INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI
SHORT ABSTRACT OF THESIS

Name of the Student	:	Deepankar Nankani
Roll Number	:	156201001
Programme of Study	:	Dual Degree (M.Tech+Ph.D.)

Thesis Title: Deep Learning Models for Cardiac Abnormality Detection from ECG Signals: An Interpretability Perspective

Name of Thesis Supervisor(s)	:	Dr. Rashmi Dutta Baruah
Thesis Submitted to the Department/ Center	:	Computer Science and Engineering
Date of completion of Thesis Viva-Voce Exam	:	29-October-2022
Key words for description of Thesis Work	:	ECG Classification, Interpretability, Explainability, Deep Learning, Machine Learning.

SHORT ABSTRACT

Cardiovascular diseases (CVD) accounted for 54 million deaths in India in 2016, and the number of patients has been rapidly rising, particularly within urban communities. Deep learning models (DLM) have been widely used for detecting cardiac abnormalities through ECG signals. Although DLM outperforms the linear models, they lack interpretability which is crucial in the medical domain. The thesis investigates the interpretability perspective of DLM for detecting cardiac abnormalities. The recordings get contaminated with noise during the ECG signal acquisition, making the classification challenging. The low-frequency baseline wander noise is removed from ECG signals using Variational Mode Decomposition. The clean ECG is used for detecting irregular heartbeats or rhythmic cardiac abnormalities. Life-threatening arrhythmias such as Atrial Fibrillation (AFib) and Ventricular Fibrillation (VFib) are caused due to prolonged occurrence of irregular heartbeats such as supraventricular ectopic beat (SVEB) and ventricular ectopic beat (VEB). Therefore, the first contribution aims at detecting and classifying SVEB and VEB. Initially, the R-peaks are extracted from clean ECG signals using fractal-based mathematical morphological operators. The peaks are used for segmenting heartbeats from ECG signals. Irregular heartbeats such as SVEB and VEB have rare occurrences stemming from complex biological and physiological systems. Therefore, these beats are synthesized using a deep convolution conditional generative adversarial network. Lastly, a Penalty-Induced Prototype-based eXplainable Residual Neural Network (PIPxResNet) classifies the heartbeats. PIPxResNet addresses the black-box nature of DLM by providing explanations supporting the model diagnosis. The commonly occurring AFib and VFib arise rhythmically in the nonstationary ECG signals with different episode lengths. Therefore, the second contribution detects AFib using an attention-based Transformer Neural Network and highlights clinically relevant signal timestamps of the input ECG signal. The third contribution investigates three model agnostic posthoc gradient-based visualization techniques, namely, Guided Backpropagation, Grad CAM, and Guided Grad CAM, that explain the reasons behind predictions of VFib from single-lead ECG signals. The single-channel ECG provides lower resolution compared to Multichannel Electrocardiogram (MECG). Therefore, the fourth contribution uses MECG to predict multiple cardiac abnormalities. Initially, ResNet is used for single-label MECG classification and compared with recurrent and attention-based models. Later, demographic and heartbeat features are incorporated with MECG and classified using a parallel CNN model. Heartbeat features increase the training and inference time multifold, and hence heartbeat features are excluded, and only demographic features are fused with a channel-specific dynamically built CNN (CSD-CNN) that eliminates manual effort and provides less trainable parameters. CSD-CNN model introduces an interpretability mechanism that highlights the crucial leads and relevant signal timestamps responsible for cardiac pathology prediction. The proposed methods would be useful for automated pre-screening for patients and potentially could be incorporated into the clinical decision support system. The visual explanations improve model assessment, increase transparency, enhance trust in the model, and increase the likelihood of model acceptance by medical practitioners.