INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI
SHORT ABSTRACT OF THESIS

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Cardiovascular diseases remain a major global health concern, requiring early and accurate diagnosis for effective treatment. While Electrocardiogram (ECG) serves as a key non-invasive diagnostic tool for cardiac assessment, manual interpretation is time-consuming and is prone to subjective variations, motivating the development of automated methods for ECG analysis. This work addresses fundamental limitations in automated ECG analysis by advancing deep learning solutions that incorporate clinical domain knowledge and provide reliable uncertainty quantification. The first part of this work focuses on enhancing diagnostic accuracy for Myocardial Infarction (MI), one of the leading causes of cardiovascular mortality. To achieve this, the Cross-Task Attention Transfer (CTAT) framework is proposed, which distills knowledge between ECG delineation and MI detection tasks to guide the model's attention toward clinically relevant waveform characteristics. Building on this foundation, the Multi-task Physics-Constrained Hierarchical MI Classification (MTPCHi-MI) framework is developed, incorporating physics-based constraints and hierarchical classification to ensure that predictions remain consistent with electrophysiological relationships among ECG leads and the clinical hierarchy of MI diagnosis. Extending beyond MI detection, the third contribution introduces an Uncertainty-Aware ECG Diagnostic Framework designed for reliable multi-label abnormality detection. By combining variational inference with a learnable condition interaction matrix, this framework captures interdependencies between cardiac abnormalities and quantifies prediction uncertainty, thereby improving robustness and safety. Finally, to extend utility to prevalent paper-based records, a multi-task framework for automated ECG image analysis is introduced, mimicking the systematic regional inspection employed by expert clinicians. Comprehensive validation across diverse ECG databases demonstrates the superior performance and enhanced interpretability of the proposed models, confirming their focus on diagnostically meaningful regions and establishing a critical pathway toward clinically reliable and safe automated cardiovascular diagnostic systems.