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A Nonlinear Approach to FECG Signal Enhancement Using an Ensemble of Convolutional Neural Networks

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Abstract:

Fetal electrocardiogram (FECG) denoising is a vital aspect of prenatal monitoring, critical for precise fetal health evaluation. While convolutional neural networks (CNNs) are widely recognized for their strength in processing multidimensional data, their adaptation for one-dimensional signals like FECG remains an emerging frontier. This article introduces a novel ensemble CNN approach specifically designed to enhance FECG signals by leveraging CNN architectures hierarchical feature extraction capabilities. Extensive testing on FECG datasets with varying noise levels highlights the model's robust performance, showing significant improvements in performance metrics, including signal-to-noise ratio (SNR) and mean squared error (MSE). The ensemble CNN approach excels at isolating FECG components from noise, achieving enhanced signal clarity and fidelity. These finding reveal the promising potential of ensemble CNN-based techniques to advance FECG denoising, thereby enhancing the accuracy of fetal health assessments in clinical applications.

Keywords: FECG, Machine Learning, Convolutional Neural Networks, Ensemble of CNN, Root Mean Square Error, Peak Signal to Noise Ratio, Signal to Noise Ratio.

1 Introduction

FECG is a specialized procedure that makes it possible to monitor the heart rate and rhythm of the fetus. It provides vital information about the health of the fetus, including heart rate, waveform, growth, maturity, and any congenital heart problems. Healthcare professionals can obtain comprehensive knowledge about fetal development and identify early indications of cardiac problems with the use of FECG [1–3].

However, noise frequently taints FECG signals during capture, masking the useful diagnostic information they carry. Thus, denoising techniques are crucial for improving the quality of FECG signals, which in turn enhances diagnostic precision by enabling better interpretation and more accurate assessments of fetal health [4, 5].

The ability of machine learning (ML) algorithms to recognize patterns in biological signals has been demonstrated to be quite successful. ML algorithms' capacity to adjust to new input across several iterations, producing accurate and reliable outputs, is one of its main advantages [6]. When processing noisy FECG data, this flexibility is especially helpful since it allows ML approaches to be optimized for denoising performance, which leads to more dependable fetal monitoring and diagnostic results.

Deep learning (DL), a potent subset of ML algorithms, is excellent at automatically identifying intricate relationships and patterns in data, doing away with the requirement for human feature extraction. DL architectures are especially well-suited for biomedical applications, where big and unstructured datasets are typical, and are inspired by human cognitive processing. In contrast to typical ML models, DL models are able to achieve high accuracy in challenging tasks and frequently outperform classic ML techniques in terms of predictive power when working with large, diverse datasets [7–10].

CNN is a well-known DL model that is fundamental to image processing because of its strong feature extraction capabilities. CNNs are typically used to process two-dimensional picture data, but by modifying their architectures appropriately, they can also handle one-dimensional (1D) data, such FECG signals, with remarkable effectiveness [11, 12]. Because of their adaptability, CNNs are especially well-suited for FECG signal analysis, where noise masks important diagnostic data.

It is well known that ensemble methods (EM) in ML, which integrate predictions from several models, increase accuracy and dependability in a variety of applications [13]. Ensembles improve generalization, decrease overfitting, and boost resilience to noise and outliers by combining various model predictions. In FECG denoising, where precision is crucial for evaluating fetal health, this method is advantageous. By utilizing each model's distinct interpretation of the data, ensemble approaches reduce bias and variation by identifying intricate patterns that individual models might overlook [14–16].

In order to enhance the denoising of FECG signals that have been tainted by noise during acquisition, this article presents a novel ensemble CNN technique. The model gains better signal integrity and improves feature extraction by merging several CNN architectures. Extensive testing on FECG datasets with varying noise levels demonstrates the model's superior performance, highlighting the potential of ensemble CNNs to transform FECG denoising through notable gains in mean squared error (MSE) and signal-to-noise ratio (SNR). This development in FECG signal processing has the potential to improve fetal health evaluations, which makes it a useful tool in clinical situations where accuracy and dependability are crucial.

2. Related Literature

Because FECG signal analysis is essential for evaluating fetal health and development, it has garnered a lot of attention. Due in large part to significant interference from the mother's ECG and other outside noise sources, it is extremely difficult to reliably acquire these signals [2]. In signal processing, traditional denoising approaches like filtering, wavelet transformations, and statistical methods have been used extensively. To reduce noise in signals, other techniques including Kalman filtering, empirical mode decomposition (EMD), and adaptive filtering are also frequently used. Due to the complex and nonlinear nature of this interference, these methods have frequently been shown to be insufficient [17, 18].

The ability of ML algorithms to extract significant patterns from noisy datasets has made them extremely effective tools in biomedical signal processing in recent years. Since CNNs can automatically learn complicated data features and adjust to changing noise settings, DL techniques—in particular, CNNs—have demonstrated significant success in a variety of denoising applications within machine learning [19, 20].

Contemporary adaptive methods for processing FECG signals can be generally divided into two categories: nonlinear and linear. Each method is designed to manage varying degrees of signal complexity. Complex and nonlinear signal overlaps have been successfully managed by nonlinear techniques such as Support Vector Machines, Recurrent Neural Networks (RNNs), Hybrid Neural Networks, Radial Basis Function Networks, Adaptive Neuro-Fuzzy Inference Systems, Particle Swarm Optimisation, Self-organizing Maps, and Extreme Learning Machines [21–23]. The Extended Kalman Filter, Kalman Filtering, Normalised Least Mean Squares, Recursive Least Squares, Recursive Maximum Likelihood, and Adaptive Linear Neuron models, on the other hand, are examples of linear adaptive techniques that perform well in situations with less complex interference and continuously adjust to the particular difficulties posed by FECG signal processing [17, 18, 24].

To increase the clarity of FECG signals, several techniques for reducing maternal ECG components have been investigated. A significant advancement was made when Matonia et al. suggested isolating and removing the maternal PQRST complex over successive cardiac cycles; nonetheless, this method has not yet completely eliminated any remaining noise artifacts, underscoring the need for more reliable solutions [25].

Fotiadou et al. made a big advancement in this field by introducing a fully convolutional deep neural network (DNN) for non-invasive FECG processing, which greatly improved signal quality while maintaining crucial morphological information [26]. Techniques for sparse representation, in particular Total Variation Denoising (TVD), have made additional contributions by successfully lowering noise while preserving sharp signal edges, which is crucial for correctly interpreting FECG signals [27, 28].

Reducing maternal cardiac interference and enhancing fetal identification have also been made possible by automatic processing and adaptive filtering techniques. These methods, however, usually only produce estimated fetal heart rates and frequently struggle with the complicated nature of FECG data, particularly when the maternal and fetal QRS complexes overlap. To deal with these overlaps, improved Kalman filters have been created; nonetheless, they have issues with computing requirements and accurately identifying R-peaks [29].

Researchers have investigated blind source separation methods such as principal component analysis (PCA), independent component analysis (ICA), canonical correlation analysis (CCA), and sparse component analysis in an effort to lessen these complications [17, 30, 31]. Although these techniques present novel viewpoints, they frequently struggle with low SNR and require careful electrode placement and extensive post-processing to achieve the best results. Blind source separation has recently been combined with adaptive filtering approaches, which has shown promise in single-channel FECG extraction.

Further advancements in fetal QRS identification accuracy are being shown by ML-driven methods such CNN-based architectures and the QRStree algorithm [32–34]. These developments highlight a developing trend towards hybrid approaches that combine the advantages of conventional signal processing with cutting-edge machine learning paradigms, potentially establishing new benchmarks for accurate and trustworthy FECG signal interpretation.

A paradigm shift in the processing of FECG signals is marked by the use of DL, which includes CNNs, generative adversarial networks (GANs), RNNs; long short-term memory networks (LSTMs), stacked denoising autoencoders, and variational autoencoders (VAEs). Even though these models are revolutionary for denoising adult and fetal ECGs, they struggle to handle severely distorted signals, highlighting the necessity for continued innovation to get past long-standing constraints [26, 35–38].

In order to increase the precision of arrhythmia detection, Luz et al. focused on pre-processing ECG data. A variety of arrhythmias have been classified using relevance vector machines (RVM) [39]. In order to accurately detect arrhythmias from ECG signals, Rajpurkar et al. created a stacked long CNN that successfully learns and recognizes patterns in the data [40].The potential of DL approaches in detecting coronary artery disease (CAD) based on ECG data was demonstrated by Avanzato et al., who used multi-layered CNNs to identify CAD from ECG datasets. They achieved an impressive accuracy rate of almost 98% [41].

Additionally, Acharya et al. concentrated on employing multi-layered CNNs to analyze long-duration ECG signals in order to identify coronary heart disease (CHD). Their study showed that DL models could efficiently process and analyze long stretches of ECG data, resulting in accurate CHD detection and demonstrating CNNs' capacity to handle extensive and complex medical datasets for precise illness diagnosis [42, 43].

3. Proposed Non Linear Ensemble based CNN FECG Signal Extraction Method

In light of the challenges and limitations observed in existing FECG signal processing algorithms, we propose a novel ensemble-based approach for enhancing FECG signal extraction using CNNs. Using the complementing advantages of several CNN models, our approach aims to reduce the inherent noise and variability in FECG data. In addition to enhancing signal extraction, this Ensemble CNN technique guarantees more dependable and consistent results in noisy settings. Figure 1 shows the architecture of the suggested FECG Ensemble CNN model.

3.1 Data Preprocessing and Normalization

The training and testing data were taken from [44]. Non-invasive normal and arrhythmia FECG signals captured at a sampling frequency of 1 kHz are included. By placing characteristics on a common scale, normalization is an essential preprocessing step that improves the stability and performance of data processing and ML algorithms. This procedure reduces problems with numerical precision, enhances interpretability, and guarantees that every feature contributes equally to the

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model. For distance-based algorithms, where unnormalized features could disproportionately affect the results, normalization is particularly helpful because it addresses differences in units and ranges. Additionally, it helps meet the presumptions of different machine learning algorithms that anticipate inputs with similar sizes.

The FECG signals were normalised to ensure consistency and highlight pertinent features, which is essential for precise analysis when noise is present. MATLAB's normalize function was used to conduct this normalization, converting the data X using the following formula for each feature x_i:

$$x_i^{normalize} = \frac{x_i - \mu}{\sigma} \quad (1)$$

where:

$x_i^{Normalized}$ normalized is the normalized FECG feature value,
x_i represents each original FECG feature value,
μ is the mean of the FECG feature, and
σ is the standard deviation of the FECG feature.

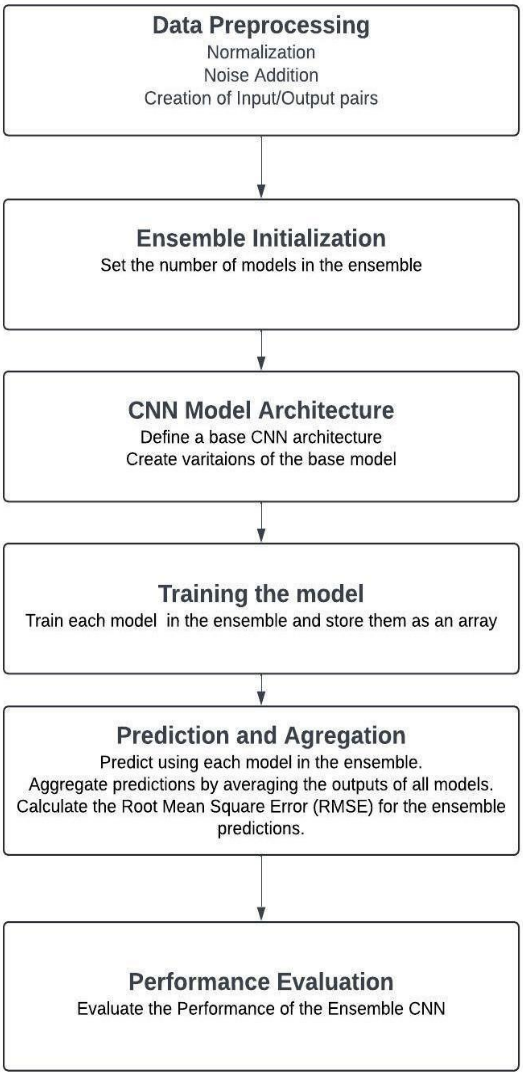

Fig.1 An Ensemble of CNNs model for Enhancement of FECG Signal Quality

Dealing with different signal magnitudes in FECG data is made easier using this z-score normalization, which changes the data to have a mean of zero and a standard deviation of one. In order to ensure that the ML models can accurately identify patterns within the FECG signals without favouring any one range or scale, the resulting normalised signals enable more consistent and comprehensible analysis.

3.2 Data Augmentation and Preparation

We applied several noise levels to the FECG signal (5dB, 10dB, 15dB, 20dB, 25dB, and 30dB) in order to create the CNN training data. To generate input-output pairings, a sliding window technique was used, with a stride of 250 samples and a window size of 1000 samples.

The equation for the sliding window approach is given by:

$$window_n = \{x_i | i \quad \in [n, n + w - 1] \tag{2}$$

where $window_n$ is the nth window of the signal, x_i represents the FECG signal data, W is the window size (1000 samples in this case) and n is the starting index of each window.

The stride S of 250 samples determines the overlap between consecutive windows, so the starting index of the next window will be:

$$n_{next} = n + S \tag{3}$$

For varying noise levels (5dB, 10dB, 15dB, 20dB, 25dB, and 30dB), Gaussian noise N dB is added to the FECG signal:

$$x_i^{Noisy} = x_i + N_{dB} \tag{4}$$

where N_{dB} the noise with a specific dB is level, and x_i^{Noisy} is the noisy FECG signal.

The output data were the clean signal segments, which served as the denoising goal. In the meantime, the CNN training process employed the relevant noisy segments as input data. The network was able to efficiently train and reduce noise from FECG signals at various noise levels because to this technique.
While the noisy signal segments x_{noisy} were utilized as the input for CNN training, the clean signal segments x_{clean} were regarded as the output for the denoising procedure. The network's input and output data relationships can be stated as follows:

$$x_{noisy} = x_{clean} + N_{dB} \tag{5}$$

where, x_{clean} is the clean segment of the FECG signal, x_{noisy} is the noisy segment of the FECG signal, and N_{dB} represents the added noise at a specific dB level.

Thus, the CNN learns to map the noisy input data x_{noisy} to the clean output data x_{clean}, allowing it to effectively reduce noise and enhance the quality of the FECG signals during training. For CNN training, the input and output signals were rearranged to fit the format specifications. A 4D array with dimensions appropriate for feeding into the neural network was created from the noisy and clean signal segments, respectively. This reshaping procedure accommodates the number of channels, the number of samples within each batch, the batch size, and the signal length, enabling the CNN to handle the signals efficiently.

The resulting data format can be expressed as:

$$X_{\text{input}} = [\text{batch size, signal length, channels, samples}] \quad (6)$$

where, X_{input} represents the input noisy FECG signal data, *batch size* refers to the number of training examples processed in one forward pass, signal length corresponds to the number of time steps per signal and channels refers to the number of signal features (e.g., in the case of multichannel signals), and samples represents the number of training examples.

By reducing noise interference, this reshaping helps the CNN process and learn from the input data during training, improving the quality of the FECG signal.

To ensure that the CNN model is trained properly and rapidly, the methodology's data partitioning and training options are essential. First, the dataset is divided into training and validation sets. Determining a training ratio in this case, 80% is how this is achieved. This implies that 20% of the data will be set aside for validation and the remaining 80% will be used to train the model. By making sure the model doesn't pick up noise or unimportant features from the training data, the validation set helps prevent overfitting and is used to assess the model's performance during training.

3.3 CNN Architecture and Ensemble Learning

The creation of an ensemble of CNN models is the next stage. Convolutional, pooling, and fully connected layers are used by CNNs, as seen in Figure 2, to separate and enhance the fetal ECG signal from noise. In order to identify local patterns in the signal and capture important characteristics while eliminating extraneous noise, the convolutional layers employ filters. These filters are very good at spotting distinct signal properties that set FECG apart from interference. The feature maps are then downsampled via pooling layers, which lowers computing complexity and increases the model's resistance to slight changes and fluctuations in the signal while maintaining a steady focus on the most important signal components.

In order to create the denoised output signal, fully connected layers use the extracted high-level features. This process synthesizes the refined data into a clear and clean representation of the FECG. A strong denoised output is produced by the CNN's efficient learning to separate noise from the fetal signal through these layers [45–47].

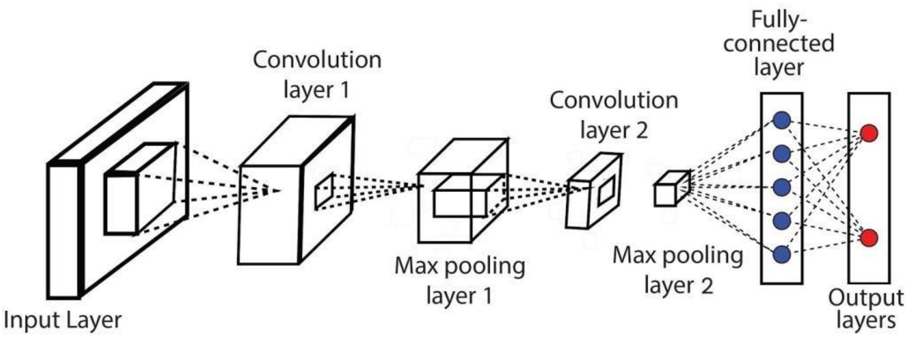

Fig.2 Basic Structure of a Convolutional Neural Network

3.4 Specifications of the Three Models in the Ensemble

Each model in the ensemble is a variant of the base CNN architecture. Below are the

Specifications for the three models used in the ensemble:

- **Model 1 (Base CNN):**
    - Input layer:*imageInputLayer([32,32,1],'Normalization','none')*
    - Convolutional layer:*convolution2dLayer(3,16,'Padding','same')*
    - ReLU activation:*reluLayer*
    - Max Pooling:*maxPooling2dLayer(2,'Stride',2)*
    - Fully connected layer:*fullyConnectedLayer(64)*
    - Output layer: *softmaxLayer*
    - Regression Layer:*regressionLayer*
- **Model 2 (Modified CNN):**
    - Input layer: *imageInputLayer([32,32,1],'Normalization','none')*
    - Convolutional layer: *convolution2dLayer(5,32,'Padding','same')*
    - ReLU activation: *reluLayer*
    - Max Pooling:*maxPooling2dLayer(2,'Stride',2)*
    - Dropout layer: *dropoutLayer(0.3)*
    - Fully connected layer: *fullyConnectedLayer(128)*
    - Output layer: *softmaxLayer*
    - Regression Layer : *regressionLayer*
- **Model 3 (Deep CNN):**
    - Input layer: *imageInputLayer([32,32,1],'Normalization','none'*)
    - Convolutional layer:*convolution2dLayer(3,64,'Padding','same')*
    - ReLU activation: *reluLayer*
    - Max Pooling:*maxPooling2dLayer(2,'Stride',2)*
    - Convolutional layer:*convolution2dLayer(3,128,'Padding','same')*
    - ReLU activation: *reluLayer*
    - Max Pooling:*maxPooling2dLayer(2,'Stride',2)*
    - Fully connected layer: *fullyConnectedLayer(256)*
    - Output layer: *softmaxLayer*
    - Regression Layer : *regressionLayer*

The number of convolutional layers filters sizes, and regularization methods used by dropout vary among these models. Model 2 has a dropout layer to avoid overfitting, Model 3 has a deeper structure with more convolutional layers to capture more complicated data, and Model 1 is the base architecture.

3.5 Training the CNN Ensemble

Backpropagation, a critical step in CNN training, involves iteratively adjusting the network's weights to reduce prediction errors [47, 48]. The network calculates gradients of the loss function with respect to each weight during backpropagation, allowing for effective updates that raise the predictive accuracy of the model. The gradient of the loss function L with respect to a weight w can be found mathematically as follows:

$$\frac{\partial L}{\partial w} = \frac{\partial L}{\partial a} . \frac{\partial a}{\partial w} \tag{7}$$

)

where *a* is the activation of the unit in the layer.

This gradient is then used to update the weights using a chosen optimizer, like the stochastic gradient descent (SGD) or Adam optimizer. The weights are updated according to:

$$w_{t+1} = w_t - \eta . \frac{\partial L}{\partial w} \tag{8}$$

where η is the learning rate, which controls the step size.

CNNs can gradually improve their filters and weights through this repeated training process, which improves their ability to identify complex patterns in data. CNNs learn hierarchical representations, which are essential for tasks like object detection, picture recognition, and medical diagnostics, through constant improvement [47, 48]. Nevertheless; a single CNN may overfit to the training set or fail to capture all data characteristics. This is where the idea of an ensemble of CNNs comes in handy because it combines several models to improve overall robustness and performance.

When compared to individual CNN models, an ensemble approach enhances overall performance and resilience by combining numerous models. An ensemble can improve generalization and lower the chance of overfitting by combining predictions from many CNNs.

The final prediction $y_{ensemble}$ from an ensemble of *n* models can be computed as:

$$y_{ensemble=\frac{1}{n}} \sum_{i=1}^{n} y_i \tag{9}$$

where y_i is the output from the i_{th} CNN model.

This simple averaging method helps mitigate the risk of overfitting present in any individual model.

There are various benefits of using an ensemble of CNNs [13]. Since the combined strengths of several models usually outperform a single model, it results in increased accuracy and performance. Because ensembles are less susceptible to the noise and oddities in the data, the system is more robust. Ensembles also aid in lowering bias and variance, which improves generalization to unknown data. Consequently, building an ensemble of CNNs makes use of the strengths of several models to create a deep learning system that is more dependable and efficient [49].

3.6 Proposed Non Linear Ensemble Approach

The method used in this article centres on building an ensemble of three different CNN models.*Convolution2dLayer*, which applies filters to input data, *reluLayer*, which introduces non-linearity through rectified linear units (ReLU), *imageInputLayer*, and *regressionLayer*, which calculates the loss between predicted and actual outputs, are some of the essential layers that are used to create a basic CNN architecture.

Input/output pairings are used to rigorously train each model in the ensemble. The *trainingOptions* function in MATLAB is essential in this case because it provides flexibility in setting important training parameters. The *adam* optimiser is selected because to its effective gradient-based optimisation and adaptable learning rate characteristics, which aid in boosting training efficacy and accelerating convergence.

The entire dataset is iterated through 30 times during training when the maximum number of epochs is set to 30. This decision achieves a careful balance between preventing overfitting and guaranteeing that the models get enough exposure to the dataset to pick up on the intricate patterns and correlations present in it. A major issue in deep learning is overfitting, which happens when models get too tuned to the training set and have trouble generalizing to new data. We want to achieve a compromise between underfitting and overfitting by restricting epochs to 30, which will enable the models to identify significant patterns without becoming overly tailored to the training data.

To make sure the model can generalize effectively, the ensemble's performance on unknown data is assessed after model training. The majority vote or the average of the forecasts from each individual model determines the final prediction in the ensemble technique, which aggregates predictions from several models. When certain models may be overfitting or underfitting the data, this ensemble approach aids in lessening the effect of model variation. The combined outcome is probably more reliable and accurate than the predictions of any one model alone.

4. Results and Discussion

The performance of the ensemble-based CNN method suggested for FECG signal extraction was assessed under various noise levels. A thorough examination of FECG denoising performance at noise levels of 5dB, 10dB, 15dB, 20dB, 25dB, and 30dB utilizing ensemble learning techniques is shown in Table 1. Initial signal-to-noise ratio (SNR_i), output signal-to-noise ratio (SNR_o), correlation coefficient (*CC*), root mean square error (*RMSE*), and peak signal-to-noise ratio (*PSNR*) are among the performance metrics evaluated.

After denoising, the output SNR_o shows a significant improvement in signal quality, ranging from 13.08 to 13.16 at 5 dB. With *RMSE* values ranging from 0.2425 to 0.2447, the signal reconstruction is accurate. The *CC* from 0.9597 to 0.9608 and *PSNR* values from 18.29 to 18.37 further supports the efficacy of the denoising procedure, demonstrating that even at low noise levels, excellent results are obtained.

With a decrease in *RMSE* from 0.1575 to 0.1545) and an increase in *PSNR* from 22.12 to 22.30, SNR_o improves to 16.91 to 17.09 at 10 dB. In comparison to the 5dB level, the correlation coefficient increases to 0.9838 to 0.9846, indicating improved denoising efficacy. This performance shows that moderate noise levels may be handled well by the ensemble method.

SNR_o drops to 19.91 to 20.01 at 15 dB, while *RMSE* values drop even lower to 0.1102 to 0.1114. The *CC* rises to 0.9925 to 0.9927 and *PSNR* values increase to 25.12 to 25.22, demonstrating the denoising technique's resilience at increased noise levels.

The output *SNR* stabilizes between 21.63 and 21.66 at 20 dB, while the *RMSE* keeps going down from 0.0911 to 0.0915. The *CC* rises to 0.9953 to 0.9954 and *PSNR* values reach 26.65 to 26.89, indicating outstanding denoising performance with low signal distortion.

The ensemble approach works significantly better at 25 dB, with SNR_o values between 25.24 and 26.74. While *PSNR* and *CC* continue to rise, ranging from 26.95 to 27.25 and 0.9963 to 0.9977, respectively, the *RMSE* values stay steadily low (0.0902 to 0.0912). These findings imply that the original signal was recovered nearly flawlessly.

At 30 dB, SNR_o exceeds 30 dB, ranging from 30.64 to 31.23, while the *RMSE* remains extremely low (0.0901 to 0.0911). *PSNR* values range from 28.84 to 28.98, and the CC is impressively high (0.9973 to 0.9993), indicating near perfect denoising even under high noise conditions.

Across a range of noise levels, the assessed denoising techniques continuously enhance the FECG signals' quality, proving their usefulness in biomedical signal processing, where precision and dependability are crucial.

Visual representations of the FECG signal extraction procedure at each noise level are shown in Figures 3, 4, 5, and 6. The capacity of the ensemble CNN approach to drastically lower noise while maintaining signal integrity is seen in these images.

In practical applications for fetal monitoring, where precise and unambiguous signal retrieval is essential for correct diagnosis and monitoring, the visual depiction further highlights the denoising approach's resilience and promise.

The denoised signal and the noisy input are graphically contrasted in each figure, which represents a different noise level and supports the quantitative findings presented in Table 1

The use of LMS and RLS filters to recover FECG signals from MECG recordings was examined by Radana et al. (2016), who showed notable gains in *SNR*. The RLS filter yielded a decent 4.6 dB improvement in *SNR*, whereas the LMS filter demonstrated a notable 7.7 dB boost [50].

In order to improve the *SNR* of ECG signals, Antczak (2018) adopted a different strategy by employing deep RNNs. Antczak made significant progress, increasing the *SNR* from its original value of -8.82 dB to 7.71 dB [51].

To reduce noise in ECG readings, Xiong et al. (2016) used deep neural networks, more especially denoising autoencoders. Their approach produced an *RMSE* as low as 0.037 and remarkable *SNR* gains, ranging from 21.56 dB to 22.96 dB [52].

Table1 Performance Parameters at Different Noise Levels

S.No	SNR_i	SNR_o	RMSE	PSNR	CC
At 5 dB					
TS1	5.02	13.11	0.2438	18.33	0.9602
TS2	4.97	13.13	0.2434	18.34	0.9602
TS3	5.04	13.16	0.2425	18.37	0.9607
TS4	4.98	13.15	0.2428	18.36	0.9603
TS5	4.96	13.08	0.2447	18.29	0.9597
TS6	5.01	13.16	0.2425	18.37	0.9608
At 10 dB					
TS1	9.97	16.95	0.1567	22.17	0.9840
TS2	10.00	17.09	0.1542	22.30	0.9846
TS3	9.96	16.91	0.1575	22.12	0.9838
TS4	10.05	17.04	0.1551	22.26	0.9845
TS5	10.03	17.07	0.1546	22.28	0.9845
TS6	10.02	17.06	0.1547	22.28	0.9844
At 15 dB					
TS1	15.00	19.91	0.1114	25.12	0.9925
TS2	14.98	20.00	0.1104	25.21	0.9926
TS3	15.02	20.00	0.1103	25.21	0.9927
TS4	14.98	19.98	0.1105	25.20	0.9926
TS5	15.02	19.94	0.1110	25.16	0.9926
TS6	15.02	20.01	0.1102	25.22	0.9927
At 20 dB					
TS1	20.03	21.64	0.0913	26.65	0.9953
TS2	20.02	21.64	0.0913	26.89	0.9963
TS3	19.97	21.63	0.0915	26.74	0.9964
TS4	19.98	21.66	0.0911	26.68	0.9922
TS5	20.04	21.63	0.0914	26.44	0.9937
TS6	19.98	21.64	0.0913	26.56	0.9954
At 25 dB					
TS1	24.91	25.24	0.0910	27.22	0.9963
TS2	24.97	25.67	0.0911	26.85	0.9969
TS3	25.16	25.54	0.0909	27.15	0.9971
TS4	25.13	25.24	0.0905	27.25	0.9969
TS5	25.03	26.74	0.0912	26.95	0.9973
TS6	25.01	26.69	0.0902	27.11	0.9977
At 30 dB					
TS1	30.01	31.14	0.0901	28.85	0.9973
TS2	29.98	30.64	0.0905	28.95	0.9984
TS3	29.97	31.23	0.0906	28.84	0.9991
TS4	30.02	30.66	0.0904	28.98	0.9979
TS5	30.04	31.13	0.0911	28.96	0.9989
TS6	30.01	30.94	0.0902	28.86	0.9993

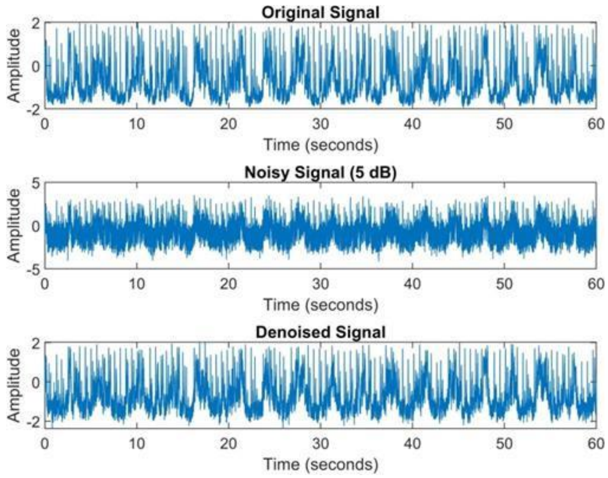

Fig. 3 FECG Signal Extraction for Sample 1– (a) Original FECG Signal, (b) Noisy FECG Signal at 5dB, (c) Extracted FECG Signal using Ensemble CNN

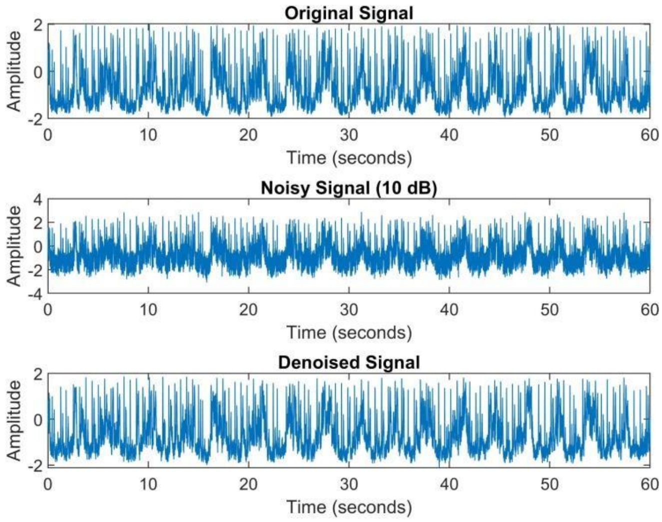

Fig. 4 FECG Signal Extraction for Sample 1–(a)Original FECG Signal, (b) Noisy FECG Signal at 10dB, (c) Extracted FECG Signal using Ensemble CNN.

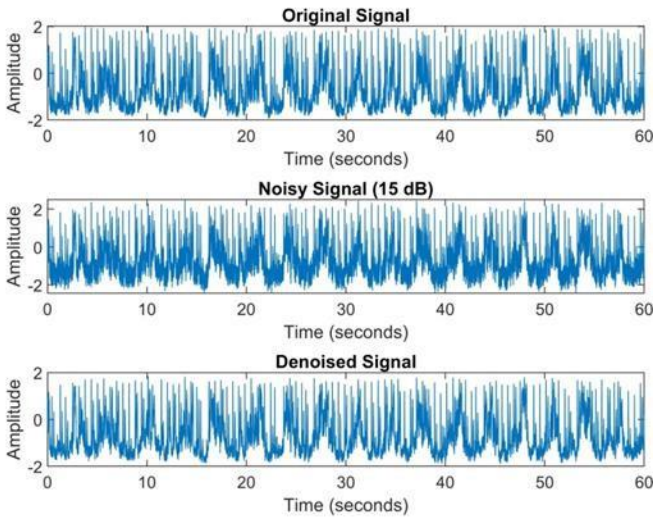

Fig. 5 FECG Signal Extraction for Sample 1– (a) Original FECG Signal, (b) Noisy FECG Signal at 15dB, (c) Extracted FECG Signal using Ensemble CNN.

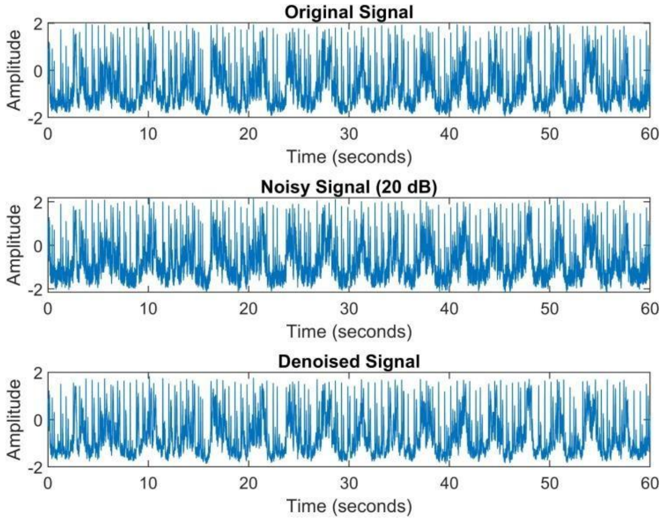

Fig. 6 FECG Signal Extraction for Sample 1– (a) Original FECG Signal, (b) Noisy FECG Signal at 20dB, (c) Extracted FECG Signal using Ensemble CNN.

An enhanced deep CNN architecture created especially for denoising FECG signals was presented by Fotiadou et al. (2020). Their network encoded the main signal properties and decoded them to recover finer information, framing the denoising task as an end-to-end process by combining convolutional and transposed convolutional layers. An impressive *SNR* enhancement of about 11 dB was achieved with this novel method [26].

The suggested ensemble learning-based method provides a notable improvement in FECG denoising, building on these earlier investigations. The approach continuously improves SNR_o, lowers *RMSE*, and sustains high *PSNR* and *CC* values at different noise levels by utilizing ensemble learning approaches. These findings highlight how well the ensemble CNN approach processes FECG signals and provide a dependable means of extracting high-quality fetal ECGs for use in biological applications.

5. Conclusions

A reliable method for FECG denoising is provided by the ensemble CNN, which efficiently uses convolutional layers to learn hierarchical feature representations. The ensemble CNN exhibits exceptional adaptability and generalization by separating pertinent signal components from noise at different noise levels, which makes it ideal for dynamic real-world biomedical signal processing applications. It is clear from the notable gains in SNR_o, *RMSE*, *PSNR*, and *CC* measures that the model can improve signal quality in a variety of noise problems. The range of SNR_o at 5 dB is 13.08 to 13.16, the range of *RMSE* values is 0.2425 to 0.2447, the range of *PSNR* is 18.29 to 18.37, and the range of *CC* values is 0.9602 to 0.9608.

SNR_o improves as the noise level rises, stabilizing between 21.63 and 21.64 at 20, 25, and 30 dB, and reaching 16.91 to 17.09 at 10 dB and 19.91 to 20.01 at 15 dB. The ensemble CNN's resilience in FECG denoising is demonstrated by the concurrent decrease in *RMSE*, increase in *PSNR*, and constant high *CC*.

In addition to improving signal quality, this method has great promise for real-time biomedical applications where precise signal extraction is essential for trustworthy monitoring and diagnosis. In order to further optimize denoising results, future research can investigate sophisticated strategies like weighted averaging, stacking, or boosting methods for merging predictions from individual

CNNs within the ensemble. Furthermore, dynamic parameter adjustments might be made possible by integrating online learning techniques into the ensemble CNN framework. This would guarantee that the model adjusts to changes in noise conditions in real time, increasing its efficacy and usefulness in real-world scenarios.

6. Competing interests

The authors have no conflicts of interest to declare that are relevant to the content of this article.

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