most of the system use one modality, whereas we are gonna use multimodal approach which gives more accurate & holistic prediction

Research Question: Can a multimodal deep learning model improve ICU mortality prediction compared to single-modality models?

LITERATURE REVIEW

Study A (Image-only): CheXNet (Rajpurkar et al.) uses DenseNet-121 to detect pneumonia from X-rays with high accuracy.

Study B (EHR-only): Many studies use gradient boosting (XGBoost) on MIMIC-III data to predict mortality.

Study C (Multimodal - Text & EHR): Some recent papers combine clinical notes using BERT with structured data.

DATASET-OVERVIEW

- **Source:** NIH Chest X-ray14 https://www.kaggle.com/datasets/nih-chest-xrays/data -

- **Size:** 112,120 images, 30,805 patients

- **Labels:** 14 thoracic diseases (multi-label)

- **Use in Project:** Extract image features for prognosis model

- **Note:** Linking to mortality is difficult → may use disease features as proxy.

METHODOLOGY

1. Preprocessing: resize images, normalize pixels, augment data, split by patient ID

2. Baseline Models: CNN (DenseNet121, ResNet50), XGBoost for tabular

3. Fusion Model: late fusion (concatenate embeddings + features → fully connected layer → sigmoid outputs)

4. Evaluation: ROC-AUC, F1-score, precision/recall, ablation (image-only vs multimodal)

5. Explainability: Grad-CAM heatmaps, SHAP feature importance

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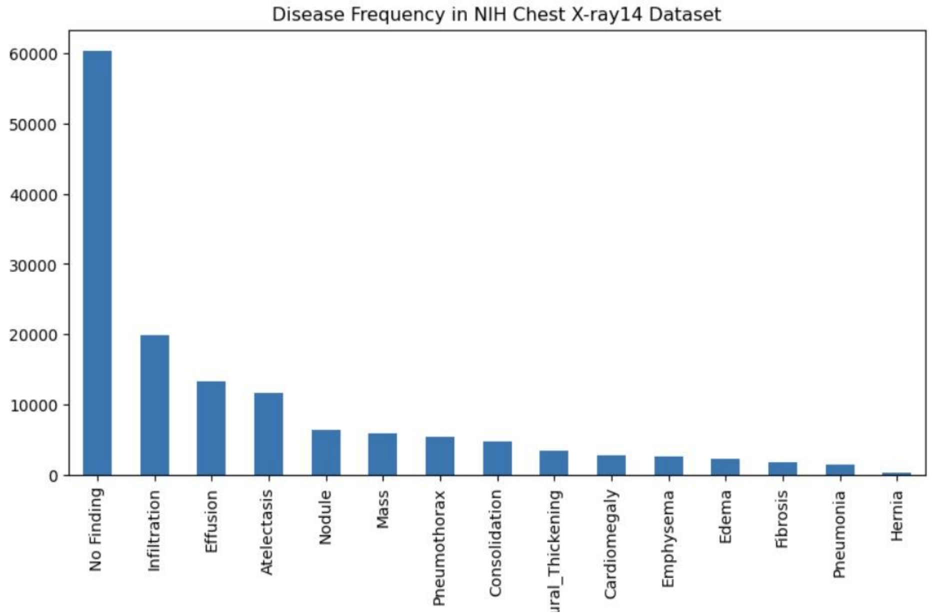
Exploratory Data Analysis (EDA)

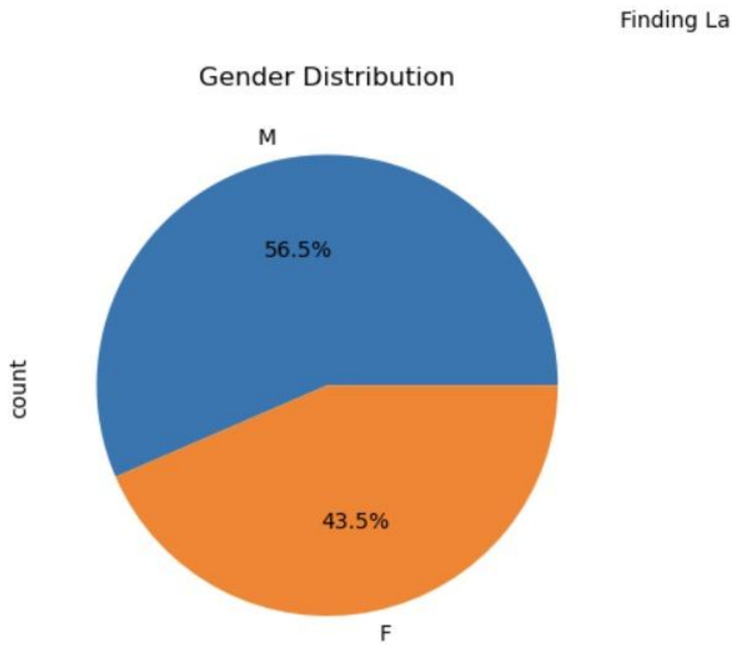
Dataset insights:

- Class imbalance: “No Finding” \~60k images vs. rare diseases (<2k each).
- Patient demographics: age distribution (infants to elderly), gender split.
- Label co-occurrence: many patients have multiple diagnoses.

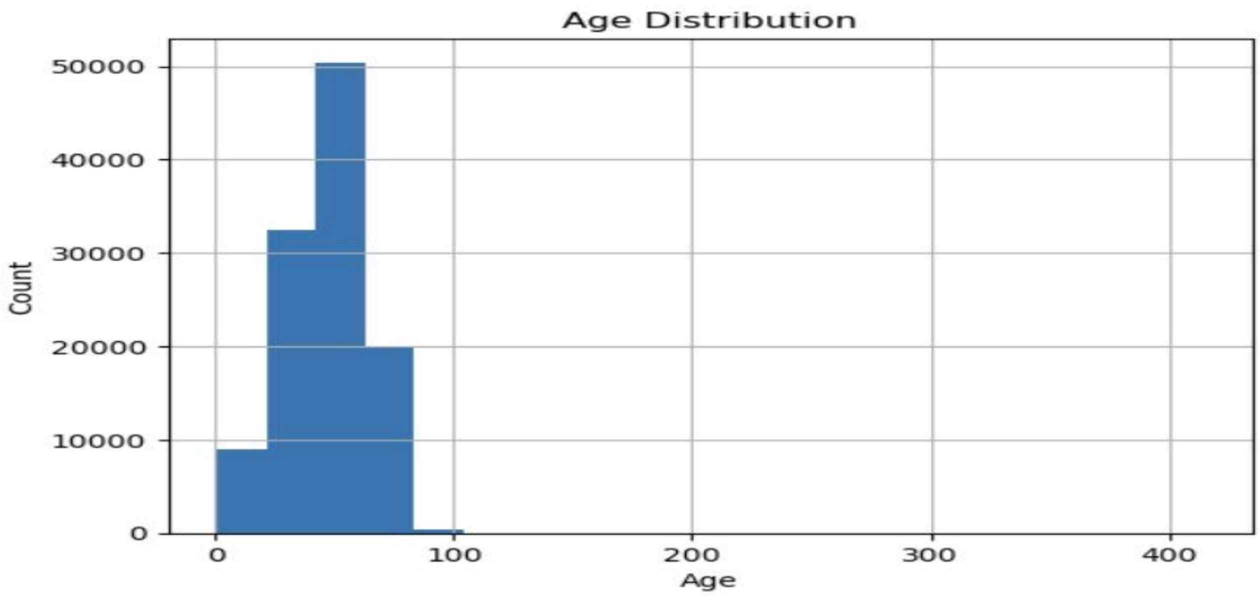
Bar chart of disease frequency



Pie chart of gender distribution

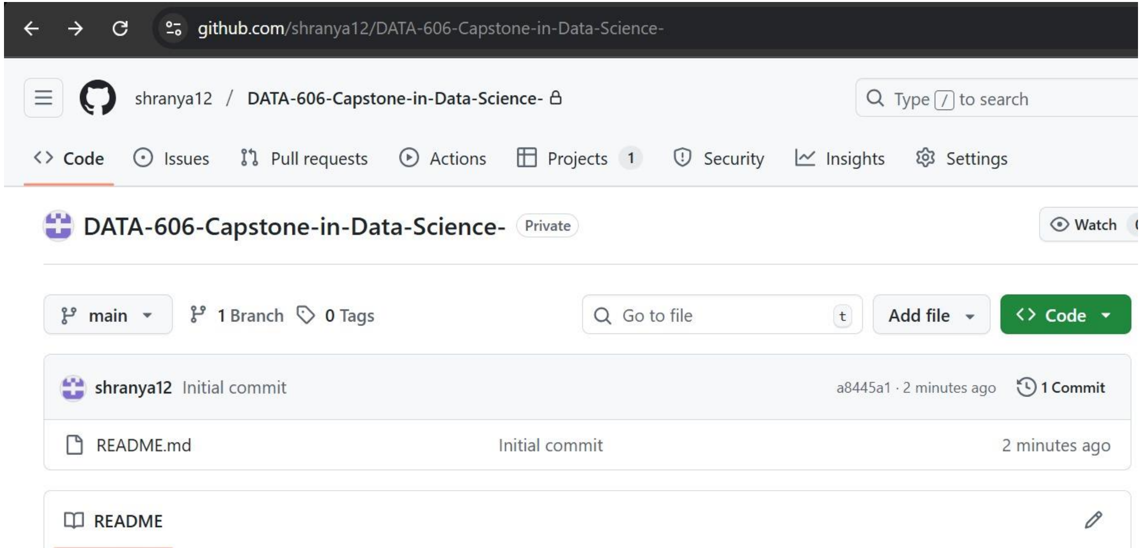


Histogram of patient age



GIT-HUB

https://github.com/shranya12/DATA-606-Capstone-in-Data-Science-



EXPECTED OUTCOMES

- Demonstrate classification performance close to state-of-the-art
- Show improvement using multimodal fusion
- Provide visual and interpretable explanations for predictions
- Deliver deployable API for inference

REFRENCES

1. Wang et al., ChestX-ray8: Hospital-Scale Chest X-ray Database (NIH, 2017)
2. Rajpurkar et al., CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning (Stanford, 2017)
3. Irvin et al., CheXpert: A Large Chest Radiograph Dataset with Uncertainty Labels (2019)
4. NIH ChestX-ray14 official dataset documentation

THANK YOU