GPU Acceleration for Deep-Learning based Comprehensive ECG analysis

Group 07

E/18/098 Ishan Fernando

E/18/100 Adeepa Fernando

E/18/155 Ridma Jayasundara

Supervisors

Prof. Roshan G. Ragel

Dr. Isuru Nawinne

Dr. Vajira Thambawita

Team Members

Ishan Fernando
E/18/098

Adeepa Fernando
E/18/100

Ridma Jayasundara
E/18/155

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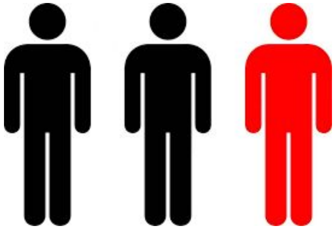
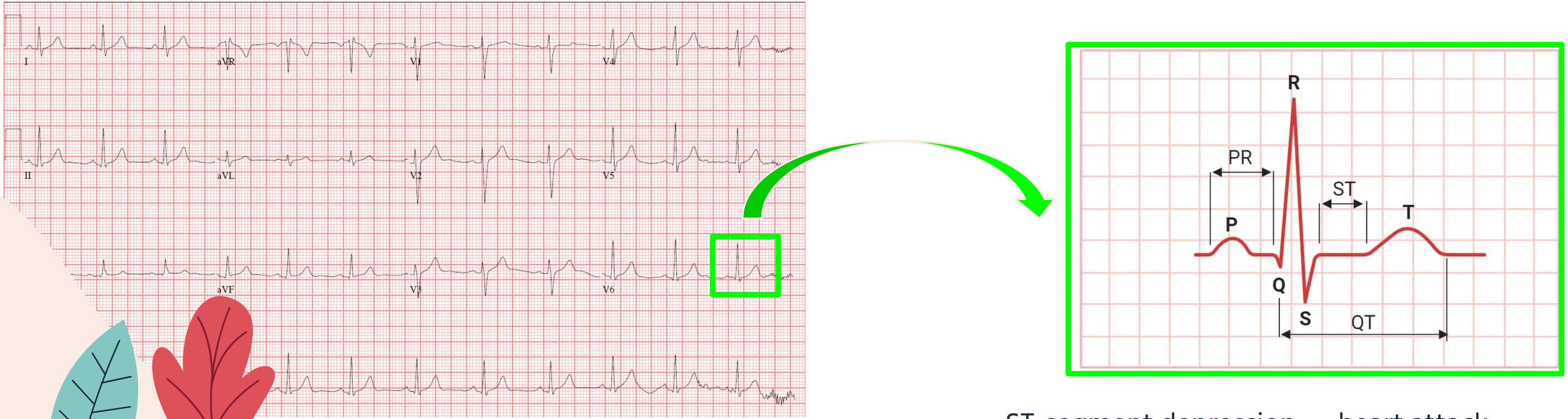
Introduction & Motivation

Introduction



- 1 out 3 human deaths are caused by cardiovascular diseases.
- Electrocardiograms is a non-invasive diagnostic test that records the electrical activity of the heart.
- In-time proper diagnosis of CVDs form ECGs could help prevent a death.



Electrocardiogram
(ECG)

ST-segment depression → heart attack
PR-segment prolongation → heart block

Introduction

- Manual analysis of ECG requires domain expertise and time
- Automated systems such as the “MUSE” ECG system by GE Healthcare are:
    - Commercial
    - Proprietary
    - Integrated
    - Inaccessible
    - Limited performance

50%
reduction in false positive admission of chest pain patients[4]

31%
reduction in CCU admission for non-AMI patients[5]

14%
increase in ECG interpretation accuracy[6]

UP TO 99%
ECG interpretation accuracy[7]

- Use of Artificial Intelligence has been practiced but with the following limitations:
    - Accuracy/ Performance
    - Privacy Issues
    - Computational efficiency
    - Data credibility

Motivation

- Development of an open-source ECG analysis system with a computationally efficient Deep Learning algorithm
- Use of synthetic generated ECG such as “DeepFake ECG”
- GPU acceleration for faster training
- Transfer Learning on limited real ECG
- Use in personal healthcare devices without commercial integration.

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Methodology

Methodology

- To find related literature work
  - The google scholar search engine was systematically searched by combining “deep learning” and keywords such as “ecg,” “ekg,” “electrocardiogram,” “electrocardiography,” and “electrocardiology.”
  - Used IEEE Xplore to access high quality papers
  - Referred to highly cited survey papers to get an overview.

- **Selection Criteria**
  - Relevance to ECG analysis, application of deep learning
  - Studies that discussed methodologies, performance metrics.

Review of MUSE ECG system

- Input → 12 lead ECG signal
- Output → No. of parameters and properties

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	
1	TestID	patid	Acquisitio	AnalysisS(	ecgday	avgrrinter	tonset	NumQRSC	VentRate	AtrialRate	pr	qrs	qt	paxis	raxi:
2	140000	0				1006	329	10	60	60	140	100	434	52	
3	140001	1				918	316	11	65	65	166	80	404	57	
4	212220	3				982	325	10	61	61	154	106	416	62	
5	223331	4				860	315	12	70	70	154	92	390	46	
6	234442	5				962	322	11	62	62	164	96	366	86	

- Uses signal processing techniques
- Commercial, Proprietary, Expensive and Hospital System Integrated
- Not the best results

50%

reduction in false positive admission of chest pain patients[4]

31%

reduction in CCU admission for non-AMI patients[5]

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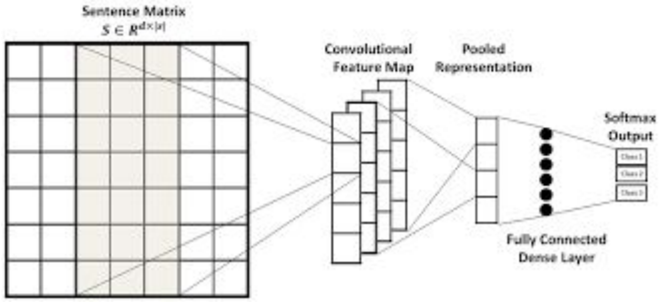
increase in ECG interpretation accuracy[6]

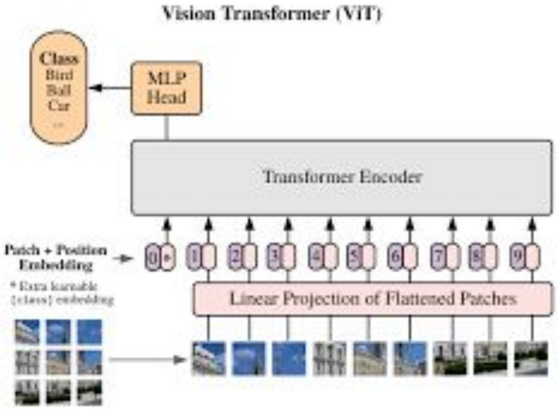
UP TO 99%

ECG interpretation accuracy[7]

Review of Deep Learning Algorithms

- CNN
- RNN
- LSTM
- SVM
- KNN, Decision Tree, Logistic Regression
- Transformer Neural Network
- Vision Transformer





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Analysis & Results

Results of Deep Learning Algorithms

Model Name	**Performance**
Residual CNN	High specificity of 99%
EffiicientNet CNN	Diagnosed multilabel abnormalities with Grad-CAM
Echo State network (ESN)	High accuracy heart beat classification
Ensemble of SVM, kNN, RF	SVM demonstrated promising performance
Logistic regression, Decision Tree, SVM	Naive bayes resulted in 94% accuracy for CAD
RNN	LSTM achieved 88.1%
1D CNN	Accuracy 86%
CNN based deep active learning	High accuracy with various sampling methods
Wide and deep transformer neural network	Accuracy 53%

Results of Deep Learning Algorithms

ConvNeXt with multimodal transformer	Multiple high accuracy values on MIT-BIH dataset
ECT-net (CNN and transformer combination)	High F1 scores on P, QURS and T waves
Heartbeat-aware transformer model	Evaluated on a large dataset for various arrhythmias
HeartBEiT (12 layer transformer)	Outperformed CNN models in classifying low LVEF, diagnosing HCM and detecting STEMI
Vision transformer with deformable attention	Outperformed ResNet, LSTM with F1 score of 0.829
ECG convolution vision transformer	Accuracy of 98.8% for the inter patient scheme

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Conclusions

- Find a deep learning model
- Use synthetic data to train models and finetune on real data
- optimising it as an **open-source**, portable, and low-power GPU alternative, capable of providing comprehensive analysis.

Research Gaps

Using Synthetic data

- To eliminate privacy concerns in using real patient ECG data
- Lage data requirement on transformers
- Unbiased dataset of all ages

Transfer Learning

- Training on synthetic dataset and fine tuning on limited real dataset

GPU Acceleration

- Optimizing parallel GPU usage

Next Steps

	Sem 7				Sem 8											
	WEEK 1 - 4		WEEK 5 - 8		WEEK 1-2		WEEK 3-4		WEEK 5-6		WEEK 7-8		WEEK 9-10		WEEK 11-12	
Literature Review	✓	✓	✓	✓												
Baseline Models			✓	✓												
Transformer Neural Networks				✓												
Vision Transformers					✓	✓	✓	✓	✓							
CNN + ViT							✓	✓	✓	✓	✓	✓				
Wave2Vec							✓	✓	✓							
Spectrogram						✓	✓	✓								

Use of AI tools

Let's go through the AI tools we used in this project

ChatGPT 3.5

- Model templates and code explanations, Generate sentences from given summary points
- Highly effective
- Bias in AI-generated content wasn't observed, largely due to it being based on provided summaries.

Gemini

- Generate sentences from given summary points, photo generation
- A bit less effective than GPT 3.5
- Bias in AI-generated content wasn't observed

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Demonstration

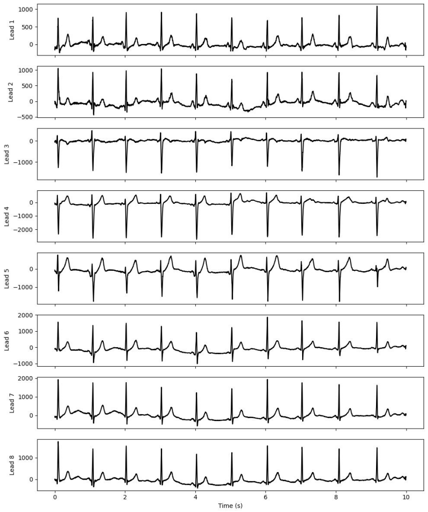
- Deepfake dataset
- Structure
- Dataloader class
- Model inputs

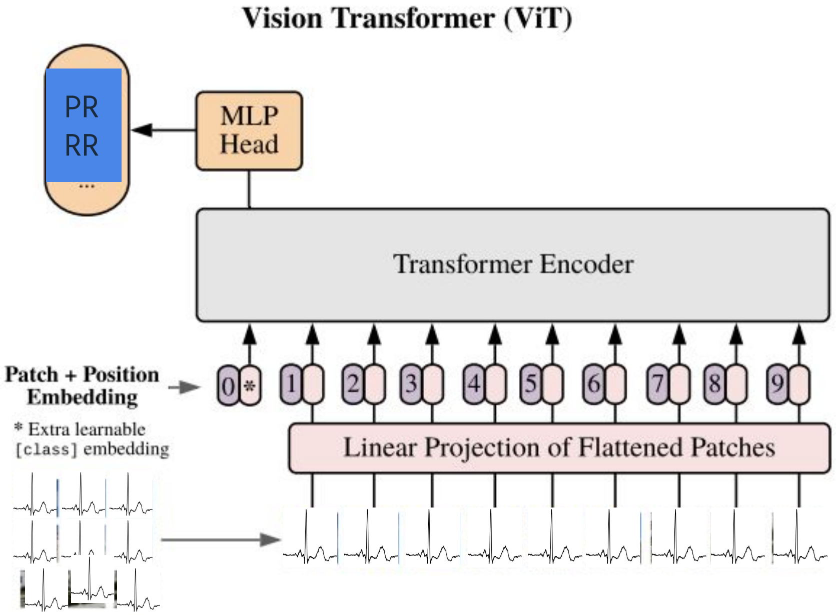
- **Code structure and models**

Weights & Biases

- **WandB Visualization**

Application of ViT





Review paper draft

Towards a Transfer Learning Approach from Attention Based Synthetic ECG Analysis

K. A. Ishan Fernando
Department of Computer Engineering
University of Peradeniya
Peradeniya, Sri Lanka
e18098@eng.pdn.ac.lk

K. N. Adeepa Fernando
Department of Computer Engineering
University of Peradeniya
Peradeniya, Sri Lanka
e18100@eng.pdn.ac.lk

J. W. K. Ridma B. Jayasundara
Department of Computer Engineering
University of Peradeniya
Peradeniya, Sri Lanka
e18155@eng.pdn.ac.lk

Prof. Roshan G. Ragel
Department of Computer Engineering
University of Peradeniya
Peradeniya, Sri Lanka
roshanr@eng.pdn.ac.lk

Prof. Vajira Thambawita
Department of Holistic Systems
Simula Metropolitan Center for Digital Engineering
Norway
vajira@simula.no

Dr. Isuru Nawinne
Department of Computer Engineering
University of Peradeniya
Peradeniya, Sri Lanka
isurunawinne@eng.pdn.ac.lk

***Abstract*—The leading cause of death in humans, Cardiovascular diseases [10] could be diagnosed by analysis of electrocardiogram (ECG) which is a non-invasive method that records electirical activity of the cardiac cycle. Due to the rise of privacy issues in using ECG records of patients for research purposes [1], synthetic generated data with similar information and distribution have become an alternative. Attention based mechanism which is the basis of Transformer Neural Networks combined with other models such as Convolutional Neural Networks, Recurrent Neural Networks and Long-Short Term Memory have been used in ECG classification tasks using real patient ecg data with promising outcomes. But analysis of properties of ECG signals using attention based regression methods on synthetic data and transferring the learned parameters for fine tuning on limited real data is the interest area of this review article.**

***Index Terms*—ECG, Deep Learning, Transfer Learning, Transformers**

I. Introduction

In recent years, the integration of machine learning techniques with electrocardiogram (ECG) data analysis has sparked significant interest and promise in the field of healthcare. The ability to accurately predict vital physiological parameters, such as heart rate, QT interval, and other cardiac metrics, directly from ECG waveforms holds immense potential for revolutionizing clinical practice. This paper aims to provide a comprehensive review of the advancements, challenges, and future directions in utilizing machine learning for ECG regression and classification tasks.

The electrocardiogram, a fundamental tool in cardiology, provides a graphical representation of the electrical activity of the heart over time. Traditionally, ECG interpretation has relied on manual analysis by skilled clinicians, which can be time-consuming and prone to subjectivity. However, with the advent of machine learning, automated analysis of ECG signals has become increasingly feasible, offering the promise of more efficient and accurate diagnosis and monitoring.

One of the primary objectives in ECG analysis is the prediction of essential cardiac parameters directly from ECG waveforms. These parameters include but are not limited to heart rate, QT interval, QRS duration, and ST segment changes. Accurate estimation of these metrics is crucial for diagnosing various cardiac conditions, assessing cardiovascular risk, and guiding treatment decisions. Machine learning models, particularly deep learning architectures, have shown remarkable success in learning complex patterns from ECG data and making accurate predictions of these parameters.

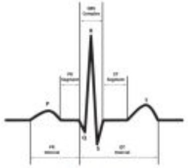


Fig. 1. ECG [9]

The electrocardiogram (ECG) shown in Figure 01 provides a visual representation of the heart's electrical activity, crucial for diagnosing various cardiac conditions. It features distinct waves – P, Q, R, S, and T – each indicative of

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Q & A

THANK YOU !