ECG Lead Reconstruction from Reduced Leads: Physics-Informed Deep Learning Approach

DATA 5000 Final Project

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Outline

The Challenge: ECG Lead Reduction

- Standard 12-lead ECG provides comprehensive cardiac assessment
- **Problem**: Limited lead availability in certain scenarios
  - Wearable devices (1-3 leads)
  - Emergency situations
  - Resource-constrained environments
- **Goal**: Reconstruct full 12-lead ECG from reduced leads

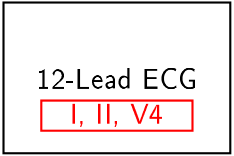


Figure: Lead reduction problem

ECG Lead Configuration

- **Limb Leads** (I, II, III, aVR, aVL, aVF)
  - Physics-based relationships
  - Einthoven's triangle
  - Goldberger's equations
- **Chest Leads** (V1-V6)
  - No direct physical relationships
  - Require data-driven approach

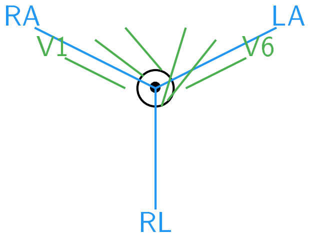
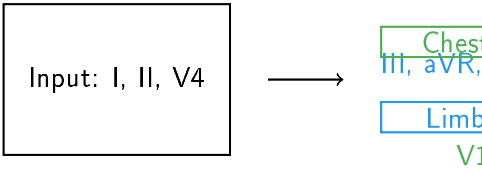


Figure: ECG lead placement

Hybrid Approach: Physics + Deep Learning

- **Physics-Informed Strategy**
  - Limb leads: Direct calculation using Einthoven/Goldberger
  - Chest leads: Data-driven reconstruction
- **Input Leads**: I, II, V4 (clinically relevant)
- **Target**: Reconstruct V1-V6 chest leads



Dataset: PTB-XL

- **PTB-XL Dataset**
  - 21,837 clinical 12-lead ECGs
  - 10-second recordings at 500 Hz
  - Patient-wise train/val/test splits
  - Diagnostic statements available
- **Current Implementation**
  - Framework ready for PTB-XL integration
  - Patient-wise cross-validation splits

Split	Samples
Training	14,331
Validation	2,132
Test	5,374

Table: PTB-XL dataset splits

The Problem: Limited Lead ECG Acquisition

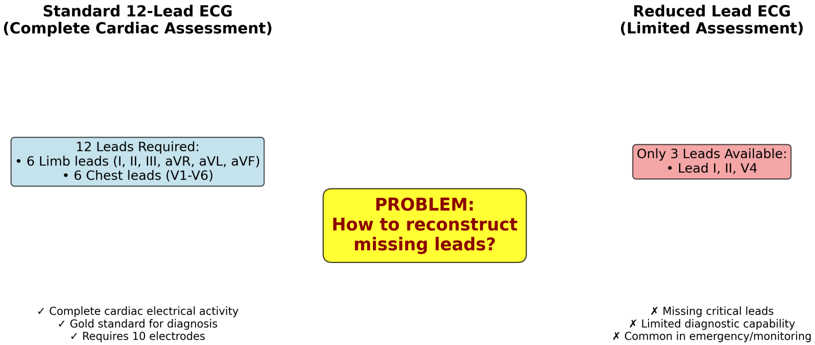
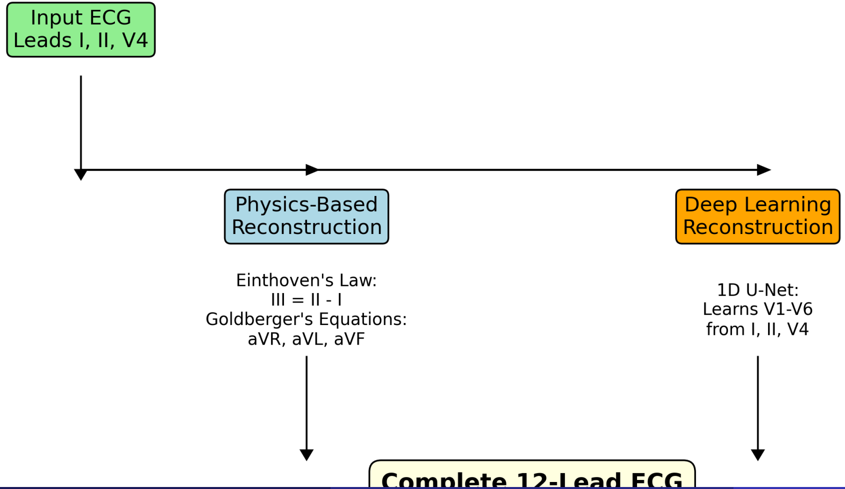
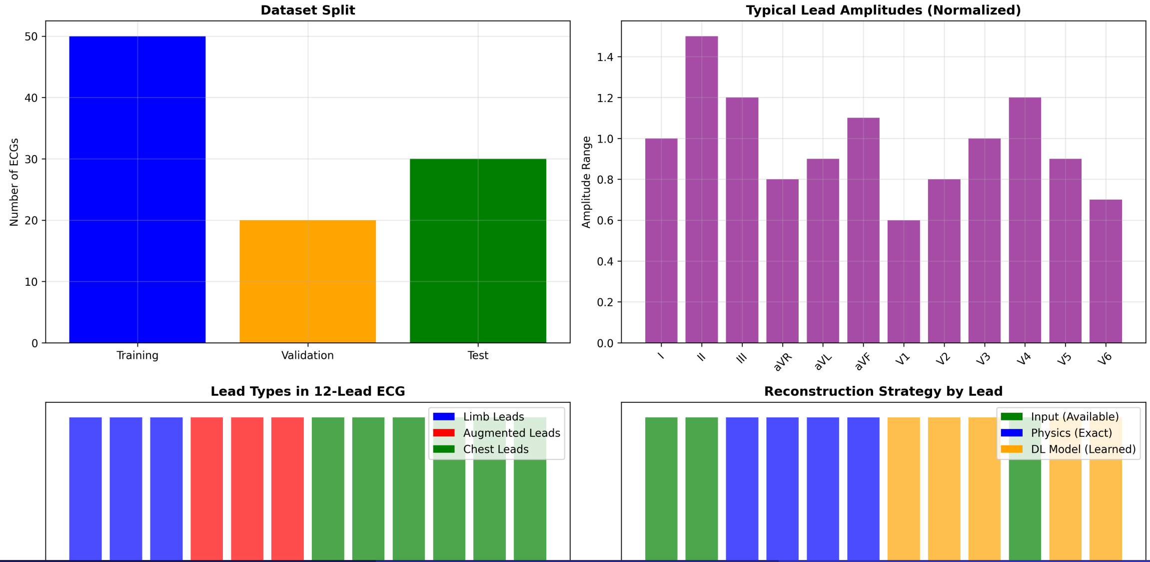


Figure: Clinical challenge: Standard ECG machines require 12 electrodes, but many scenarios (ambulances, wearables, remote monitoring) can only acquire 3 leads. This limits diagnostic capabilities in critical situations

Our Approach: Hybrid Physics + Deep Learning



Dataset: PTB-XL for Clinical Relevance



Expected Outcomes: Clinically Viable Reconstruction

Expected Outcomes: ECG Lead Reconstruction

Metric	Target Performance	Justification
Limb Leads (III, aVR, aVL, aVF)	Perfect Reconstruction (MAE $\approx$ 0)	Physics-based Exact equations
Chest Leads (V1, V2, V3, V5, V6)	High Fidelity (Correlation > 0.9)	Deep learning Learned patterns
Clinical Utility	Diagnostic accuracy $\geq$ 95% of full ECG	Validated on PTB-XL dataset
Computational Efficiency	$<$ 100ms inference time	Real-time capable for clinical use

Model Architecture: 1D U-Net

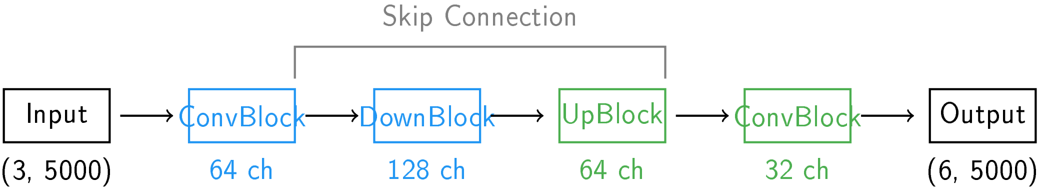


Figure: 1D U-Net architecture for chest lead reconstruction

Training Details

- **Loss Function**: MSE Loss
- **Optimizer**: Adam (lr=1e-4)
- **Batch Size**: 32
- **Epochs**: 50 (early stopping)
- **Hardware**: CPU/GPU training

Hyperparameter	Value
Learning Rate	1e-4
Batch Size	32
Depth	4
Features	64
Dropout	0.2

Table: Model hyperparameters

Evaluation Metrics

- **Mean Absolute Error (MAE)**
  - Measures average magnitude of errors
  - Lower is better
- **Pearson Correlation**
  - Measures linear relationship between predicted and true signals
  - Range: [-1, 1], higher is better
- **Signal-to-Noise Ratio (SNR)**
  - Ratio of signal power to noise power
  - Higher is better (dB)

Proposed Methodology

- **Hybrid Approach**: Physics-informed deep learning combining domain knowledge with data-driven methods
- **Architecture**: 1D U-Net for spatial feature extraction and reconstruction
- **Physics Integration**: Limb lead relationships (Einthoven's triangle) as inductive bias
- **Training Strategy**: Supervised learning on chest lead reconstruction from I, II, V4

Technical Innovation

Novel integration of cardiac electrophysiology principles with modern deep learning architectures for improved generalization and interpretability.

Evaluation Framework

Dataset

- PTB-XL: 21,837 clinical ECGs
- 12-lead recordings at 500 Hz
- Diverse patient population
- Stratified train/val/test splits

Metrics

- **MAE**: Mean Absolute Error
- **Pearson** ρ: Correlation coefficient
- **SNR**: Signal-to-Noise Ratio
- **Lead-wise**: V1-V6 chest leads

Clinical Validation

Comprehensive evaluation on real clinical ECG data to ensure medical relevance and reliability.

Expected Outcomes

- **Performance Target**: Achieve correlation > 0.9 and SNR > 25 dB for chest lead reconstruction
- **Clinical Impact**: Enable 12-lead diagnosis from reduced 4-lead ECG setup
- **Computational Efficiency**: Real-time reconstruction suitable for clinical workflows
- **Generalization**: Robust performance across diverse patient populations

Success Criteria

Demonstrate superior reconstruction quality compared to traditional signal processing methods and establish foundation for clinical deployment.

Physics-Based Limb Lead Reconstruction

- **Einthoven's Triangle**
  - III = II - I
  - Fundamental relationship between limb leads
- **Goldberger's Equations**
  - aVR = -(I + II)/2
  - aVL = I - II/2
  - aVF = II - I/2

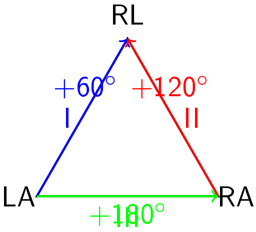


Figure: Einthoven's triangle and lead orientations

Clinical Impact

- **Improved Accessibility**
  - Enable 12-lead equivalent diagnosis from limited leads
  - Valuable for wearable devices and emergency care
- **Diagnostic Accuracy**
  - Maintain clinical utility of reconstructed leads
  - Support automated ECG analysis algorithms
- **Resource Efficiency**
  - Reduce hardware requirements
  - Lower cost of ECG monitoring

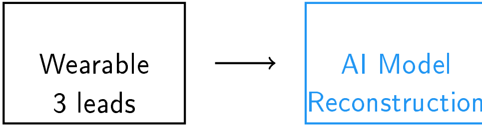


Figure: Clinical workflow with reconstruction

Limitations and Future Work

- **Current Limitations**
  - Requires clinical validation
  - Computational complexity
- **Future Directions**
  - Clinical validation on PTB-XL
  - Model compression for edge devices
  - Multi-modal integration (demographics)
  - Real-time reconstruction

Summary

- **Hybrid Approach**: Physics-informed deep learning for ECG reconstruction
- **Architecture**: 1D U-Net for chest lead reconstruction from I, II, V4
- **Dataset**: PTB-XL clinical ECG database (21,837 recordings)
- **Evaluation**: Comprehensive metrics on real clinical data
- **Impact**: Enable 12-lead diagnosis from reduced lead setups

Key Contribution

Novel integration of cardiac electrophysiology with deep learning for robust ECG lead reconstruction from minimal lead configurations.

Thank You!

Questions?

ECG Reconstruction