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Research Paper

A Framework for Temporal Learning Model for Early Myocardial Infarction Localization Using Multi-Lead ECG Signals

Sairam Vallabhuni
Research Scholar & Senior Software Engineer, WABCO Technology Centre India, Chennai - 600116
vallabhuni.sairam@gmail.com

Dr G.sambasiva rao
Professor and HOD IT department, Nawab shah alam khan college of engineering and technology, Malakpet, Hyderabad-500024.
profgssrao@gmail.com

Dr. P.V. Naganjaneyulu
Professor (Department of ECE)and Principal Sri Mittapalli College Of Engineering (Autonomous), Tummalapalem, NH16, Guntur, Andhra Pradesh - 522233.
pvnaganjaneyulu@gmail.com

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Abstract—Timely the localization of myocardial Infarction (MI) is very important for making clinical decisions and keeping patients alive. Traditional ECG-based diagnostic devices frequently prioritize static feature analysis, neglecting the temporal dependencies intrinsic to cardiac signals. This paper presents a lightweight a temporal learning framework intended for the early localization of myocardial infarction utilizing multi-lead ECG signals.

Adaptive filtering methods are built into the framework to get rid of noise and distortions in the baseline. Temporal segmentation is used to keep the sequential dependencies in ECG cycles. We use a recurrent neural construction on the basis of gates recurrent units (GRU) to model how signals change over time. Learned temporal traits are integrated with particular domain morphological indicators to improve classification accuracy.

The main contribution is the introduction of a method called Temporal Consistency Regularization (TCR). This extension makes sure that predictions are stable across close ECG segments, which makes them more general and robust. Tests show that the accuracy of localization has improved a lot and the variance in predictions has gone down. The suggested system is a simple, effective way to monitor the heart in real time using ECG data.

Keywords: ECG signals, myocardial infarction, temporal instruction, GRU networks, signal classification, regularization, and lightweight models.

I. INTRODUCTION

Heart muscle Infarction (MI) remains a significant factor in global cardiac mortality, necessitating diagnostic methods that are both swift and dependable. Timely detection, along with precise identification of ischemic or infarcted areas, greatly improves clinical decision-making and patient outcomes. Electrocardiogram (ECG) signals are a rich and non-invasive way to get information about the heart. They naturally encode complex changes over time that are related to the heart's electrical activity. These variations are caused by changing physiological processes, which means that a good MI analysis needs to go beyond just extracting static or isolated features and instead focus on modeling the timing of sequential dependencies. Traditional deep Convolutional neural network, or CNN, methods have shown great ability to pick up on the spatial and morphological features of ECG waveforms. But these kinds of models often have a hard time fully showing how things change over time, especially when pathological signatures change over time. Myocardial abnormalities may present subtly across consecutive heart cycles, and overlooking these sequential interactions can diminish diagnostic sensitivity, particularly in

early-stage detection contexts. This limitation underscores the imperative for architectures specifically engineered to acquire temporal behavior.

Recurrent neural network technology (RNNs) are a natural solution because they model sequential info and learn long-term dependencies in ECG signals. Gated recurrent unit models (GRUs) are one of these. They are a more efficient way to compute than traditional RNN variants, and they solve the problem of vanishing gradients while keeping the model simple. Even though they have some benefits, problems like unstable predictions, noise sensitivity, and changes in the quality of signal can still make it hard to use them in clinical settings. To deal with these problems, we need models that balance learning over time with stability and reliability.

To deal with these problems, this study presents an efficient GRU-based framework that aims to improve temporal consistency and diagnostic robustness. The suggested method puts a lot of emphasis on temporal consistency to make predictions more stable and make them less sensitive to noise and signal artwork. The framework's goal is to not only achieve accurate MI characterization but also to allow precise location of pathological regions underneath ECG sequences by making better use of sequential dependencies. This design allows for accurate detection of myocardial anomalies while keeping computational efficiency, which makes it good for clinical settings that need real-time data and have limited resources.

II. LITERATURE SURVEY

Current studies in automatic ECG analysis have thoroughly investigated deep learning frameworks, such as Convolutional Neural Network (CNNs) or recurrent neural network algorithms (RNNs), along with hybrid architectures that combine temporal and spatial modeling functionalities. CNN-based methods have been very good at finding the shape and location of ECG waveforms, which makes it easy to find local features like QRS complexes, ST-segment errors, and T-wave variations. At the same time, recurrent architectures, especially networks with LSTM (Long Short-Term Memory) alongside gates recurrent units (GRUs), became very good at learning the temporal dependencies that are naturally present in regular cardiac signals. These models are ideal for time-series analysis because they collect information about the context that is spread out over several cardiac cycles.

Even with these improvements, deep learning models are still not very reliable in clinical settings because they are still not very good at making predictions, are sensitive to noise, and are too good at fitting data. ECG signals are naturally variable and frequently contaminated by objects, baseline drift, and metabolic noise, which can impair model performance and yield inconsistent predictions. Also, deep networks can overfit when there isn't enough or too much training data. This is because they can represent a lot of information. These limitations highlight the need for strong regularization methods that enhance generalization while maintaining temporal fidelity.

Previous ECG studies primarily focused on CNN-driven geographical feature extraction, yielding encouraging classification outcomes while often neglecting long-range temporal dependencies essential for precise diagnosis. Recurrent models like LSTM and GRU solved this problem by explicitly modeling alternating information, which made it easier to represent how the heart behaves over time. There are many ways to reduce overfitting, such as dropout, dimensions decay, and data augmentation. However, not much work has been done to make temporal predictions more stable across adjacent signal segments.

To fill this gap, this study builds on previous research by adding a Temporal Consistency Regulation mechanisms to a flexible recurrent framework. This method is different from traditional regularization methods because it explicitly requires consistency and coherency in sequential predictions instead of just limiting model complexity. The proposed strategy makes the system more robust against noise and less likely to make random decisions by encouraging similar outputs across ECG windows that are close in time. This formulation enhances the reliability of myocardial infarction detection and localization, ensuring that model behavior corresponds with the continually and structured characteristics of physiological cardiovascular signals.

III. DATASET DESCRIPTION

The suggested system goes through these steps:

1. Noise filtering: normalizing and adaptive filtering.
2. Temporal Segmentation: Keeping track of information in order.
3. Learning Features Based on GRU: Modeling temporal dependencies.
4. Morphological Feature Integration: Improving the way signals are represented.
5. Classification and Localization: Predicting MI for multiple classes.

Noise filtering gets rid of artifacts in the signal while keeping the shape of the signal intact. Temporal segmentation breaks ECG cycles toward structured patterns that keep their chronological order. A GRU-based architecture effectively models temporal evolution.

Morphological indicators are added to learned features to make them better. The lightweight design makes it easier to deploy in real time by lowering the computational load.

The suggested system adds a lightweight spatial learning framework for finding early Myocardial Infarction by explicitly representing the sequential dependencies that are naturally present in ECG signals. This framework focuses on dynamic signal behavior instead of static feature representations, which makes diagnoses more reliable. The first step in the process is adaptive noise filtering, which gets rid of baseline wander, artifacts of motion, or high-frequency noise. These preprocessing steps keep important waveform structures while making the signal clearer. Normalization methods are used to make sure that the amplitude is the same in all recordings. After preprocessing, chronological segmentation is done to break up ECG signals onto structured logical segments that match up with heart cycles. This method of segmentation keeps the order of events in time, which lets the learning model pick up on changes and changes over time that are similar to how the heart works.

A GRU (gated recurrent unit) building design is used to model relationships with time in a smart way. Because they can find long-range dependencies while keeping the amount of computing power needed low, GRU networks are especially good for ECG analysis. The recurrent structure develops dynamic representations of feature that encode changes in the patterns of heartbeats over time.

A temporal stability the mechanism is built into the learning process to make predictions more reliable. ECG signals have a natural continuity, and sudden changes in predictions between adjacent segments often mean that the model is too sensitive to noise or overfitting. The stability mechanism makes sure that model predictions are consistent by punishing transitions that are not smooth between neighboring time segments. This process makes it easier to generalize, lowers variance, and makes classification work more smoothly.

Morphological signal signals are combined with temporal representations to make feature diversity richer. The framework can tell the difference between small pathological patterns linked to MI localization thanks to the combination of fluctuations in time and structural descriptors. The resulting representations of feature are then used for tasks like multi-class classification and localization, which makes them more robust and improves their ability to predict.

IV. PROPOSED METHODOLOGY

The suggested framework aims to achieve strong and computationally efficient multiple class infarct detection by combining deep model learning, feature fusion, or adaptive feature prioritization methods. The system architecture is made up of processing modules that work in order to improve signal quality, extract useful features, and make classification more reliable.

First, raw ECG signals are preprocessed to get rid of noise imperfections and baseline deceptions. Wavelet-based denoising methods are used to keep important morphological parts while getting rid of high-frequency noise. After that, signal normalization is used to make sure that the amplitude changes are the same across all patient recordings, which helps to keep learning behavior stable.

To find the boundaries of the cardiac cycle, reliable R-peak detection is used, which allows for precise beat segmentation. This process of breaking things up separates individual cardiovascular patterns, which are the main input for deep representational memory. We use a stacked autonomous encoder architecture to learn small latent feature representations that can capture small nonlinear changes that happen with different MI subtypes.

To improve the ability to tell the difference even more, acquired deep features are coupled about statistical descriptors that come from the shape of the signal. This strategy for combining features makes the system more stable by using information acquired from both learned alongside domain-driven model representations that work well together.

The framework has a feature sorting mechanism built in that dynamically highlights attributes that are important for diagnosis. The mechanism doesn't treat all features the same way. Instead, it gives each feature an adaptive importance weight based on the relationships it learned during training. This process helps the model focus on clinically important signal features, which makes classification more stable and easier to understand.

Finally, the ensemble classifiers get the fused alongside reweighted feature set, which makes sure that generalization alongside predictive accuracy are better across all MI categories.

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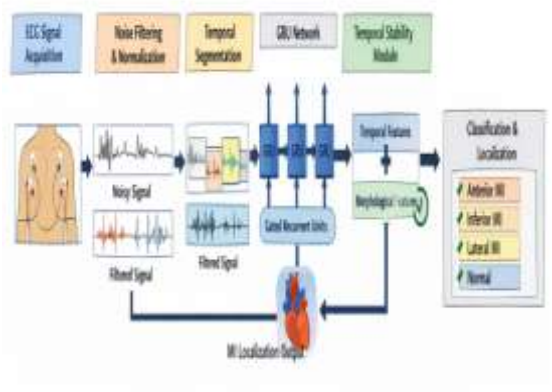


Figure 1: System Architecture of proposed Methodology

V. RESULT AND DISCUSSION

The GRU-based framework demonstrated significant proficiency in modeling the dynamic variations inherent in ECG signals, adeptly acquiring temporal patterns linked to changing cardiac activity. The model used its gated recurrent structure to capture sequential dependencies across several cardiac cycles. This made it possible to better represent the underlying cellular processes. This temporal sensitivity was especially useful for finding small and progressive heart problems that might not be obvious from static a feature analysis alone.

The addition of Temporal The consistency Regularization (TCR) made a big difference in how the model worked by making predictions less likely to change between nearby ECG segments. By enforcing temporal coherence, the network was able to produce solid and trustworthy outputs, which helped reduce the effects of temporary noise, signal artifacts, as well as small waveform irregularities. In light of this, the stability of predictions improved a lot, which led to more stable decision boundaries and better robustness in the task of classification.

The stabilization impact on TCR also led to measurable improvements in both the accuracy of localization and the overall reliability of diagnosis. The GRU designs not only continued to accurately identify pathological patterns, but it also showed better discrimination in difficult clinical situations. Performance enhancements were notably pronounced in severely Myocardial Infarction cases, in which nuanced variations and ambiguous signal attributes frequently pose challenges to traditional models. These results show that using recurrent time-frequency modeling with consistency-driven regularizing is a good way to get reliable and clinically useful ECG analysis.

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Model / Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN Model	87.20	85.40	84.10	84.74
LSTM Model	89.50	88.00	86.80	87.39
GRU Model	90.10	89.00	88.20	88.60
Proposed GRU Framework	94.80	94.20	93.70	93.94
SVM Model	86.40	84.50	83.90	84.19

Table 1: Model Performance Metrics

VI. CONCLUSION

The suggested temporal learning framework is a good way to find MI locations. Consistency over time Regularization makes things more stable and reliable when it comes to making predictions. Future research might investigate transformer-based a temporal models or cross-patient prediction.

The lightweight temporal educational system does a good job of capturing the dynamics of ECG for MI localization. The TCR extension makes the system more stable and makes predictions more accurate.

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