Predicting Myocardial Injury From Continuous Single-Lead Electrocardiographic Monitoring in the Emergency Department

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Background

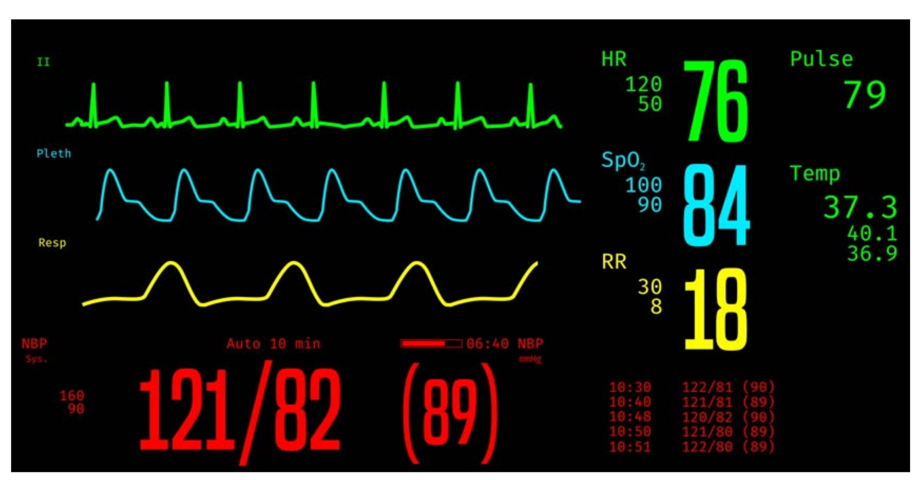
7-9 million annual patient visits to the Emergency Department (ED) with chief complaint of chest pain.

Only 10% of patients have Acute Coronary Syndrome (ACS) but most undergo hours of evaluation.

Problem: Risk-stratification of chest pain patients is costly and time-consuming.

Potential Solution: Train a predictive model for myocardial injury using continuous data collected by bedside patient monitors.

Challenges:
ECG data is often noisy, missing, and only lead II.



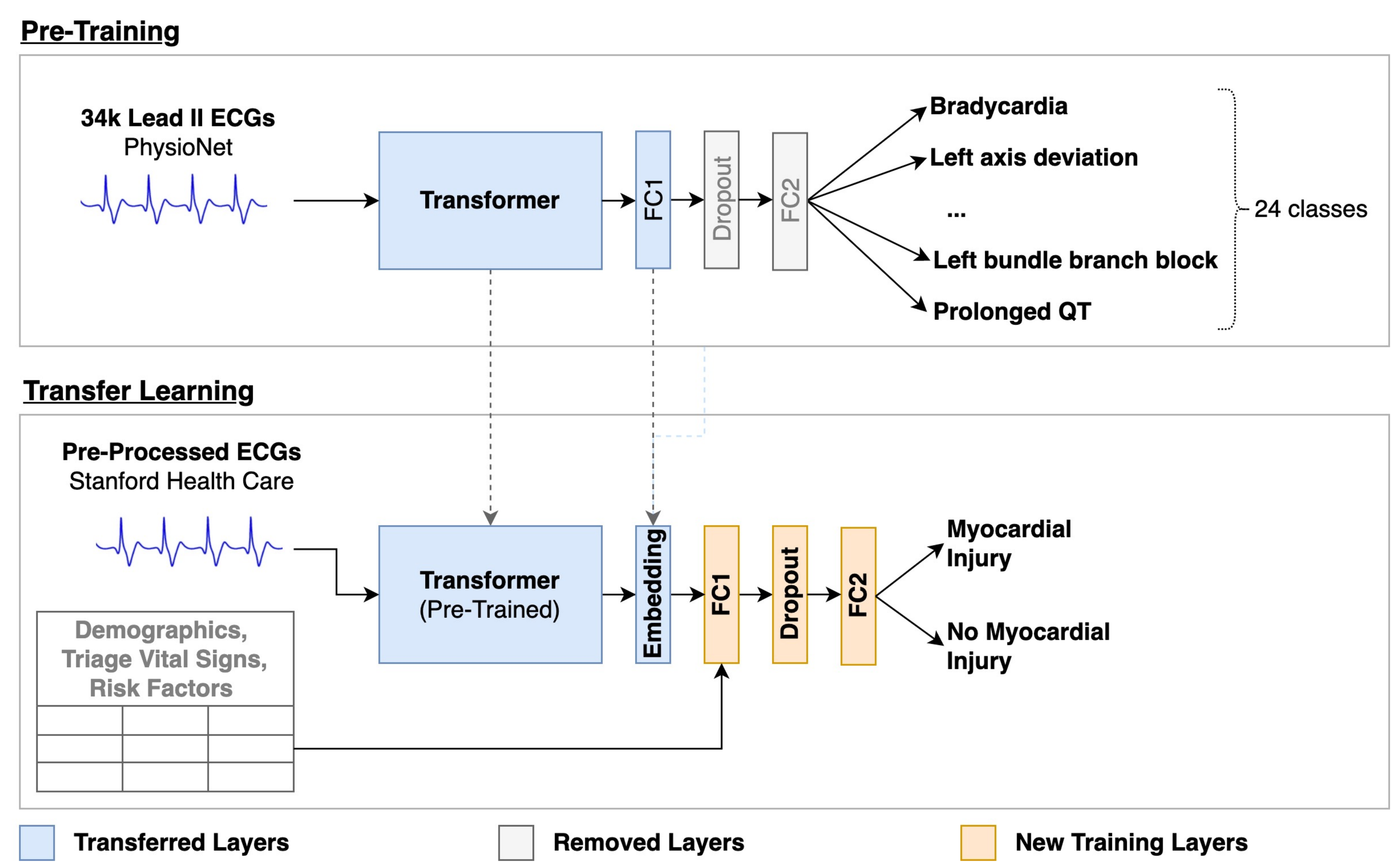
Recently, transformer models have performed well in predicting cardiac abnormalities from ECG data.

Goal: Use **transfer learning** to develop a predictive model for myocardial injury using lead II ECG signal from bedside monitoring data.

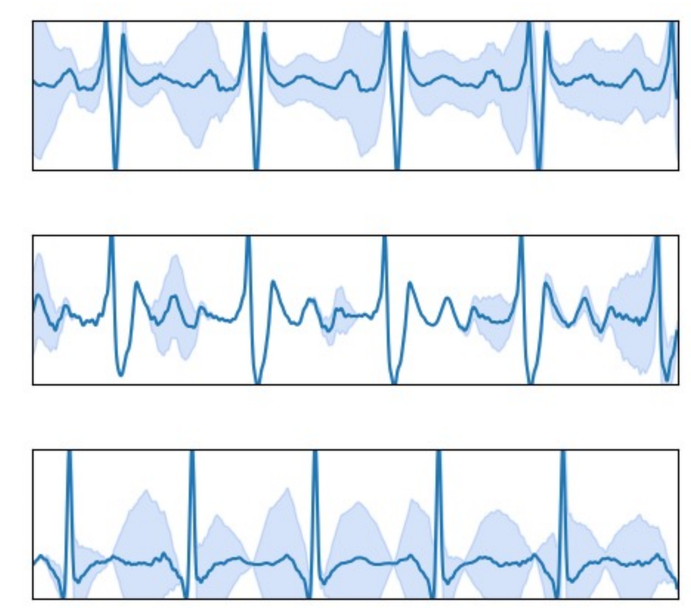
Transfer Learning for Predicting Myocardial Injury

Dataset: 10,874 Stanford Health Care ED patients.

1) Pretrain a transformer model using a large corpus of static ECG data to predict 24 cardiac abnormalities.
2) Fine-tune on 15-second lead II ECG segments and patient features to predict myocardial injury.



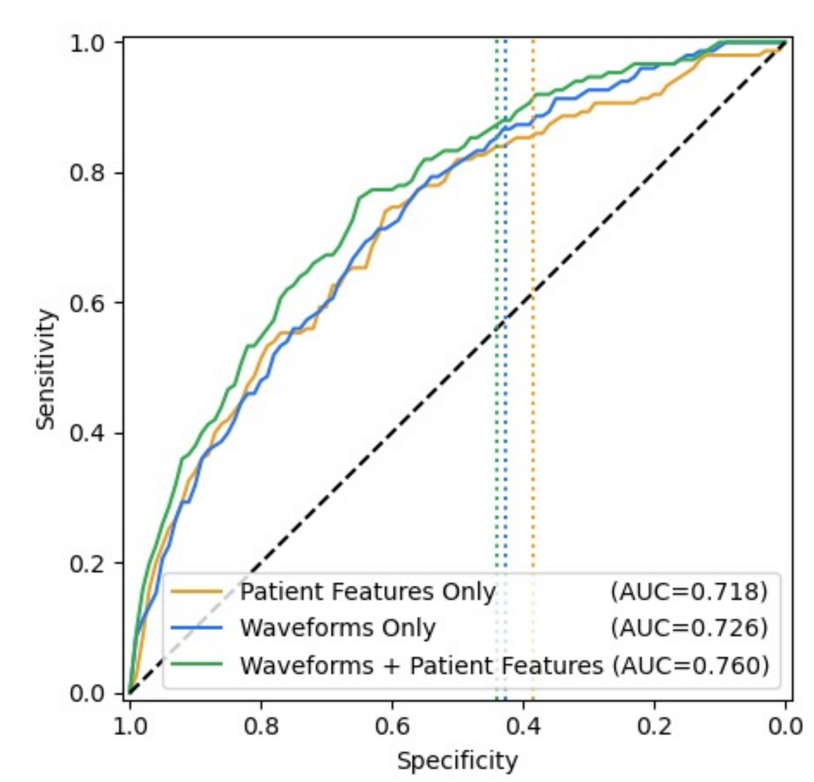
True Positive



Model Evaluation

Model **increases accuracy by 11%** compared to clinicians.

Transfer learning enables model to learn relevant features associated with myocardial injury such as T-wave abnormalities.



Discussion

Pretrained deep learning model obtains **high negative predictive value for myocardial injury.**

Transfer learning strategy produces **single-lead predictions comparable to predictions from 12-lead ECGs**.

Model can **expedite disposition** of low-risk patients and **prioritize testing** for high-risk patients, especially in low-resource settings.

Continuous monitoring data can enable **pre-clinical screening from wearable devices.**

Future Work

- Train model on larger and more diverse ECG datasets.
- Validate model clinically.
- Use passive, continuous monitoring data for other predictive tasks, such as epilepsy and heart failure.