AUA American University of Armenia

Multimodal Deep Learning for Cardiac Diagnostics

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Problem & Motivation

- Cardiovascular diseases are the leading cause of death globally (32%) and in Armenia (54%).
- Diagnostics are often single-modality.
- Multimodal learning = a path to early & accurate diagnosis

Challenge

Designing an architecture capable of handling and integrating multiple input modalities.

Goal

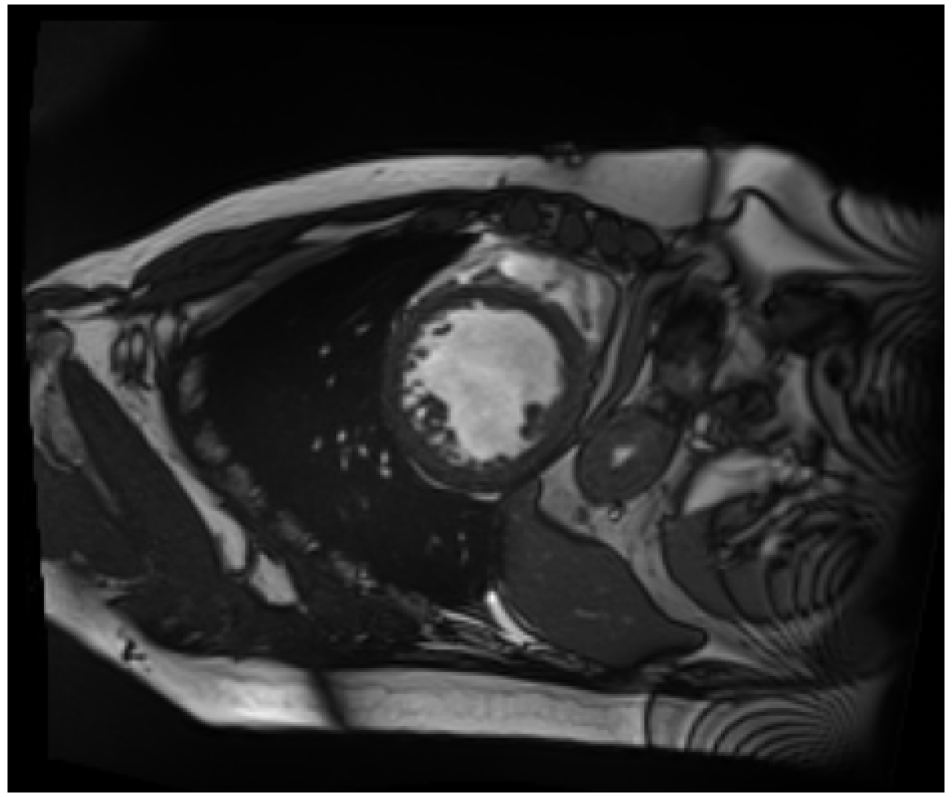
Develop such a multimodal architecture and explore its performance in cardiac disease classification.

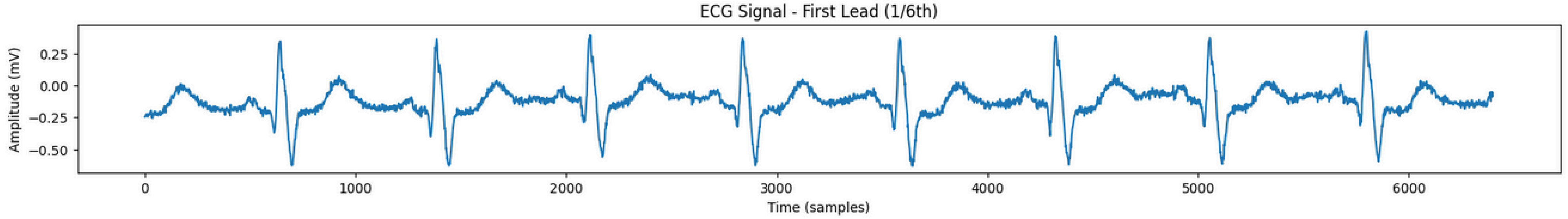
Data Overview

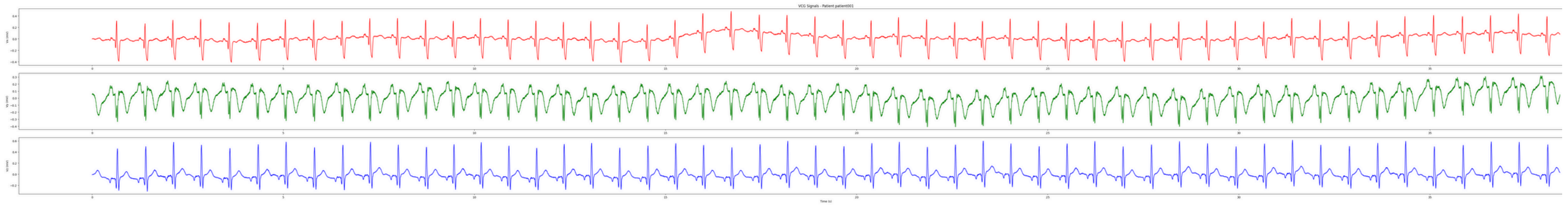
Three Modalities:

- ECG (signal-based, from PhysioNet/PTB) - 294 records
- MRI (3D imaging data from ACDC dataset) - 150 records
- Metadata (age, sex, smoking habits, etc.)

Patient: patient001 - Slice 5

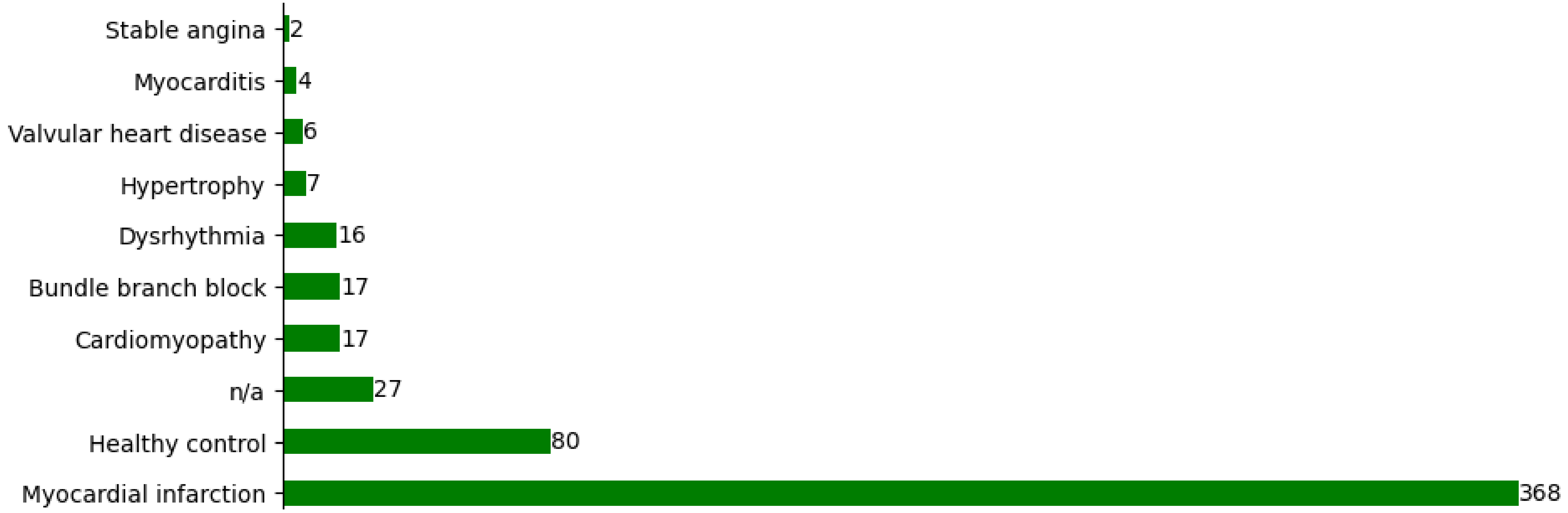






Data Overview

- MRI dataset: Balanced – equal number of samples across all categories.
- ECG dataset: Imbalanced – some diagnoses significantly underrepresented.



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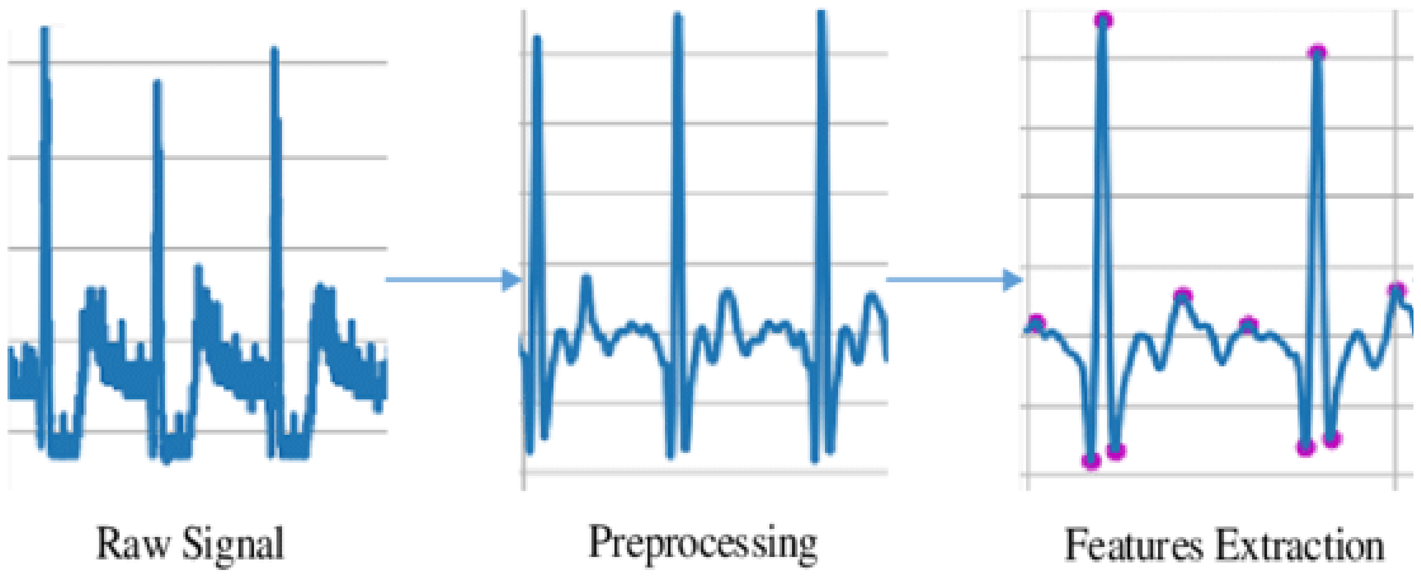
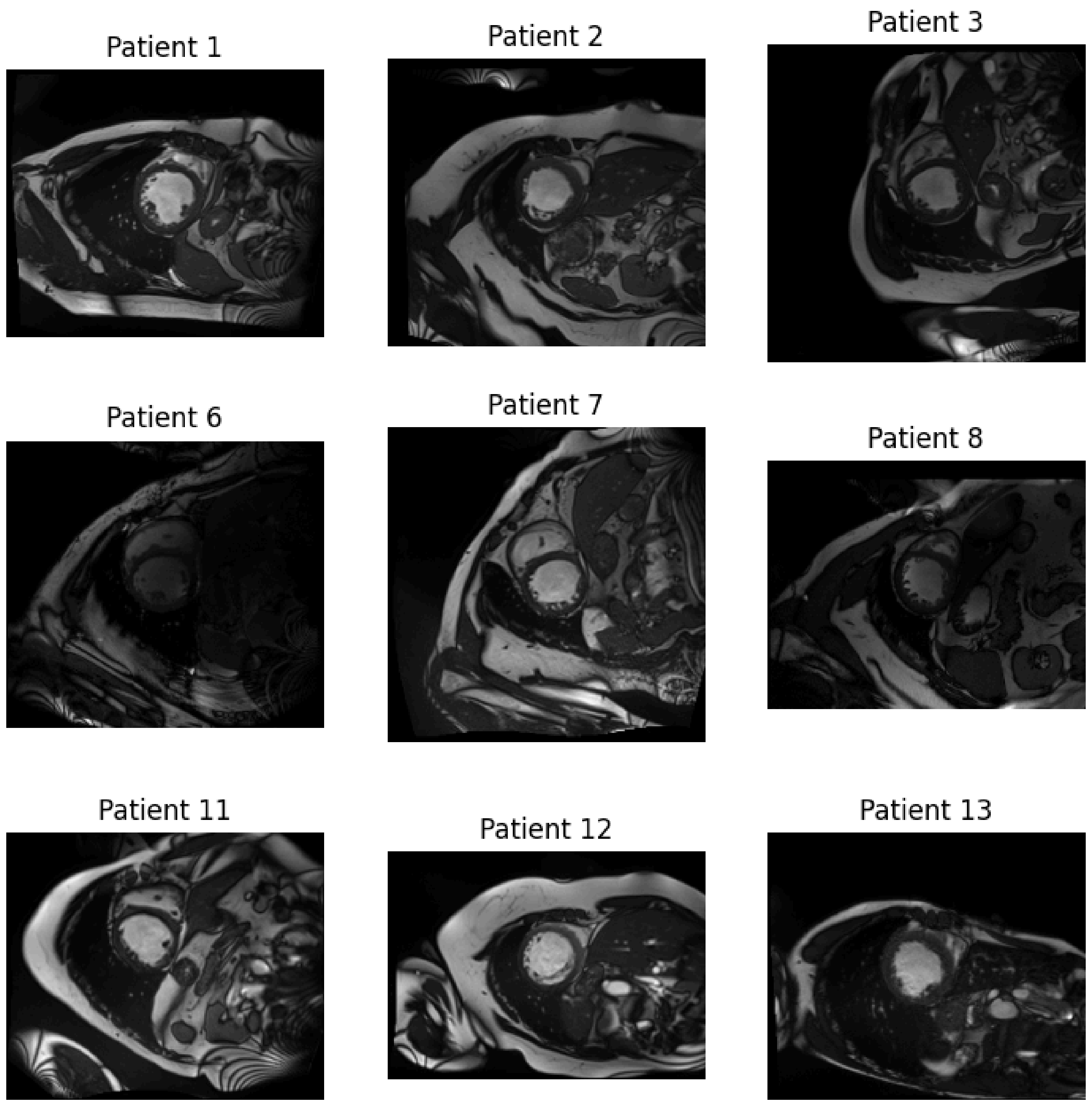
Data Preprocessing

- **ECG**: filtering, downsampling, z-normalization
- **MRI**: rescaling, normalization, interpolation to fixed shape
- **Metadata**: label encoding, normalization





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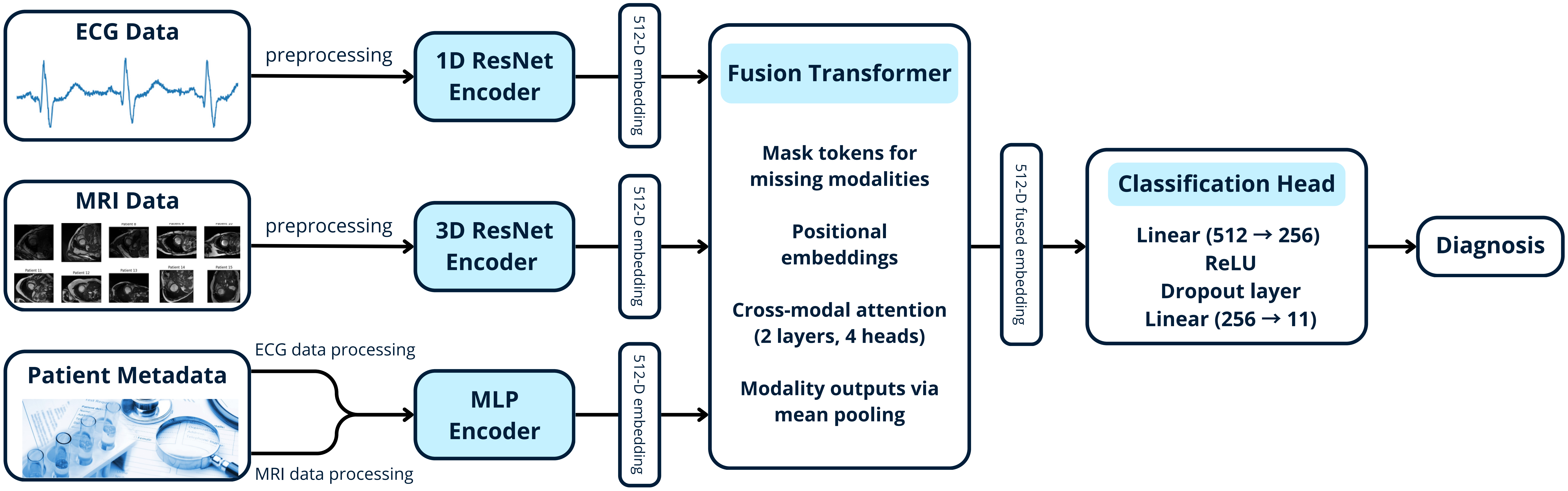
Model Architecture



Training & Evaluation

Training Strategy

1. Pretrain MRI and ECG encoders separately, ECG class merging, regularization
2. Freeze encoders, train fusion model
3. Cross-entropy loss, Adam optimizer
4. Early stopping and dropout used

Evaluation Setup

- Stratified split for ECG
- MRI and ECG used as independent datasets (no patient-level fusion in data)
- Metrics: Accuracy, Recall, F1-score (weighted), Confusion matrix

Results & Findings

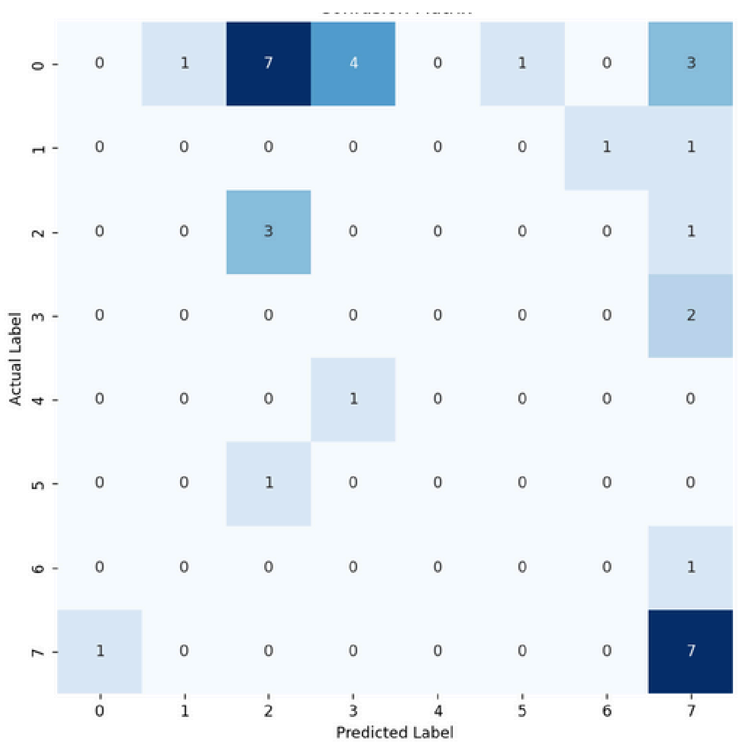
ECG Model

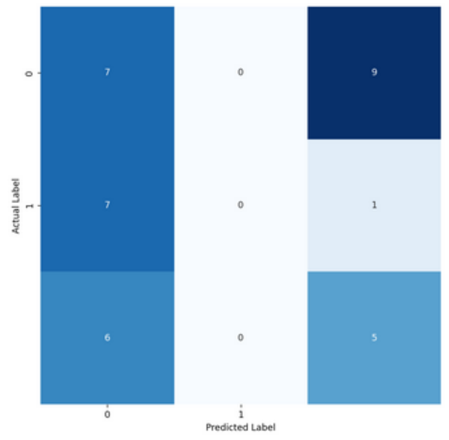
Before changes

- Accuracy: 28.6%, F1-score: 0.19
- Strong overfitting to majority class (0, 8)
- Minority classes often misclassified

After changes (class merging, regularization)

- Accuracy: 34.3%, F1-score: 0.30
- Class 9 (merged) now detected
- Broader class coverage, reduced overfitting



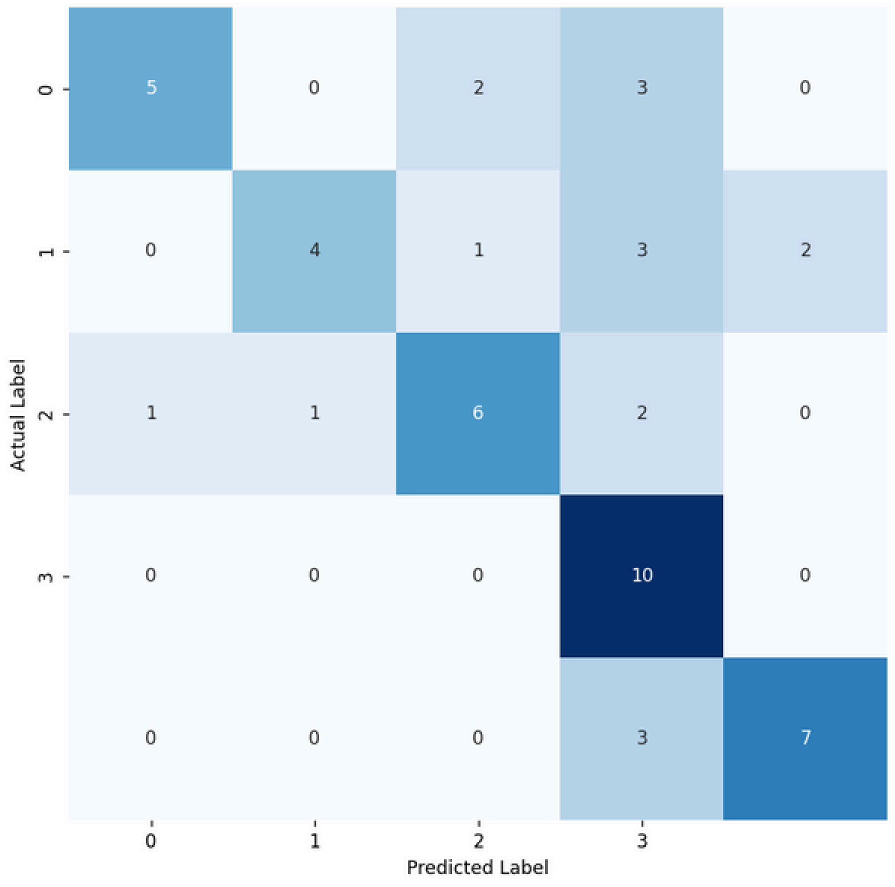


Results & Findings

MRI Model

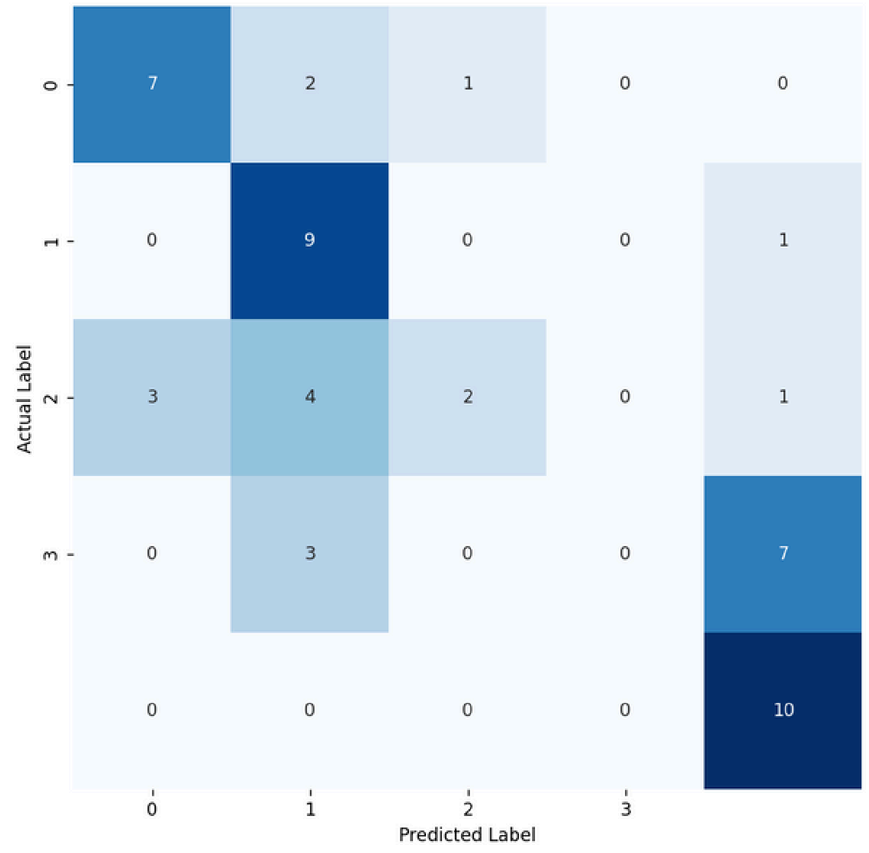
Before changes

- Accuracy: 64%, F1-score: 0.63
- Strong bias toward class 3



After changes

- Accuracy: 56%, F1-score: 0.47
- Wider class prediction (0,1,4), but performance on class 3 and 2 dropped
- Mixed results



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Conclusion

Contribution

- Demonstrated a full pipeline across modalities.
  EDA → preprocessing → model training → evaluation
- Built and tested modular architecture for scalable experimentation.

Challenges

- No **ECG-MRI** alignment (patients differ)
- Small dataset size

Future Work

- Use alternative encoders (e.g., **pure transformers, ViT, EfficientNet, 3D U-Net, LSTM, ECG-BERT**).
- Gather matched patient data with all modalities.
- Expand to more disease classes and more diverse data.

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Acknowledgments

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Thank You