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Fetal ECG Signal Analysis with Bi-directional Long Short-Term Memory Networks for Neonatal Applications

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ABSTRACT

Fetal electrocardiogram (FECG) signals are essential for tracking the health of the fetus's heart because they offer important information about heart rate trends, fluctuations, and possible anomalies that can call for prompt medical attention. Noise and artifacts, on the other hand, present a serious problem since they frequently degrade signal quality and result in inaccurate diagnoses. Reliable fetal monitoring requires precise FECG signal categorization and efficient noise suppression. Throughout pregnancy and labor, continuous FECG analysis along with clinical assessments is essential to guaranteeing the best possible health for both the mother and the fetus. This study employs deep learning techniques to automate the classification of FECG signals as normal or abnormal using a Bidirectional Long Short-Term Memory (BiLSTM) classifier. The model processes FECG signals directly, without pre-processing, and achieves robust performance metrics: 91.98% accuracy, 90% precision, 85% recall, 87.5% F1 score, and 97% specificity. These results highlight the classifier's reliability and its potential as a valuable tool for real-time fetal health monitoring in clinical settings.

Keywords: *FECG, Classification algorithms, Artificial neural networks, Convolutional neural networks, Deep neural networks, Long Short Term Memory Networks.*

1. INTRODUCTION

Assessment of fetal heart health through FECG monitoring is crucial during pregnancy [1–3]. Traditionally, FECG acquisition involves invasive scalp electrodes, which pose risks to both the mother and fetus. As a safer alternative, non-invasive belly electrodes are used, though they often result in noisy FECG signals. Continuous monitoring relies on electrode patches placed on the maternal abdomen to capture signals from its surface [4]. These signals are highly complex, containing maternal breathing noise, frequency interference, and faint FECG mixed with maternal ECG (MECG). The amplitude of the MECG in abdominal signals is typically 2–3 times greater than the FECG, making fetal signal extraction particularly challenging [5].

The need for a reliable, non-invasive technique to accurately capture FECG is evident [6]. Electrocardiography, which records cardiac electrical activity, is believed to provide more detailed information than conventional sonography, as many cardiac issues manifest in these signals [3]. However, FECG recorded non-invasively has a low signal-to-noise ratio (SNR), and no signal processing method has reliably generated an accurate FECG signal to date [7, 8]. Despite the critical importance of FECG waveform features, they remain absent from standard fetal monitoring protocols, which primarily rely on fetal heart rate. This technological limitation hinders the clinical adoption of FECG as a key diagnostic tool, restricting research into correlations between FECG characteristics and newborn outcomes [9–11].

While FECG may not visualize specific structural abnormalities effectively, its primary value lies in detecting broader concerns, such as ischemia, often linked to fetal positions that obstruct the umbilical cord [12]. Non-invasive FECG, however, is influenced by several factors, including fetal brain activity, myographic signals, motion artifacts, and the various biological layers through which electrical signals pass [13, 14]. The presence of noise significantly impacts FECG properties, complicating the differentiation of normal and abnormal signals.

FECG classification plays a vital role in ensuring fetal well-being during pregnancy and labor. This study aims to leverage deep learning (DL) techniques to classify FECG signals as normal or abnormal. The paper is organized as follows: Section II reviews current algorithms for FECG categorization. Section III discusses relevant literature related to the proposed method. Section IV presents the results of the classification model, and Section V concludes the study.

2. EXISTING FECG CLASSIFICATION METHODS

A variety of methods have been developed for classifying FECG signals, with many approaches focusing on distinguishing between FECG and MECG signals based on their unique characteristics. Classification techniques that emphasize clinically significant features also help to highlight FECG's relevance in a clinical context. FECG signals are frequently categorized into regular and irregular classes to facilitate clinical interpretation [15–17].

Previous research has explored the classification of normal and abnormal ECG signals across both adult and fetal cases, utilizing a wide array of algorithms. These include support vector machines (SVM), linear discriminant analysis, quadratic analysis, K-nearest neighbors (KNN), fuzzy classifiers, fuzzy KNN, neuro-fuzzy systems, and others [9, 18–21]. For instance, Karpagachelvi et al. (2012) classified ECG beats into five categories using Extreme Learning Machines (ELM) and SVMs [22]. Andreotti et al. (2017) employed Convolutional Neural Networks (CNNs) to classify ECG signals into four classes, highlighting the potential advantages of deep learning models over feature-based classifiers when working with large datasets [23].

Deep learning techniques have also been used to classify specific ECG features. Jun et al. developed a deep neural network with six hidden layers to identify premature ventricular contraction (PVC) beats from ECG recordings [24]. Pourbabaee et al. (2016) demonstrated the effectiveness of CNNs for classifying signals into paroxysmal atrial fibrillation (PAF) and regular heartbeats [25]. Zhong et al. (2018) applied a modified CNN to categorize QRS complexes from single-channel FECG signals extracted from maternal ECG recordings [26].

To address the temporal dependencies in ECG signals, researchers have utilized Recurrent Neural Networks (RNNs) and Bidirectional RNNs. These models, particularly Long Short-Term Memory (LSTM) networks, are well-suited for time-series prediction tasks due to their ability to retain information from previous inputs [27, 28]. Gao et al. (2019) introduced an LSTM-based recurrent neural network with Focal Loss (FL) for arrhythmia detection, demonstrating its effectiveness on the MIT-BIH arrhythmia dataset [29].

In this study, we propose using Bidirectional LSTM models to automatically classify unprocessed FECG signals into normal and abnormal states, capitalizing on their capability to handle temporal dependencies and improve classification accuracy. This approach aids clinicians in making informed decisions, ultimately improving neonatal outcomes and reducing risks associated with undetected fetal abnormalities.

3. ENHANCING FETAL ECG CLASSIFICATION: LEVERAGING BIDIRECTIONAL LONG SHORT-TERM MEMORY NETWORKS

LSTM networks have demonstrated significant advantages over traditional neural networks (NNs) and Recurrent Neural Networks (RNNs), particularly in addressing challenges such as vanishing gradients and capturing long-range dependencies in extensive datasets [30]. By selectively retaining patterns over extended time periods, LSTMs excel in identifying and modeling temporal dependencies within sequential data [31, 32].

Bidirectional LSTM (Bi-LSTM) networks further enhance this capability by combining two separate LSTM layers. This architecture processes input sequences in both forward and backward directions, granting the model access to both preceding and subsequent data points at every time step [33]. As illustrated in Figure 1, Bi-LSTM networks incorporate long-range temporal information from both the past and the future, enhancing the depth and accuracy of sequence modeling in their outputs [34, 35].

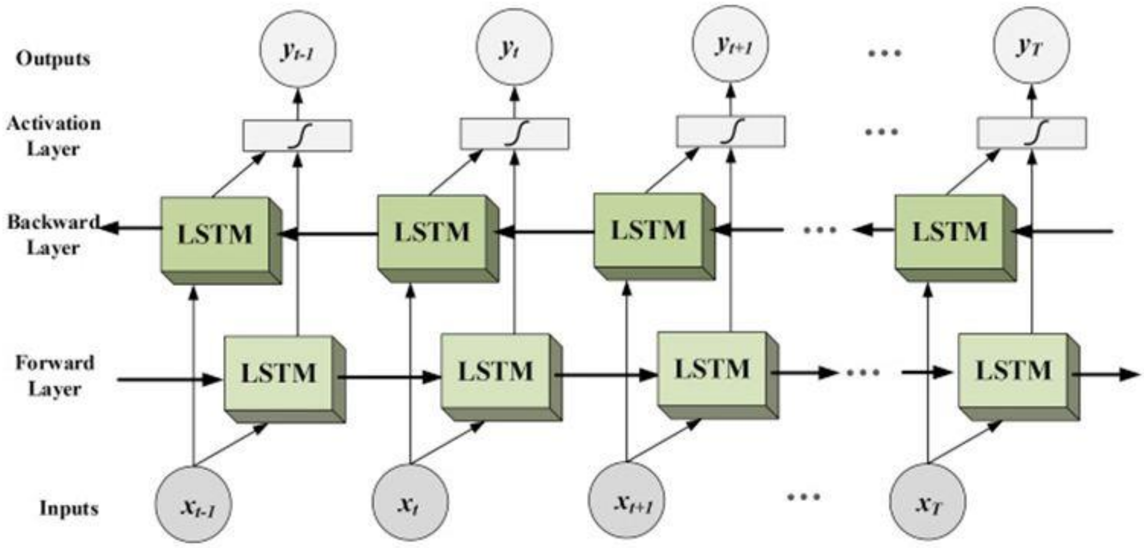

Figure 1: Bi LSTM Architecture

The BiLSTM network computation comprises two primary stages: the forward LSTM and the backward LSTM. Suppose we have an input sequence of length t, with each input element denoted as x_t, and weight matrices W along with bias terms b. The forward LSTM computation unfolds as follows: Firstly, we calculate the input-to-hidden state (input gate) for time step t:

$$i_t = \sigma(W_i \cdot x_t + U_i \cdot h_{t-1} + b_i) \quad (1)$$

Following that, the forward state (forget gate) is determined:

$$f_t = \sigma(W_f \cdot x_t + U_f \cdot h_{t-1} + b_f) \quad (2)$$

Subsequently, we compute the output state (output gate):

$$o_t = \sigma(W_o \cdot x_t + U_o \cdot h_{t-1} + b_o) \quad (3)$$

Then, we apply the tanh activation function to compute the cell state:

$$g_t = \tanh(Wg \cdot x_t + U_g \cdot h_{t-1} + b_g) \quad (4)$$

Finally, we calculate the cell state and hidden state for time step t:

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t h_t = o_t \odot \tanh(c_t) \quad (5)$$

The backward LSTM follows a similar process but works on the input sequence in reverse order. After calculating the forward and backward hidden states, they are concatenated to create the final output of the BiLSTM:

$$output_t = [ht; h't] \quad (6)$$

In this context, ht denotes the forward hidden state, h ′ t signifies the backward hidden state, and [;] denotes concatenation. Although Bi-LSTMs offer advantages in capturing long-range dependencies, they require longer training times and more training memory compared to standard LSTMs. Implementing dropout in Bi-LSTMs can be challenging, and they are susceptible to overfitting due to their increased complexity.

BiLSTM Algorithm for FECG Classification

Training Data: Arrange the input sequences as (x1, y1),(x2, y2), . . . ,(xN , yN), where N represents the number of input/output pairs or training pairs. In this study, the output is classified as either 'normal' or 'abnormal'.

BiLSTM Architectural Parameters: Include parameters such as weight matrices W and bias vectors b for all gates and layers. Set hyper parameters like learning rate α, sequence length T, and input/output dimensions D and C, respectively.

Output: Trained BiLSTM model with forward and backward hidden states.

1. Initialize LSTM parameters (W and b) with small random values.

2. For each training example (x1, y1):

• **Forward Pass:**

- Initialize forward hidden states h_0^f and cell states c_0^f as zeros.
- For each time step t = 1 to T:
  - Compute forward LSTM gate values (input, forget, output) and candidate updates (h_t^f , c_t^f , o_t^f , C_t^f).
  - Update forward cell state and hidden state (c_t^f , h_t^f) based on gate values and candidate updates.

• **Backward Pass:**

- Initialize backward hidden states h^b_{T+1} and cell states c^b_{T+1} as zeros.
- For each time step t = T to 1:
  - Compute backward LSTM gate values (input, forget, output) and candidate updates (h_t^b , c_t^b , o_t^b , C_t^b).
  - Update backward cell state and hidden state (c_t^b , h_t^b) based on gate values and candidate updates.

• **Combine Hidden States:**

- Compute h_t using equation (6).
- Pass concatenated hidden states h_t through a linear layer followed by a softmax activation to obtain predictions y_t.

• **Calculate Loss:**

- Compute the loss between predicted sequence [y = y1, y2, ...y_T] and true output sequence yi .

• **Backpropagation:**

- Calculate gradients with respect to the loss and LSTM parameters.
- Update LSTM parameters using gradient descent (e.g., Adam optimizer).

3. Repeat the training process for multiple epochs until convergence.

The proposed algorithm combines forward and backward information, capturing dependencies in both directions to enhance its sequence modeling capabilities. To ensure training stability and improved performance, techniques such as regularization, gradient clipping, and batch processing are incorporated.

For training, testing, and analysis, the algorithm employs datasets from the Non-Invasive FECG Arrhythmia Database [36]. This database comprises 12 fetal abnormal signals and 14 normal rhythm recordings, each containing 4–5 channels of FECG and one channel of MECG. The signals are sampled at rates of 500 Hz or 1 kHz. To augment the dataset, the input data is segmented into blocks, each containing 3000 samples. A total of 100 abnormal and 112 normal signals are used for performance evaluation, with the dataset split into 80% for training and 10% each for testing and validation.

The choices made for this model architecture, training process, and implementation environment are carefully selected to balance performance, computational efficiency, and the problem's specific requirements.

First, the input size of 5 channels is selected based on the nature of the data. In the case of fetal electrocardiogram (FECG) classification, multiple sensors or electrodes are often used to capture different aspects of the signal, allowing the model to extract richer features and improve classification accuracy. Using 5 channels provides enough data diversity to learn from while maintaining a manageable level of complexity.

The 200 hidden units in the model are chosen to strike a balance between model complexity and the risk of overfitting. With a relatively moderate number of hidden units, the model is given enough capacity to learn complex relationships in the data without being excessively large, which could lead to longer training times and difficulty generalizing. The choice of 200 hidden units reflects a compromise to capture the intricate features of FECG while avoiding unnecessary computational overhead.

The binary classification task with two output classes normal and abnormal is appropriate for the given problem. FECG signals typically need to be classified into clear categories (such as normal vs. abnormal), and this setup simplifies the problem by focusing on this binary decision. A single output neuron with a sigmoid activation function works well for this scenario, as it provides a probability score that directly corresponds to the likelihood of an "abnormal" classification.

Training the model over 100 epochs ensures that the network has ample opportunity to refine its parameters and minimize the error over time. Epochs are important because the model learns iteratively, adjusting its weights based on feedback from previous rounds. In this case, 100 epochs offer a sufficient number of training iterations to fine-tune the model without leading to excessive training times or overfitting, assuming the batch size and regularization are appropriately chosen.

The batch size of 27 is selected to optimize the training process. A batch size that is too small might cause noisy updates, whereas a batch size that is too large could lead to slower convergence. A batch size of 27 is a moderate choice that balances these concerns, allowing the model to learn efficiently without sacrificing too much in terms of computational speed or stability.

Finally, the use of the ADAM optimization algorithm is a deliberate decision to ensure that the model converges efficiently. ADAM combines the strengths of both the RMSprop and Adagrad algorithms, making it suitable for complex problems like this one where the gradients can change direction frequently. It adapts the learning rate based on the moving average of the gradients, which often leads to faster convergence and better overall performance compared to traditional optimization algorithms.

The architecture of the classifier is depicted in Figure 2:

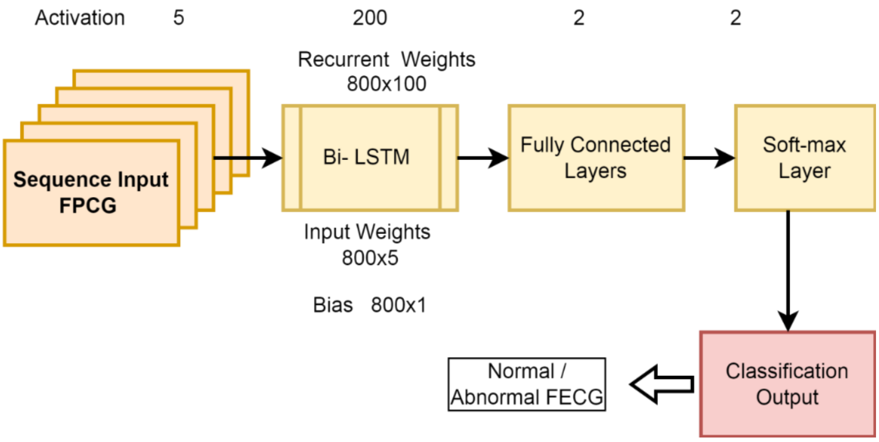

Figure 2: Architecture of the Classifier

4. RESULTS AND DISCUSSION

The data utilized in this study is sourced from [36], with the proposed classifier trained in the Matlab environment. Its performance is evaluated using standard metrics, including accuracy, sensitivity, precision, recall, F1 score, and specificity. These metrics collectively determine the model's effectiveness, with higher values indicating better performance. For optimal classification, accuracy, precision, and recall must be maximized.

The proposed model demonstrates impressive performance in classifying FECG signals, achieving an accuracy of 91.98%. This means the model correctly classifies approximately 92% of all instances, which a strong result is given the inherent noise in FECG signals. Remarkably, this accuracy is achieved without requiring complex pre-processing steps like noise filtering or signal enhancement, further highlighting the model's robustness. The precision of 90% indicates that when the model predicts an abnormal signal, it is correct 90% of the time, which shows its reliability in distinguishing abnormal cases from normal ones while minimizing false positives. The recall of 85% reflects the model's ability to correctly identify 85% of all actual abnormal instances, making it effective in detecting positive cases, although there is still a small percentage of abnormal signals that go undetected. The F1 score of 87.5% demonstrates a good balance between precision and recall, meaning the model effectively manages both false positives and false negatives. Finally, the specificity of 97% showcases the model's proficiency in correctly classifying normal (non-abnormal) signals, ensuring that very few normal instances are misclassified as abnormal. Overall, these metrics indicate that the model performs well in classifying FECG signals, balancing accuracy, sensitivity, and specificity, making it a reliable tool for real-world applications.

Comparative studies demonstrate the efficacy of advanced deep learning approaches. For instance, the work in [37] employs a variational autoencoder for feature extraction, achieving 92% accuracy on a non-fetal dataset from the MIT-BIH Arrhythmia Database using only 399 training samples. Similarly, the study in [38] evaluates various classification techniques, reporting accuracies of 87.5% for SVM, 93% for Adaboost, 94% for ANN, and 99.7% for Naïve Bayes. In another noteworthy example, Arnaout et al. [39] utilize a CNN-based model for fetal classification, achieving sensitivity and specificity rates of 100% and 90%, respectively, in distinguishing hypoplastic left heart syndrome from normal hearts using 685 echocardiograms from fetuses aged 18 to 24 weeks.

Future advancements in FECG classification can leverage emerging deep learning architectures, such as attention mechanisms, transformers, and hybrid models, to enhance performance. Incorporating additional data modalities, including maternal ECG, uterine contractions, and other physiological parameters, could further improve model accuracy and robustness. Moreover, the development of interpretable models capable of providing transparent, clinically meaningful insights is essential for medical applications where explainability is critical.

Addressing the limited availability of labelled FECG data through data augmentation and synthetic data generation can enable the creation of more generalized and reliable models. Integrating FECG classification into wearable devices and mobile health applications represents a promising avenue for empowering pregnant individuals to monitor fetal health autonomously and share critical data with healthcare providers, thus enhancing prenatal care and outcomes.

5. CONCLUSIONS

This research systematically explored the classification of FECG signals without any pre-processing, focusing on the raw form of both normal and abnormal signals. By deliberately choosing a smaller dataset with a sufficient number of data points, we were able to evaluate the performance of the classifier with limited data. The BiLSTM classifier was successfully trained on this dataset, and despite the increased training time due to the extended signal length, the model delivered performance metrics within acceptable ranges. The results show that although the existing model is effective, there is a lot of room for improvement, especially in terms of honing its capacity to categorize FECG signals into other groups. In order to improve the model's clinical usability for fetal monitoring and neonatal care, future research could concentrate on increasing the model's accuracy and resilience.

6. CONFLICT OF INTEREST

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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