Predicting 30-Day Hospital Readmissions Using Attention-Based Deep Learning and Explainable AI on Clinical Discharge Summaries

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https://github.com/ShravyaD-coder/30-Day-Readmission-XAI.git

Introduction

Hospital readmissions within 30 days affect one in five Medicare beneficiaries and cost over $26 billion annually. Current prediction models rely on structured data and overlook rich clinical narratives in discharge summaries that contain modifiable risk factors. While MIMIC-III has been widely used for readmission prediction research, MIMIC-IV clinical notes remain underexplored.

Objectives

To develop and validate an attention-based deep learning model that predicts 30-day hospital readmissions directly from discharge summaries, with explainable AI techniques to identify clinically relevant risk factors

Materials

- **Data**

MIMIC-IV Note: Deidentified free-text clinical notes from patients at the Beth Israel Deaconess Medical Center in Boston. Contains **331,794** de-identified **discharge summaries** from **145,915 patients**

MIMIC-IV Hospital: Contains **546,028** unique **hospitalizations** for **223,452** unique **individuals** admitted to the BIDMC emergency department.

- **Pre-processing**

Data Integration: Merged clinical notes with hospital admission records by patient ID

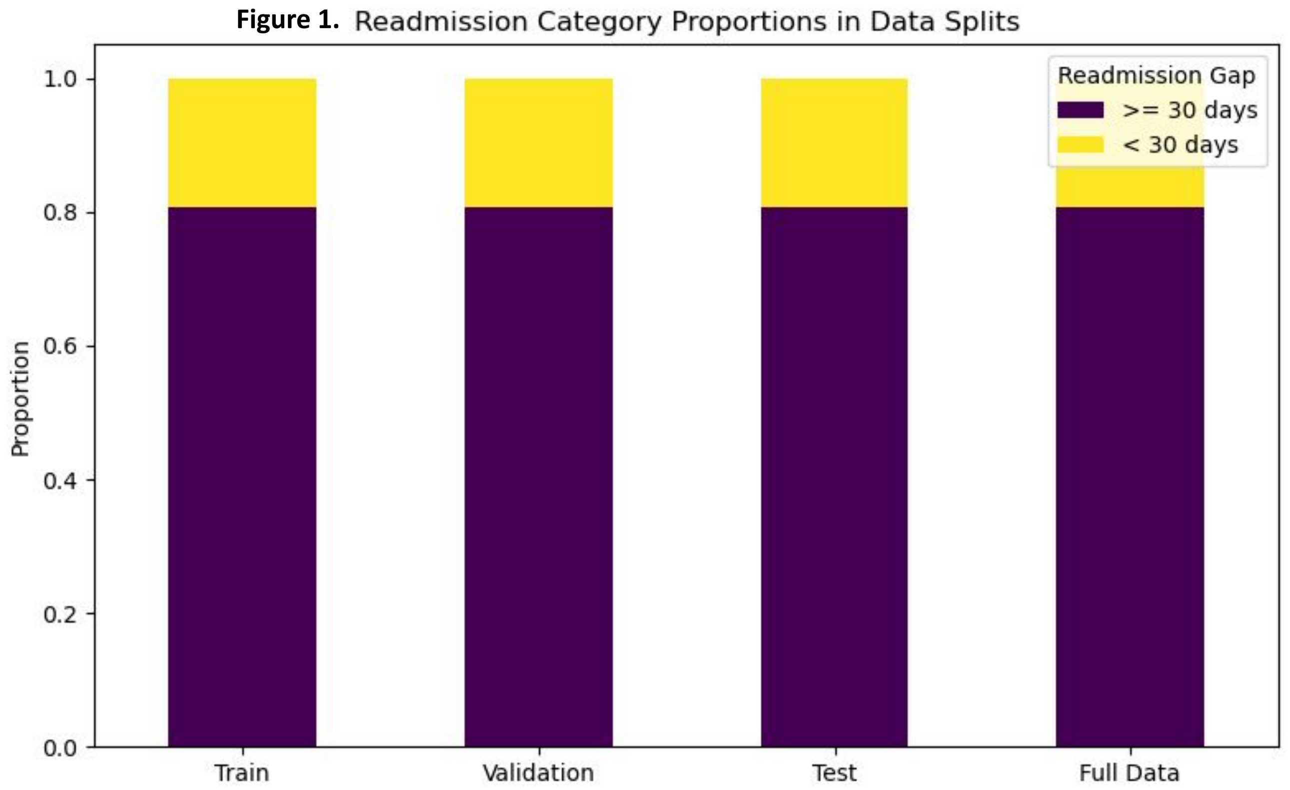
Outcome Definition: Calculated 30-day readmission from discharge-to-admission dates; excluded deaths and missing dates

Text Cleaning: Removed extra whitespace, special characters, and de-identified artifacts

Data Split: Patient-level grouping with stratified split (**Train: 72%, Validation: 8%, Test: 20%**) to prevent data leakage and maintain readmission proportion across sets

Training Comparison: 10% subset (3 epochs) vs. full dataset (1 epoch

Figure 1. Readmission Category Proportions in Data Splits



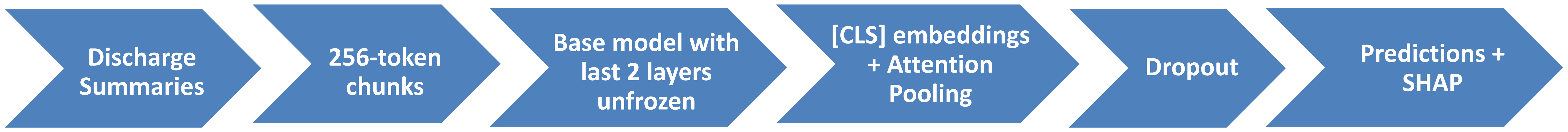
- **Model Architecture:**

Base Model: BioClinicalBERT, a BERT model trained on PubMed articles and the entirety of MIMIC-III notes

- **Evaluation Metrics:**

AUPRC, AUROC, Accuracy

Methodology



Results

```
Readmission Probability: 77.3%
Prediction: Readmitted

[Chunk 4] Attention Weight: 0.428
--------------------------------------------------------------------------------
---
##ine hcl 100 mg tablet sig: one (1) tablet po daily (daily). 2. folic acid 1
mg tablet sig: one (1) tablet po daily (daily). 3. amitriptyline
... (truncated)

[Chunk 3] Attention Weight: 0.273
--------------------------------------------------------------------------------
---
##bral compression fracture. brief hospital course: abdominal distention /
pain: she was treated empirically due to concern for spontaneous bacterial
peritonitis with ceftriaxone 2g x 1. a diagnostic paracentesis was performed
... (truncated)

[Chunk 1] Attention Weight: 0.242
--------------------------------------------------------------------------------
---
history of present illness : with recently diagnosed alcoholic hepatitis,
persistent ascites, and persistent fevers and leukocytosis which have been
atributed to her hepatitis who presented to today with worsening abdominal
distention, pain, and persistent fever. she denies
... (truncated)
```

Figure 2: Chunks of note having the highest attention weight contributing to high probability of readmission

Table 1: Performance Comparison of 2 fine-tuning approaches

Metric	10% Data (3 Epochs)	Full Data (1 Epoch)
AUROC	0.692	0.730
AUPRC	0.372	0.415
Accuracy	64%	73%

```
Top chunks INCREASING readmission risk (positive SHAP):

1. SHAP: +0.288
   ##ine hcl 100 mg tablet sig : one ( 1 ) tablet po daily ( daily ). 2. folic acid 1 mg tablet sig : one ( 1 ) tablet

2. SHAP: +0.274
   ##bral compression fracture. brief hospital course : abdominal distention / pain : she was treated empirically due

3. SHAP: +0.187
   name :. service : medicine patient recorded as having no known allergies to drugs chief complaint : abdominal diste
```

Figure 3: SHAP on the high attention weight chunks to see how they contribute to readmission prediction

Conclusion, Limitations and Future Work

- **Conclusion:** The attention-based model achieves AUROC 0.730 with interpretable predictions, identifying specific discharge summary sections containing modifiable risk factors
- **Key-Takeaways:** Training on full data for 1 epoch outperformed 10% data for 3 epochs, demonstrating that data quantity is more impactful than additional training epochs for this task
- **Limitations:** Since the data was collected from a single center, it limits the scope of generalizability of our data and the high class imbalance impacts our precision negatively
- **Future Work:** With the availability of sufficient computing resources, the entire dataset will be used for analysis and if possible, clinical notes from different medical centers will be used for evaluation to test generizabilty of the approach

Acknowledgement and Contact

I gratefully acknowledge the MIMIC-IV database provided by the MIT Laboratory for Computational Physiology, Beth Israel Deaconess Medical Center, and PhysioNet, which made this research possible. I thank Griffith Hughes for his invaluable guidance and support throughout this project. I am deeply grateful to The Tensor Lab for Computational Medicine for providing this research opportunity and fellowship support.