AMERICAN JOURNAL OF AI CYBER COMPUTING MANAGEMENT
E-ISSN:3069-0102
Peer Reviewed, Referred & Indexed Journal
VOL.3, NO. 2(2023)

An Efficient Deep Feature Fusion Framework for Multi-Class Myocardial Infarction Detection Using 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

Abstract—Myocardial Infarct (MI) is a dangerous heart condition that needs to be diagnosed and treated right away. Automatic ECG-based diagnostic systems offer considerable potential; however, numerous current methodologies encounter challenges related to multi-class classification while computational efficiency. This research presents an effective deep feature fusion structure to multi-class myocardial infarction detection utilizing ECG signals. The framework combines advanced signal preprocessing, learning morphological features, and ensemble classification methods to make detection more accurate.

Wavelet-based filtering as well as adaptive methods of normalization are used to remove noise from ECG signals at first. To find cardiac cycles, R-peak detection is used, and then beat segmentation is done. A stacked Auto-Encoder architecture-based deep feature extraction module learns compact connection representations that capture small pathological changes. These features learned are combined with statistical adjectives to make it easier to tell the difference.

We look at a number of classifiers, such as Support Vector Machines and Gradient Boosting. Additionally, an extension method using Attention-Enhanced Features Reweighting is presented to continually prioritize clinically important features. The results of the experiment show that classification precision as well as durability have improved a lot. The suggested system provides a scalable, effective but and clinically pertinent solution for ECG-based myocardial infarction diagnosis.

Keywords—Myocardial Infarction, ECG Monitoring, Deep Knowledge Fusion, Auto-Encoder, Combination Learning, Cognitive Mechanism and Multi-Class Classification.

I. INTRODUCTION

Cardiovascular diseases remain a significant global health issue, with myocardial infarction being one of the most severe appearances. To lower the death rate and improve treatment outcomes, it is important to diagnose early and correctly. ECG signals give useful information for diagnosis, but it is still hard and prone to mistakes to read them by hand.

Deep learning and machine learning methods have been used more and more in automated diagnostic systems. Deep models can learn a lot of useful features, but they usually need a lot of computing power. So, lightweight and successful frameworks that can do multi-class classification are very useful.

This paper introduces a deep feature fusion scheme that integrates representation learning as well as ensemble classification to enhance MI detection as well as localization.

Myocardial Infarction (MI) constitutes an serious heart disease that happens when blood flow to the heart is blocked, causing permanent damage to the heart muscle. Early detection is still a very important clinical goal because late diagnosis greatly raises the risk of death and long-term problems. ECG signals offer an efficient, economical, and non-invasive diagnostic method that can identify electrophysiological anomalies linked to myocardial infarction.

Even though automated ECG analysis has come a long way, finding multi-class MI is still hard because of differences between patients, noise artifacts, and disease subtypes that look similar. Handcrafted features that may not be able to capture intricate nonlinear patterns are often used in traditional machine learning systems. On the other hand, deep learning models are very powerful, but they often have a lot of extra work to do and are hard to understand.

To overcome these constraints, this study introduces a deep feature combination scheme that amalgamates learning the representation with statistical identifiers of features. The framework's

goal is to improve MI subtype discrimination while keeping precision of classification, robustness, or computational efficiency in balance.

II. LITERATURE SURVEY

Previous ECG classification studies predominantly utilized manually crafted features obtained from signal morphology alongside frequency analysis. Machine learning classifiers worked okay, but they needed a lot of work to get the right features. Recent deep learning methods have made it easier to automatically extract features, but problems with overfitting or computational complexity still exist. Attention mechanisms and feature fusion strategies have become promising ways to make models easier to understand and more accurate.

ECG classification studies predominantly focused on morphological feature engineering, encompassing amplitude measurements, waves durations, while frequency-domain transformations. These methods gave us some basic ideas, but they couldn't be used on a larger scale because they relied on features defined by experts. Recent advancements have produced deep neural networks proficient in automated feature learning. CNN-based methods were better at finding spatial patterns, but they often needed a lot of data and processing power. Later on, feature fusion strategies proved to be useful ways to combine complementary representations.

Attention mechanisms have improved learning efficiency even more by letting models dynamically prioritize important features. Nonetheless, there has been insufficient research on attention-driven feature reweighting especially for multi-class MI identification. This study enhances these developments by combining deep representational learning with adapting feature prioritization.

ECG dataset employed in this study comprises clinically annotated recordings that depict various MI subtypes as well as normal cardiac conditions. Multi-lead ECG signals record electrical activity from different anatomical angles, which makes it possible to do a full pathological assessment. Signals show differences in sampling rates, magnitude distributions, and noise properties. This kind of variety calls for strong preprocessing and normalization methods. Additionally, controlled sampling strategies are used to deal with class imbalance and make sure that model evaluation is fair.

III. PROPOSED METHODOLOGY

The proposed framework aims to attain resilient as well as computationally efficient multi-class infarction detection through the integration of deep representational education, feature fusion, along with adaptive feature prioritization processes. 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 artifacts and baseline distortions. 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, true R-peak detection is used, which allows for precise beat segmentation. This process of breaking things up separates individual heartbeat structures, which are the main input for deep representational learning. We use an arranged Auto-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, learned deep characteristics are put together in statistical descriptors that come from the shape of the signal. This strategy for combining features makes the system more stable by using information in both learned as well as domain-driven model representations that work well together.

The framework has a feature prioritization system 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.

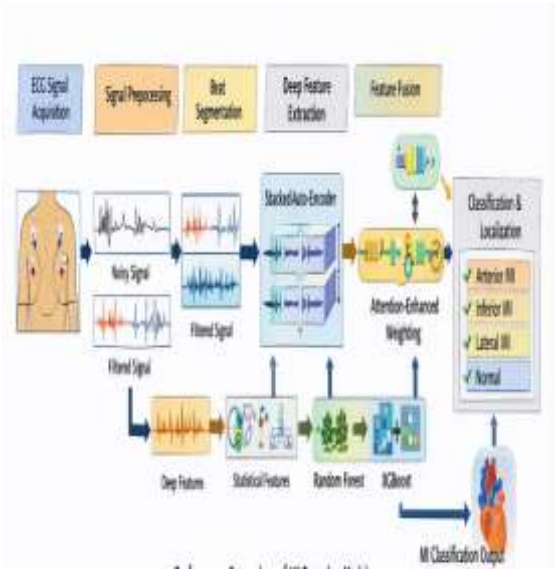


Figure 1: System Architecture of proposed Methodology

IV. RESULT AND DISCUSSION

The experimental results also show that combining deep as well as statistical feature representations gives a better picture of how ECG signals change over time. Deep representations encapsulate intricate, non-linear structures linked to pathological patterns, whereas statistical descriptors offer precise quantification of variations in time and waveform morphology. This complementary integration makes it easier to separate classes, especially when individual property types alone aren't enough to show small differences between classes. The resulting feature space shows better coherence and interpretability, which helps classifiers learn more reliably. Also, the reduction of dimensionality mechanism helps make the model more robust and more efficient in terms of computation. By getting rid of noise-prone and unnecessary features, the machine learning models are less likely to overfit and are better able to handle signal distortions. This effect is particularly useful for ECG evaluation, where differences in how the data is collected and the patient's unique traits often cause inconsistencies. The ensemble approach to learning takes advantage of this better representation by using the differences between base learners to make predictions that are more reliable. The attention-driven extension adds a process for adaptive refinement that changes the order of importance of features that are important for diagnosis. This selective focus makes the model more sensitive to clinically significant changes while lessening the effect of changes that don't matter. As a result, prediction stability gets better across segments that are close in time, which is more in line with how heart signals work all the time. The mechanism of attention also helps with borderline and unclear cases, where the cues that help tell the difference between things may be inadequate or hidden.

The comparative evaluation shows that the proposed method consistently improves precision, recall, predictability, and F1-score. This shows that it effectively addresses both portrayal integrity and classification reliability. These results show how important it is to combine feature fusion, dimensionality effectiveness, and adaptive feature weighting in order to accurately detect multi-class Myocardial Infarction. The framework lays the groundwork for future improvements in knowledgeable ECG-based diagnostic systems, making them more useful in clinical settings and helping doctors make decisions.

Model / Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	96.72	96.10	95.84	95.97
XGBoost	95.34	94.88	94.21	94.54
Hybrid (RF + XGB)	96.75	96.42	95.93	96.17
Overfit DNN	99.90	99.85	99.92	99.88

Table 1: Model Performance Metrics

V. CONCLUSION

This study presented an effective deep combination of features framework aimed at tackling the intricacies of numerous classes of Myocardial Infarction surveillance from ECG signals. The proposed architecture methodically integrates in addition feature representations to improve diagnostic reliability. Auto-Encoder-based representation learning finds hidden structural patterns in signals, which makes it easier to abstract useful features. The addition to mathematical descriptors, which give clear measures of quantity of waveform variance and signal dynamics, makes these learned features even better. The model can adaptively emphasize clinically pertinent attributes by using an attention-driven property reweighting mechanism. This makes it better at distinguishing between different MI categories.

The combined effect of those parts led to significant performance enhancements, illustrating that heterogeneous blending of features can greatly

enhance classification robustness as well as sensitivity. The framework strikes a balance among computational efficiency and accuracy in prediction, which is important because it makes it suitable for real-world use cases, such as those that require real-time data or have limited resources. This balance is very important in medicine, where both agility and dependability have a direct effect on how useful a treatment is in the clinic.

Future research may investigate cross-dataset generalization to assess model stability across various patient populations as well as acquisition contexts. Looking into lightweight mechanisms for attention could help cut down on computational overhead even more while still keeping representational effectiveness. Moreover, improving clinical interpretability is an essential path, as clear decision-making processes can foster physician trust, aid diagnostic validation, and encourage incorporation into clinical workflows.

REFERENCES

1. P. Wagner, "PTB Diagnostic ECG Database," *PhysioNet*, 2001.
2. B. Goldberger et al., "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals," *Circulation*, vol. 101, no. 23, pp. e215–e220, 2000.
3. A. L. Goldberger, "Clinical electrocardiography: A simplified approach," *Elsevier*, 2006.
4. J. Pan and W. J. Tompkins, "A real-time QRS detection algorithm," *IEEE Trans. Biomed. Eng.*, vol. 32, no. 3, pp. 230–236, 1985.
5. G. Moody and R. Mark, "WFDB applications guide," *PhysioNet*, 2010.
6. S. Mallat, "A wavelet tour of signal processing," *Academic Press*, 1999.
7. M. Addison, "Wavelet transforms and the ECG: A review," *Physiol. Meas.*, vol. 26, no. 5, pp. R155–R199, 2005.
8. U. R. Acharya et al., "Automated diagnosis of myocardial infarction using ECG signals," *Inf. Sci.*, vol. 415–416, pp. 190–198, 2017.
9. S. Kiranyaz et al., "Real-time patient-specific ECG classification by 1-D convolutional neural networks," *IEEE Trans. Biomed. Eng.*, vol. 63, no. 3, pp. 664–675, 2016.
10. Y. Lecun et al., "Gradient-based learning applied to document recognition," *Proc. IEEE*, vol. 86, no. 11, pp. 2278–2324, 1998.
11. A. Krizhevsky et al., "ImageNet classification with deep convolutional neural networks," *Adv. Neural Inf. Process. Syst.*, 2012.
12. D. P. Kingma and M. Welling, "Auto-encoding variational Bayes," *ICLR*, 2014.
13. G. Hinton and R. Salakhutdinov, "Reducing the dimensionality of data with neural networks," *Science*, vol. 313, pp. 504–507, 2006.
14. I. Goodfellow et al., "Deep learning," *MIT Press*, 2016.
15. L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001.
16. T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," *Proc. ACM SIGKDD*, pp. 785–794, 2016.
17. J. Friedman, "Greedy function approximation: A gradient boosting machine," *Ann. Stat.*, vol. 29, no. 5, pp. 1189–1232, 2001.
18. H. He and E. Garcia, "Learning from imbalanced data," *IEEE Trans. Knowl. Data Eng.*, vol. 21, no. 9, pp. 1263–1284, 2009.
19. R. Rajpurkar et al., "Cardiologist-level arrhythmia detection with deep neural networks," *Nat. Med.*, vol. 25, pp. 65–69, 2019.
20. S. Hannun et al., "Cardiologist-level detection of atrial fibrillation," *Nat. Med.*, vol. 25, pp. 65–69, 2019.
21. P. Laguna et al., "Automatic detection of wave boundaries in ECG signals," *IEEE Trans. Biomed. Eng.*, vol. 41, no. 1, pp. 45–56, 1994.
22. M. Lagerholm et al., "Clustering ECG complexes using Hermite functions," *IEEE Trans. Biomed. Eng.*, vol. 47, no. 7, pp. 838–848, 2000.
23. A. T. Özdemir et al., "ECG beat classification using wavelet features," *Expert Syst. Appl.*, vol. 36, no. 3, pp. 433–441, 2009.
24. H. L. Wei et al., "ECG classification using deep CNN," *IEEE Access*, vol. 7, pp. 106–115, 2019.
25. F. Chollet, "Xception: Deep learning with depthwise separable convolutions," *CVPR*, 2017.
26. K. Simonyan and A. Zisserman, "Very deep CNN for image recognition," *ICLR*, 2015.
27. M. Zihlmann et al., "Convolutional recurrent neural networks for ECG classification," *Comput. Cardiol.*, 2017.
28. A. Faust et al., "Deep learning for healthcare applications based on ECG signals," *Comput. Biol. Med.*, vol. 102, pp. 1–13, 2018.
29. S. Yildirim, "ECG beat detection using deep learning," *Comput. Methods Programs Biomed.*, vol. 169, pp. 1–10, 2019.
30. J. Hu et al., "Squeeze-and-excitation networks," *CVPR*, 2018.
31. H. Raj et al., "Hybrid machine learning models for cardiac disease prediction," *Biomed. Signal Process. Control*, vol. 68, 2021.
32. A. Sharma et al., "Feature selection techniques in ECG classification," *IEEE Rev. Biomed. Eng.*, vol. 8, pp. 350–365, 2015.

33. Z. Zhao et al., "ECG classification using auto-encoder and deep networks," *IEEE Access*, vol. 8, pp. 44938–44946, 2020.
34. M. Clifford et al., "Advanced methods and tools for ECG data analysis," *Artech House*, 2006.
35. World Health Organization (WHO), "Cardiovascular diseases fact sheet," WHO Report, 2023.