

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 solutions. 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

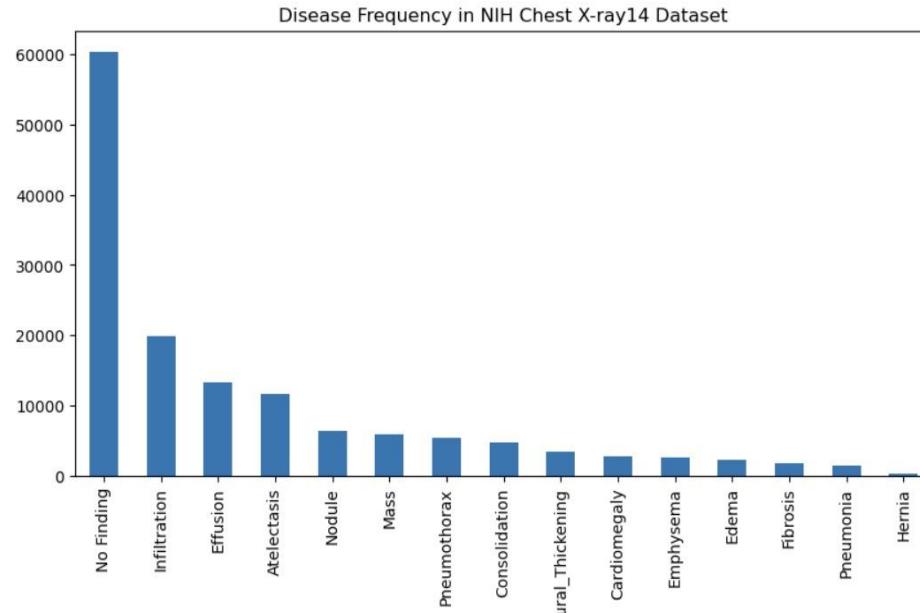
1. Preprocessing: resize images, normalize pixels, augment data, split by patient ID
2. Baseline Models: CNN (DenseNet121, ResNet50), XGBoost for tabular
3. Fusion Model: late fusion (concatenate embeddings + features → fully connected layer → sigmoid outputs)
4. Evaluation: ROC-AUC, F1-score, precision/recall, ablation (image-only vs multimodal)
5. Explainability: Grad-CAM heatmaps, SHAP feature importance

Exploratory Data Analysis (EDA)

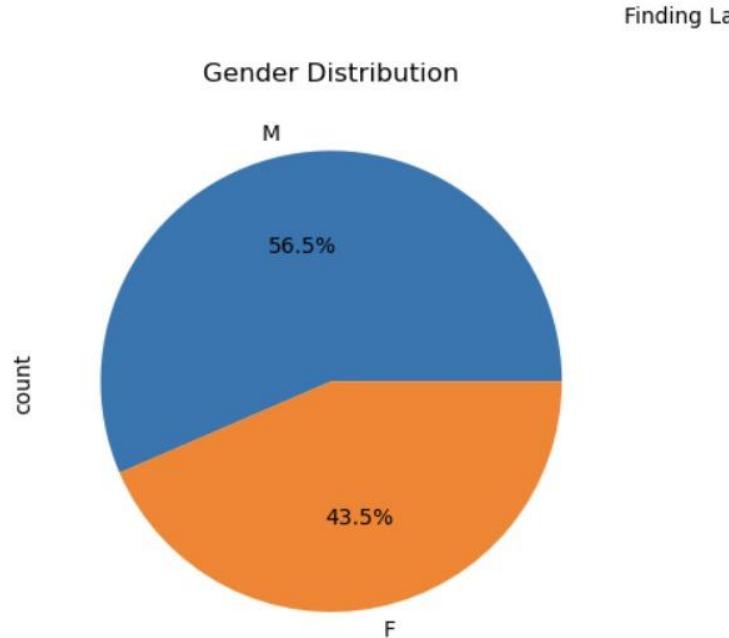
Dataset insights:

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

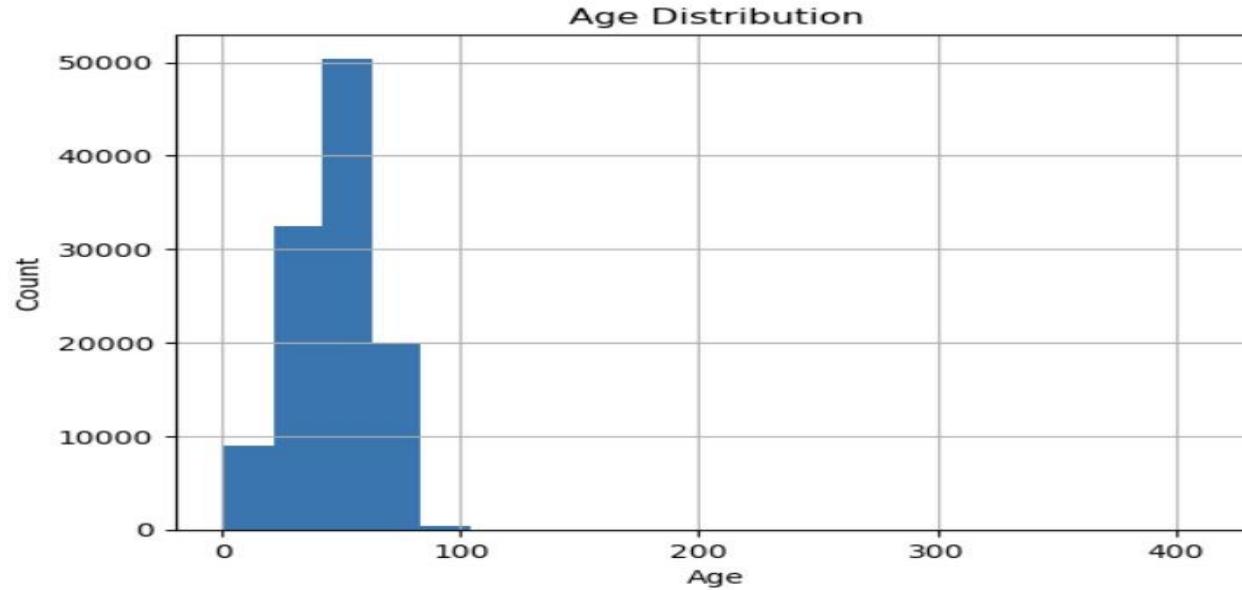
Bar chart of disease frequency



Pie chart of gender distribution

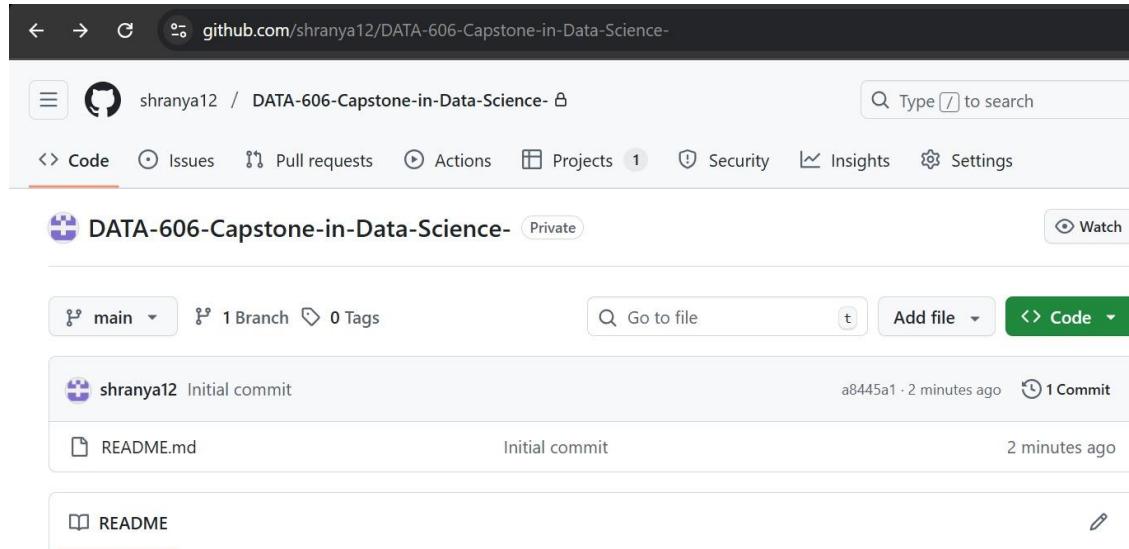


Histogram of patient age



GIT-HUB

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



The screenshot shows a GitHub repository page. At the top, there is a navigation bar with back, forward, and search icons, followed by the URL "github.com/shranya12/DATA-606-Capstone-in-Data-Science-". Below the URL is a header with a user icon, the username "shranya12", the repository name "DATA-606-Capstone-in-Data-Science-", and a search bar. A sidebar on the left contains links for Code, Issues, Pull requests, Actions, Projects (1), Security, Insights, and Settings. The main content area shows the repository details: "DATA-606-Capstone-in-Data-Science-" (Private), a "Watch" button, and a "Code" dropdown menu. Below this, it shows "main" branch, 1 Branch, 0 Tags, a "Go to file" search bar, an "Add file" button, and another "Code" dropdown menu. A commit history is listed, showing an "Initial commit" by "shranya12" at "a8445a1 · 2 minutes ago" with "1 Commit". A file named "README.md" is shown with its "Initial commit" at "2 minutes ago". At the bottom, there is a "README" section with a pencil icon for editing.

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

REFERENCES

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