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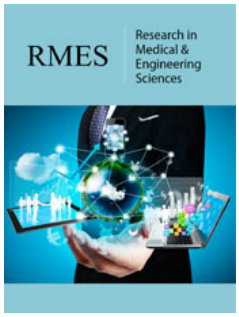
Mini Review

Use of Artificial Intelligence for the Classification of Fetal Electrocardiograms (fECG) using the MIT-BIH Arrhythmia Database

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Abstract

Non-invasive fetal electrocardiography (fECG) is essential for prenatal monitoring and detection of cardiac abnormalities. However, signal extraction remains complex due to maternal ECG noise and interference. This research proposes a method combining the Discrete Wavelet Transform (DWT) and a one-dimensional Convolutional Neural Network (CNN) to classify five clinical categories (Normal, Infarction, ST-T Changes, Conduction Disorders, and Hypertrophy) from the MIT-BIH base. The DWT extracts approximation and detail coefficients as descriptors. The study compares the Haar wavelet and the Daubechies wavelet of order 4 (db4). The DWT-db4 approach coupled with the CNN proves to be superior, achieving an accuracy of 98.7%, a recall of 98.5% and an F1 score of 98.6%. Thanks to a drastically reduced computational cost compared to heavy models (ResNet, VGG), this efficient architecture is ideal for embedded telemedicine systems and portable monitors, paving the way for reliable decentralized diagnostics.

Keywords: Fetal Electrocardiography (ECGf); Artificial Intelligence; Convolutional Neural Networks (CNN); Discrete Wavelet Transform (DWT); MIT-BIH Arrhythmia Database; Embedded Clinical Diagnosis

Introduction

Fetal cardiovascular pathologies and intrauterine hypoxia are major causes of neonatal mortality worldwide, requiring accurate prenatal monitoring. If cardiotocography (CTG) and Doppler ultrasound are commonly used, CTG suffers from a high rate of false positives, leading to unjustified emergency caesarean sections. Fetal electrocardiography (ECGf) [1] presents itself as a much superior alternative. By analyzing the morphology of the signal (P waves, QRS complex, T wave), it provides direct pathophysiological indicators on cardiac metabolism. The study of the ST segment and the QT interval allows in particular to detect early myocardial ischemia or hypertrophy related to hypoxic stress [2]. However, extracting the ECGf non-invasively via abdominal electrodes remains a major technological challenge [3]. The extremely weak fetal signal (5 to 20μV) is masked by maternal ECG (10 to 100 times stronger), uterine contractions (EMG), respiration and instrumentation sounds [4]. Classical algorithms (ICA, adaptive filtering, EMD) are limited in terms of non-stationarity of signals and are difficult to execute in real time on lightweight architectures [5]. Some work from the literature review has served us as references: Al-Mansoor and Zhang [6] adapt AlexNet in 1D for raw abdominal fetal ECG, achieving 94.2% accuracy in detecting hypoxia. Gauthier et al. [7] modify VGG16 with 1D convolutional blocks to analyze raw cardiotocography, obtaining an F1-score of 91.8% to classify stress. Santos et al. [8] transpose ResNet50 into a one-

dimensional architecture with residual connections for the raw fetal phonocardiogram, identifying heart abnormalities with an accuracy of 98.5%. Similarly, traditional deep convolutional neural networks (CNNs) are too resource-intensive for portable medical devices [9]. To overcome these obstacles, this work proposes an innovative hybrid AI methodology. It combines dimensional reduction by Discrete Wavelet Transform (DWT) and a lightweight one-dimensional CNN. Evaluated on the MIT-BIH Arrhythmia Database, this model automatically classifies five fetal heart conditions. By drastically reducing the number of parameters, this approach aims at optimal integration within embedded telemedicine systems.

Theoretical Fundamentals and Methods

A detailed understanding of the proposed methodological framework requires a mathematical formalization of the concepts of multiresolution wavelet analysis, as well as the non-linear transfer mechanisms employed within the neural classification architecture.

A. Discrete Wavelet Transform (DWT)

The Discrete Wavelet Transform (DWT) [2] is ideal for analyzing non-stationary biomedical signals such as ECGf. Unlike the Fourier method, which wastes time, DWT offers a time-frequency decomposition using the translations and expansions of a master wavelet ψ(t).

Mathematically, the DWT coefficient for a discrete signal f[tm] at a scale a and a position b is formally expressed by the following equation (1): t_m

$$D[a,b] = \frac{1}{\sqrt{a}} \sum_{m=0}^{p=1} f\left[t_m\right] \psi\left(\frac{t_m - b}{a}\right) \quad (1)$$

Where D[a,b] denotes the resulting wavelet coefficient, f[t_m] represents the sampled time value of the original signal at the instant t_m, P is the total number of samples, and psi corresponds to the mathematical function of the selected wavelet. In the practical field of multiresolution analysis, this process is implemented via a bank of quadrature mirror filters. The signal undergoes low-pass filtering to extract approximation coefficients (cA), which model the general trend at low frequency, and simultaneous high-pass filtering to capture detail coefficients (cD), containing the high-frequency dynamics and abrupt changes in the signal.

B. Activation and Non-Linearity Functions

In order to allow the convolutional neural network to learn complex and non-linear feature representations from the coefficients extracted by DWT, the integration of appropriate activation functions is essential within the nucleus of the artificial neuron. The most widely adopted activation function in deep layers is the Rectified Linear Unit (ReLU). The standard mathematical formulation of the ReLU function is expressed according to equation (2):

$$f(x) = \max(0, x) \quad (2)$$

ReLU accelerates convergence and offers high computational efficiency. However, it suffers from the phenomenon of dead neurons when the inputs are strictly negative, which cancels the gradient. To correct this limitation in sensitive layers, the Leaky ReLU variant is sometimes implemented according to equation (3):

$$f(x) = \{x, \text{si } x \geq 0; \alpha x, \text{si } x < 0\} \quad (3)$$

Where alpha represents an extremely low positive leakage rate (typically α=0.01), ensuring that a small numerical contribution remains even for negative values, thus maintaining an active learning dynamic for all network parameters during the error backpropagation phase.

Experimental methodology

The deployment of our automatic classification system for ECGf relies on a rigorous process chain, from data acquisition to neural modelling.

A. MIT-BIH arrhythmia database

To validate our approach, we use the MIT-BIH database arrhythmia, a state-of-the-art simulator generating realistic non-invasive fetal ECG signals. This system models the uterine environment through various clinical configurations: heart rate variations, fetal arrhythmias and controlled maternal noises. Finally, a uniform sampling at 300Hz ensures optimal temporal resolution to accurately capture all the waves of fetal heart activity.

B. Pretreatment and extraction strategy by DWT

Before injection into the neural network, raw physiological signals undergo sliding window segmentation to isolate fetal heart cycles, followed by filtering by Discrete Wavelet Transform (DWT).

The study compares two parent wavelets for the extraction of descriptors:

- The Haar wavelet: discontinuous and simple to calculate.
- The Daubechies wavelet (db4): regular and structurally close to a real ECG.

The resulting approximation coefficients (cA) eliminate high-frequency noise and intelligently reduce data size to serve as direct inputs for the final classification step.

Architecture of the Convolutional Neural Network (CNN)

This classifier is based on a one-dimensional convolutional neural network (1D-CNN) optimized to be precise and lightweight. From a reduced vector of wavelet coefficients of the fetal heart wave, the network chains several successive layers:

- Conv1D: extracts local patterns.
- Batch Normalization: stabilizes training.
- ReLU: brings non-linearity.
- Max-Pooling 1D: reduces dimensionality.
- Dense and Softmax: classify data in a probabilistic way.

To avoid overfitting, a 30% Dropout is inserted before the final stage. Finally, the training is based on the Adam optimizer associat-

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ed with the categorical cross-entropy loss function. This model thus combines structural efficiency and regularization.

Experimental results and discussion

This section presents the quantitative evaluation of the classification performance obtained from the MIT-BIH Arrhythmia Database, followed by a critical analysis of algorithmic efficiency.

A. performance benchmarking

The effectiveness of the proposed methodology is measured using three standard clinical evaluation metrics: Precision (P), Recall (R), and F1-score.

$$F1-score=\frac{P.R}{P+R} \quad (5)$$

The model must classify fetal heart signals into five distinct categories: Normal (NORM), Myocardial infarction (MI), ST segment and T wave changes (STTC), Conduction disorders (CD), and Hypertrophy (HYP).

The analysis of the data summarized in Table 1 reveals a glaring disparity in performance, which is conditioned by the mathematical nature of the master wavelet used. The approach based on the Haar wavelet displays acceptable but perfectible scores, oscillating between 89.5% and 94.2%. This limitation is explained by the rectangular and discontinuous shape of the Haar wavelet, which introduces slight frequency distortions during the decomposition of P-QRS-T smooth waves in the fetal signal. Conversely, the implementation of the fourth-order Daubechies family (db4) results in a significant increase in all performance indicators, reaching a remarkable overall accuracy of 98.7% and an average F1-score of 98.6%. The regularity and compact support properties of the db4 wavelet optimally fit the intrinsic geometry of fetal myocardial electrical potentials, preserving all the micro-pathological variations of the ST segment and ventricular repolarization within the approximation coefficients transmitted to the CNN.

Table 1: The analysis of the synthesized data.

Parent Wavelet	Disease Class	Accuracy (%)	Recall (%)	F1 Score (%)
Haar	Normal (NORM)	94.2	93.8	94.0
Haar	Infarctus (MI)	91.5	90.2	90.8
Haar	Chang. ST-T (STTC)	92.0	91.1	91.5
Haar	Troubles Cond. (CD)	93.1	92.4	92.7
Haar	hypertrophy (HYP)	90.8	89.5	90.1
Daubechies db4	Normal (NORM)	99.4	99.1	99.2
Daubechies db4	Infarctus (MI)	98.1	97.9	98.0
Daubechies db4	Chang. ST-T (STTC)	98.5	98.2	98.3
Daubechies db4	Troubles Cond. (CD)	98.9	98.6	98.7
Daubechies db4	hypertrophy (HYP)	98.6	98.7	98.6

B. Discussion on digital efficiency and deployment

Beyond the raw classification scores, the major advantage of the DWT-db4 strategy lies in its digital frugality and low algorithmic complexity. By applying the DWT upstream of the convolutional network, the spatial dimension of the input vector is divided by two at each decomposition level. As a result, the convolutive layers of the 1D CNN operate on condensed representations containing only relevant pathophysiological information, stripped of redundancies and background noise. This drastic reduction in the size of the inputs allows to configure an extremely light CNN with a total number of drive parameters reduced by more than 75% compared to standard state-of-the-art models (such as AlexNet, VGG16 or ResNet50) applied directly to the raw time signals. This massive gain translates mathematically into an immediate reduction of training time and a decrease in the computational load during the real-time inference phase. This high energy and hardware efficiency directly qualifies this model for native integration within low-resource embedded microcontrollers (ESP32) [9] and portable telemedicine devices, making it possible to monitor fetal distress clinically at home in an autonomous, reliable, and secure manner.

Conclusion and Perspectives

This research work formalized the development of an artificial intelligence approach optimized for the highly accurate classification of non-invasive fetal electrocardiography (fECG) signals. By coupling the Discrete Wavelet Transform (DWT) and an efficient One-Dimensional Convolutional Neural Network (1D-CNN), we have demonstrated that it is possible to combine excellent diagnostic performance with high computational efficiency. The rigorous evaluation on the MIT-BIH ARRHYTHMIA DATABASE reference database validates the striking superiority of the decomposition variant based on the Daubechies wavelet (db4) over the Haar wavelet, reaching an overall accuracy of 98,7% to identify major pathologies such as fetal infarction, hypertrophy or conduction disorders.

The future perspectives of this work will be oriented towards the large-scale clinical validation of this model on real databases acquired in vivo from patients in a hospital setting, in order to confront the algorithm with real noise environments not modeled by the simulators. Furthermore, a major research focus will be to physically implement this DWT-db4-CNN network within a hardware architecture such as FPGA or low-power microcontroller,

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to develop a functional prototype of a stand-alone portable ECGf monitor for remote monitoring of high-risk pregnancies.

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