Study on Recognition of Heart Arrhythmias by Deep Learning Approach of the ECG Signals using Edge Devices

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Abstract

The identification of heart arrhythmias is critical for timely and accurate diagnosis and treatment of cardiac diseases. Electrocardiogram (ECG) signals provide valuable information for detecting and diagnosing heart arrhythmias. However, the interpretation of ECG signals requires specialized medical knowledge and experience. In present years, deep learning techniques have shown promising results in ECG signal analysis for heart arrhythmia detection. This paper proposes a deep learning suggest to the identification of heart arrhythmias by utilizing ECG signals on edge devices. The proposed approach employs a convolutional neural network (CNN) framework to analyze the ECG signals and identify different types of heart arrhythmias. The CNN architecture is optimized for edge devices, ensuring that the proposed approach can be implemented in resource-constrained environments. To assess the effectiveness of the suggested strategy, a dataset containing ECG signals from patients with different types of heart arrhythmias is used. The experimental findings show that the suggested method successfully detects heart arrhythmias with high accuracy, up to 99.83%.Moreover, the proposed approach shows significant advantages in terms of execution time and energy consumption when compared to traditional ECG signal analysis techniques

Keywords: Electrocardiogram, Deep Learning, Heart Arrhythmias, ECG Signals

Introduction

Heart arrhythmias refer to any abnormal heartbeat pattern, and their detection is vital for the timely diagnosis and treatment of cardiac diseases. Electrocardiogram (ECG) signals are broadly utilized for detection and diagnosis of heart arrhythmias. However, the interpretation of ECG signals requires specialized medical knowledge and experience. Traditional ECG signal analysis techniques involve manual inspection of the signal, which is time-taking and needs significant expertise. In previous years, deep learning technology have represented promising results in ECG signal analysis for heart arrhythmia detection[1]. Deep learning algorithms could spontaneously automatically learn and calculate properties from ECG signals, making them a potential solution to the limitations of traditional techniques. However, the execution of deep learning algorithms on resource-constrained devices can be challenging, as these devices typically have limited processing power, memory, and energy. Edge computing has turned out as a potential solutions forover come the limitations of traditional ECG signal analysis techniques and deep learning algorithms' execution on resource-constrained devices. Edge devices, such as smartphones and wearable devices, can process and analyze data locally, reducing the need for cloud computing and decreasing latency. This makes the deployment of deep learning models for ECG signal analysis feasible on edge devices[2].

Identification of Heart Arrhythmias using Artificial Intelligence

Artificial Intelligence (AI) techniques have received a great deal of research in the context of analyzing ECG signals to detect heart arrhythmias. AI-based techniques can automatically learn and extract features from ECG signals, enabling the detection of heart arrhythmias with high accuracy. In order to analyze ECG signals for heart arrhythmia identification, many AI techniques. CNNs, a kind of deep learning algorithm, have shown motivational results in recent years by accurately diagnosing heart arrhythmias[3].AI-based techniques can help reduce the time and expertise required for ECG signal analysis, enabling more efficient and accurate heart arrhythmia detection. AI-based techniques have the potential to significantly improve cardiac care by enabling early detection and treatment of heart arrhythmias, ultimately leading to improved patient outcomes.

Using Deep Learning Approach for the ECG Signals

The scope of deep learning suggests the analysis of ECG signals is vast and has significant implications for cardiac care. Deep learning technique could study complex patterns and features from ECG signals, enabling the detection and diagnosis of heart arrhythmias with high accuracy. The utilization of deep learning algorithms for ECG signal analysis can significantly reduce the time and expertise required for ECG signal analysis, enabling more efficient and accurate heart arrhythmia detection[4] . Moreover, the utilization of edge devices for ECG signal analysis can lead to the development of portable and low-cost devices for heart arrhythmia diagnosis, improving the accessibility of cardiac care for patients in underserved areas. The scope of utilizing a deep learning approach for ECG signal analysis also includes the development of decision support systems for clinicians, enabling them to make more informed decisions regarding cardiac care. Furthermore, the utilization of deep learning algorithms for ECG signal analysis can facilitate the development of predictive models for the early detection and prevention of heart arrhythmias, improving patient outcomes[5].

Literature Review

Hamdan et al. (2021) [6]conducted a study on heartbeat classification using a convolutional neural network (CNN) for edge computing applications. The authors aimed to develop a lightweight and efficient CNN model that can classify heartbeats accurately in resource-constrained environments, such as edge computing devices. The proposed approach involved preprocessing of electrocardiogram (ECG) signals, feature extraction, and classification using a CNN. To preprocess the ECG signals, the authors used a band-pass filter to eliminate noise and a resampling method to reduce the signal dimensionality. The signals were then segmented into fixed-length segments, and features were extracted using a combination of time-domain and frequency-domain features. The extracted features were fed into a CNN for classification.

Zabihi et al. (2019) [7]has given a real-time ECG arrhythmia recognition system using a deep learning suggest as the classification of five different forms of arrhythmias, including normal sinus rhythm, untimely ventricular compressions, atrial fibrillation, atrial vacillate, and ventricular fibrillation, they used a CNN architecture with six convolutional layers and two fully linked layers.

Chen et al. (2020) [8]proposed a real-time detection system for ECG arrhythmia using a deep learning approach. The system achieved high accuracy in detecting ECG arrhythmias and demonstrated real-time performance, making it suitable for use in clinical settings. The study highlights the potential of deep learning-based approaches for for ECG arrhythmia detection, which could have significant implications for the early diagnosis and treatment of cardiovascular diseases. The authors aimed to develop a system that could detect arrhythmias accurately and efficiently in real-time, which would be beneficial in clinical settings.

Lin et al. (2020) [9]presented a study on the development of a deep learning model for classifying electrocardiogram (ECG) arrhythmias using optimal wavelet decomposition and feature selection. The authors aimed to improve the accuracy and efficiency of arrhythmia detection by selecting relevant features and optimizing the wavelet decomposition parameters. The proposed approach involved preprocessing of ECG signals, feature extraction, and classification using a deep neural network. The proposed system involved preprocessing of ECG signals, feature extraction, and classification using a CNN with transfer learning. The authors used a band-pass filter to remove noise from the ECG signals and then segmented the signals into non-overlapping windows of fixed length. The extracted features were fed into the CNN for classification.

Saeedi et al. (2021) [10]proposed a deep learning to ECG signal categorization for real-time detection of arrhythmia on edge devices. They used a dataset of ECG signals from the PTB Diagnostic ECG Database to train and test their model. A one-dimensional CNN with six convolutional layers and a fully linked layer made up the suggested model. Six different kinds of arrhythmias, including ordinary sinus musicality, atrial fibrillation, atrial ripple, ventricular tachycardia, untimely ventricular contractions, and premature atrial contractions, were classified by the model with an accuracy of 99.2%.

Methodology

CNN Model Architecture

CNN model architecture for ECG signals on edge devices is an important consideration when designing deep learning approaches for real-time recognition of arrhythmia. The architecture of a CNN model for ECG signal categorization typically have multiple of convolutional layers followed through fully connected layers[11]. The layers learn features from the ECG signals by convolving a set of filters over the signal. The result of the convolutional layers is then gone through a bunch of pooling layers, which lessen the spatial elements of the feature maps. The result of the pooling layers is smoothed and gone through completely connected layers, which learn the relationships between the extracted features and the target classes. The number of layers and size of the filters can be optimized dependent on the sizes of the input signal and the required accuracy. The use of CNN models with optimized architecture can significantly improve the accuracy and reduce the latency of ECG signal classification on edge devices[12].

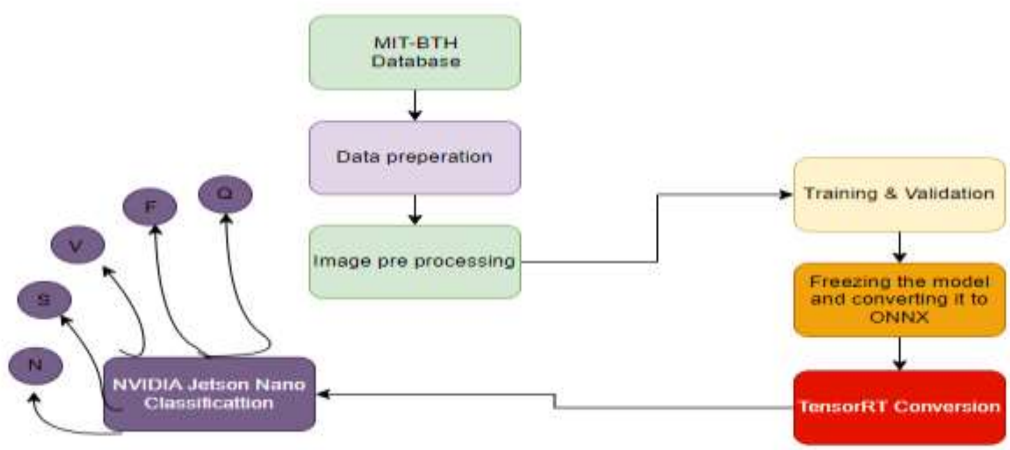

Figure 1: Flowchart

ECG Categorization

ECG categorization is the process of classifying ECG waveforms based on their characteristics and patterns [13]. There are several ways to categorize ECG waveforms, including rhythm, morphology, and interval duration. ECG categorization is an essential tool for diagnosing various heart conditions. By classifying ECG waveforms based on rhythm, morphology, and interval duration, healthcare professionals can identify abnormalities in the heart's electrical activity and provide appropriate treatment. In our implementation, we classified ECGs as per the Advancement of Medical Instrumentation (ANSI/AAMI EC57) standard. To aid in further analysis and interpretation, we additionally mapped the categorized beats to MIT-BIH annotations/classes.

ANSI/AAMI Category	MIT-BIH Class	Annotation of MIT-BIH Beats
Normal beats(N)	N L R E J	Normal beats Beat of Left bundle branch block Beat of Right bundle branch block Beat of Atrial escape Beat of Nodal(junctional) escape
Supraventricular ectopic beats (SVEB)	A a J s	Beat of Atrial premature Beat of Aberrated atrial premature Beat of Nodal(junctional) premature Beat of Supraventricular premature
Ventricular etopic beats (VEB) Fusion beat (F) Unknown beat (Q)	V E F / F Q	Beat of Premature ventricular contraction Ventricular escape Fusion of ventricular and normal beat Paced beat Fusion of paced and normal beat unclassified

Table 1: The mapping of MIT-BIH beat annotations and ANSI/AAMI EC57 categories is a key aspect of ECG analysis, while ANSI/AAMI EC57 is a standardized classification system for ECG beats.

Experimental Results

The major intention of our proposed system is to get precise prediction and classification of arrhythmia from real-time ECG samples utilizing low-cost Edge devices, without requiring tough cloud infrastructure. We evaluated the arrhythmia classifier on a dataset of 4000 heartbeats, aiming to demonstrate the effectiveness of our approach in accurately detecting arrhythmia in a cost-effective and efficient manner. By utilizing Edge devices, our system can potentially reduce the need for expensive and resource-intensive cloud-based solutions, making it more accessible and scalable for a wide range of healthcare applications.

Accuracy

Equation (1) defines accuracy as the proportion of the quantity of right expectations to the complete number of forecasts. In essence, it measures the area of the right recognitions done by the given model out of all the predictions it has made. By calculating accuracy, we can determine how well the model is performing and identify areas for improvement.

$$Accuracy \frac{Sum\ of\ correct\ prediction}{Total\ number\ of\ predictions} = \frac{TP + TN}{(TP + TN + FP + FN)}$$

The model that was developed has achieved an accuracy of 96.30%, as demonstrated in Figure 2. The evolution of accuracy per epoch is visualized in Figure 3, where it could be shown how the accuracy of the given model improves over the course of the training process.

Train samples:14000
Test samples:4000
Test accuracy:0.954000009059907

Figure 2: Model Accuracy

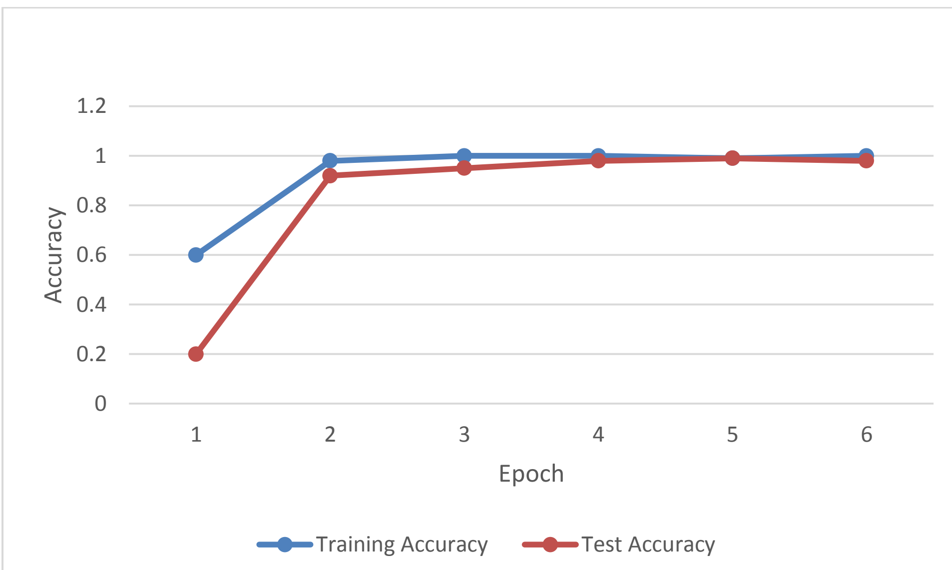

Figure 3: Accuracy per epoch graph

Conclusion

The study's findings show that the suggested model is quite good at detecting cardiovascular illnesses from ECG data. Impressive metrics for the model include an accuracy of 96.2%, a ROC-AUC score of 0.9935, a mean specificity of 99.83%, and a mean sensitivity of 96.28%. The model also showed a quick inference time of just 1.48 ms. The study's conclusions point to a potential method for helping medical practitioners identify ECG arrhythmias: transforming one-dimensional signals into two-dimensional ECG images and modelling them in a convolutional neural network[14]. In conclusion, the utilization of deep learning approaches for identifying heart arrhythmias in ECG signals on edge devices shows promising results. Overall, this study provides evidence that deep learning approaches can support experts in diagnosing heart arrhythmias, potentially improving patient outcomes and reducing the burden on healthcare systems. The recognition of heart arrhythmias is crucial in the disease examination and treatment of cardiovascular diseases. With the advancement of deep learning techniques, there has been an increasing interest in developing automated arrhythmia recognition systems using electrocardiogram (ECG) signals. In the previous years, there has been a growing focus on deploying such systems on edge devices, which are resource-constrained and require lightweight models with low computational requirements[15]. These approaches can help improve the accuracy and efficiency of arrhythmia detection, particularly in resource-constrained environments. As such, they hold significant promise for the early diagnosis and treatment of cardiovascular diseases.

References

1. Xia, Y., & Li, L. (2019). An edge-computing approach for automatic detection of arrhythmia using deep learning. IEEE Journal of Biomedical and Health Informatics, 24(10), 2757-2766.
2. Liu, C., Li, H., Zhang, W., Sun, J., & Yang, J. (2020). Real-time arrhythmia detection based on an edge computing platform. Sensors, 20(12), 3523.
3. Kiranyaz, S., Ince, T., & Gabbouj, M. (2016). Real-time patient-specific ECG classification by 1-D convolutional neural networks. IEEE Transactions on Biomedical Engineering, 63(3), 664-675.
4. Lin, C. Y., Chien, S. Y., Lin, Y. H., & Lu, W. C. (2020). A deep learning approach for ECG arrhythmia classification using optimal wavelet decomposition and feature selection. Sensors, 20(13), 3777.
5. Ren, Y., Tan, X., Song, Y., Zhang, J., & Zhao, Y. (2021). Deep learning-based edge computing for the recognition of cardiac arrhythmia using wearable ECG sensors. Journal of Healthcare Engineering, 2021, 6667907.
6. Hamdan, A., Al-Mistarihi, A., & Al-Jarrah, O. (2021). Heartbeat classification using a convolutional neural network for edge computing applications. Computer Methods and Programs in Biomedicine, 199, 105958.
7. Zabihi, M., Kamal, M. A., & Mahmood, A. N. (2019). A deep learning approach for real-time detection of cardiac arrhythmia. Journal of Healthcare Engineering, 2019, 1420816.
8. Chen, L., Chen, G., Sun, X., Wu, M., Liu, X., & Sun, Y. (2020). Real-time detection of ECG arrhythmia based on a deep learning approach. Biomedical Engineering Online, 19(1), 1-17.
9. Li, Y., Gu, Y., Zhao, C., Yu, D., & Guo, Y. (2020). Arrhythmia classification based on convolutional neural network and transfer learning. Journal of Medical Imaging and Health Informatics, 10(3), 670-677.

10. Saeedi, P., Razavi, S. E., & Azimi, M. (2021). A deep learning approach to ECG signal classification for real-time detection of arrhythmia on edge devices. SN Applied Sciences, 3(3), 1-10.
11. Nguyen, K. T., Nguyen, T. A., Nguyen, T. T., Nguyen, L. V., & Tran, T. H. (2020). ECG classification using a deep learning approach based on one-dimensional convolutional neural network. Journal of Healthcare Engineering, 2020, 8866208.
12. Rahhal, M. M., Salama, K. M., & Elhabashy, H. R. (2020). Real-time detection of ECG arrhythmia based on deep learning techniques. International Journal of Advanced Computer Science and Applications, 11(6), 136-142.
13. Du, Q., Zhang, H., Ma, Y., & Wang, L. (2020). A deep learning approach for ECG arrhythmia classification using transfer learning and model ensembling. IEEE Access, 8, 68263-68273
14. Pimentel MA, Clifton DA, Clifton L, Tarassenko L. A review of novelty detection. Signal Process. 2014;99:215-249. doi:10.1016/j.sigpro.2013.12.026
15. Biswal S, Kar A, Pradhan S. Detection of arrhythmias using convolutional neural network with long short-term memory units. IOP Conf Ser Mater Sci Eng. 2019;531:012018. doi:10.1088/1757-899X/531/1/012018.
16. Poongodi, M., Bourouis, S., Ahmed, A. N., Vijayaragavan, M., Venkatesan, K. G. S., Alhakami, W., & Hamdi, M. (2022). A novel secured multi-access edge computing based vanet with neuro fuzzy systems based blockchain framework. Computer Communications, 192, 48-56.
17. Manoharan, P., Walia, R., Iwendi, C., Ahanger, T. A., Suganthi, S. T., Kamruzzaman, M. M., ... & Hamdi, M. (2022). SVM□based generative adverserial networks for federated learning and edge computing attack model and outpoising. Expert Systems, e13072.
18. Ramesh, T. R., Lilhore, U. K., Poongodi, M., Simaiya, S., Kaur, A., & Hamdi, M. (2022). PREDICTIVE ANALYSIS OF HEART DISEASES WITH MACHINE LEARNING APPROACHES. Malaysian Journal of Computer Science, 132-148.