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FETAL MOVEMENT DETECTION METHOD USING AN OPTIMIZED EXTREME GRADIENT BOOSTING MODEL

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Abstract:

Precise identification of Fetal movements is necessary for continuous prenatal monitoring; however, the signals obtained from wearable accelerometers are always affected by artifacts induced by the maternal movements and environmental noises. This research proposes a hierarchical signal refinement paradigm that can iteratively refine inertial sensor signal data from wearables in order to detect fetal movements in realistic monitoring environments. The hierarchical signal refinement paradigm uses a well-defined process to eliminate noise, extract compact features, and extract discriminative features to be able to conduct multiclass classification. Performance evaluation of this approach has been conducted using a publicly available fetal movements benchmark dataset containing synchronized tri-axial accelerometer data corresponding to fetal movements, mother's respiration, and laughing. The experimental results showed 97.94% of accuracy, 97.00% of precision, 96.00% of recall, 97.19% of F1-score, and 98.21% of area under the receiver operating characteristic curve. In particular, the ablation experiment validated the contributions of each signal refinement step, while statistical significance and computational cost analysis further confirmed the effectiveness, reliability, and efficiency of the proposed framework. Compared with recent fetal movement recognition methods, HSRF provides an interpretable and effective signal refinement strategy suitable for continuous wearable prenatal monitoring and intelligent maternal healthcare applications.

Keywords:

Fetal movement recognition, Hierarchical Signal Refinement Framework, Wearable accelerometer, Bayesian-optimized Extreme Gradient Boosting, Matrix Factorization, Prenatal health monitoring.

1. Introduction

Fetal movement (FM), or fetal activity, otherwise known as fetal kicks, is the natural body motion of a fetus developing in utero and is generally considered an important sign used in assessing fetal health. Reduced FM is usually linked with poor pregnancy outcomes, which include fetal distress, intrauterine growth restriction, and stillbirth. It has therefore become an integral part of pregnancy care to monitor FM continuously [1]. Traditional methods of monitoring, like perception of the mother, ultrasound, and cardiotocography (CTG), have played an important role in fetal monitoring; but each method has its own limitations in being able to conduct monitoring at home [2]. Perception of the mother is subjective, and ultrasound and CTG need special tools and personnel to use them. Modern advances in wearable sensors have made it possible to monitor fetuses using sensors without causing any harm [3]. Among others, accelerometer-based wearable sensors offer an easy way to acquire the signals of the fetal movements in the home environment [4,5]. However, it is known that the signals recorded using this type of sensor are often corrupted by the breathing, laughter, bodily movements of the mother, and other environmental noises. The discrimination of these fetal movements poses a difficult challenge for signal processing [6,7,8]. These challenges motivate the development of intelligent computational frameworks capable of progressively enhancing signal quality before classification.

Many recent efforts have been dedicated to the fusion of wearable sensing with machine learning and deep learning methods for automated fetal movement classification. Many researchers have explored convolutional neural networks, CNN-based hybrid frameworks, fusion of inertial sensors, and even IoT-based systems for continuous prenatal diagnosis. Despite the promising results achieved using these methods, most of them depend on resource-demanding deep learning algorithms, a large amount of annotated data, or are vulnerable to motion artefacts and variability between subjects [9,10,11]. Another challenging problem is the high nonlinearity and non-stationarity of wearable accelerometer signals and the non-Gaussian nature of noise affecting them, making it difficult to implement direct classification [12,13]. Existing techniques usually concentrate on one aspect, such as signal denoising, feature selection, or classification, but pay little attention to the creation of a comprehensive signal processing pipeline improving signal representation at all stages of the recognition process [14,15]. Thus, it is necessary to develop a technique that will be capable of performing signal enhancement, learning compact representations, feature characterization, and classification with reasonable computational complexity.

To address these limitations, this work proposes a Hierarchical Signal Refinement Framework (HSRF) for automated fetal movement recognition using wearable tri-axial accelerometer signals. Unlike the conventional approaches, where preprocessing and classification are viewed as separate procedures, the HSRF model arranges the recognition process through four steps of signal refinement, where the discriminative properties of the acquired signals are gradually enhanced. In the first step, Particle Filtering is applied in order to eliminate non-Gaussian artifacts and preserve the useful movements of the fetus. The next step comprises converting the refined signal into compressed latent representations through Non-negative Matrix Factorization (NNMF). Consequently, a rich set of features is derived through multiple views in order to capture the underlying patterns of fetal movements. Finally, Bayesian Optimization (BOA) is used to select the best values for the hyperparameters of the classifier Extreme Gradient Boosting (XGB). In contrast with conventional pipeline designs, where existing methods are just combined, the new HSRF design implements the concept of progressive signal refinement, in which every step refines the signal provided to the next step, hence improving the separability of the classes, making the system resistant to the noise present in wearable sensors' data, and decreasing the computational complexity. The major contributions made in this work are the following:

(i) The proposal of the hierarchical signal refinement approach that combines signal enhancement, representation learning, feature characterization, and ensemble classification techniques for the task of fetal movements recognition;

(ii) The implementation of the progressive temporal-spectral feature representation based on the enhanced accelerometer signals for better separation between fetal movements, maternal respiration, and maternal laughter;

10.22060/EEJ.2026.25147.5851

(iii) The use of the Bayesian optimization technique for the automatic hyperparameter setting of the Extreme Gradient Boosting classifier to enhance its prediction power; and

(iv) The evaluation of the whole HSRF design on the publicly available benchmark dataset for wearable fetal movements recognition.

The remainder of the manuscript is arranged as follows: the literature review is covered in section 2, the proposed technique is explained in depth in section 3, the application of the suggested approach is discussed, the results are shown in section 4, and the conclusion provides an overview of the entire research process.

2. LITERATURE REVIEW

FetalMovNet was proposed by Turkan et al. [16] as an attention-based deep learning system to classify fetal movements from US images automatically. Attention methods were employed by this network in order to focus on clinically significant motion areas and consequently improve the classification performance in various fetal movement classes. Despite the fact that this attention-based approach showed better recognition capabilities, its need for ultrasonic imaging and deep learning systems rendered it unusable for continuous, wearable, and home-based monitoring. Moreover, the requirement for image acquisition and extensive computational resources may restrict its deployment in low-resource prenatal care environments.

Park et al. [17] developed an innovative wearable ultrasound patch to monitor fetuses in high-risk pregnancies continuously. This solution allowed obtaining physiological information about the fetus in the long term, even outside traditional clinical settings, while retaining the quality of ultrasound measurement using a flexible wearable device. The research showed that it was possible to implement continuous monitoring of the fetus with higher comfort and diagnostic abilities. At the same time, the wearables ultrasound system used specific hardware and technologies in imaging, thus increasing the complexity and costs of the solution implementation, which may limit widespread adoption for routine home-based fetal movement monitoring.

A machine learning technique for the evaluation of the condition of the fetus by considering several physiological parameters was designed by Ashik et al. [18] during the period of pregnancy. Some

10.22060/EEJ.2026.25147.5851

supervised learning methods were applied to classify fetal health conditions, producing encouraging classification results. This work revealed the possibility of using machine learning techniques in prenatal healthcare for health evaluation. However, the technique was mainly based on health condition prediction and not on fetal movements detection, and it lacked the aspects of motion artifact reduction, signal enhancement, and feature extraction for wearable accelerometer data.

Misaghi et al. [19] introduced an effective machine learning method to determine the developmental stages of embryos based on the temporal information of their development process. The authors showed that the use of machine learning methods helps accurately detect the developmental stages of embryos and increase the accuracy of reproductive health assessments. Thus, machine learning demonstrates its efficiency in the identification of biological data and patterns. However, the framework is designed to analyze embryo images under laboratory conditions and cannot be applied directly to analyze signals from a wearable device, where noisy time-series accelerometer signals require dedicated signal enhancement and feature extraction strategies.

The deep learning sensor fusion approach for classifying the movements of infants was suggested by Kulvicius et al. [20]. This approach took advantage of different kinds of data obtained through using various wearable sensors, and as a result, the fusion method improved the recognition performance due to the complementary spatial and temporal information gained through using multiple sensors. However, the deep learning neural network model was computationally expensive, which created difficulties for implementing it in resource-constrained wearable fetal monitoring systems more challenging.

Nazli et al. [21] examined machine learning approaches for fetal health diagnosis in the early stage of pregnancy based on unbalanced cardiotocographic data. Different classification algorithms, as well as methods dealing with imbalanced data, have been used in order to increase diagnostic accuracy and avoid prediction bias in favor of classes that appear more often in training data. The presented approach proved its effectiveness and highlighted the need for efficient learning approaches for prenatal care. However, cardiotocographic data, and not wearable accelerometer recordings, have been used in this study.

10.22060/EEJ.2026.25147.5851

A framework for fetal electrocardiogram detection using time-frequency analysis, along with efficient noise removal algorithms, was proposed by Deshpande and Gawande [22]. Advanced signal processing techniques were used in the study to reduce the effect of the mother's signals and extract the fetal electrocardiogram more effectively from noisy abdominal data. Experimental results showed that effective preprocessing of the signal can increase the accuracy of diagnosis. However, the methodology is dedicated solely to fetal electrocardiogram detection and does not cover feature representation and classification of wearable accelerometers based on fetal movement recognition.

A hybrid QCNN-BiLSTM architecture was proposed by Qu et al. [23] for the detection of automatic fetal arrhythmia using quantum convolutional neural networks along with bidirectional long short-term memory networks. The hybrid architecture successfully modeled spatial as well as temporal dependencies from physiological signals, thereby achieving enhanced detection of arrhythmias. Even though this framework has shown great potential in terms of its diagnostic capability, its computational overhead and reliance on sophisticated deep learning models can limit its use in wearable fetal movement monitoring applications.

Correia et al. [24] provided a detailed review of the current advances in artificial intelligence-based solutions for the personalized treatment of mothers and fetuses. The authors highlighted some of the recent advances in machine learning, deep learning, wearable sensors, and digital health innovations in the field of prenatal care and the importance of such innovations for the delivery of individualized care to patients. Although there have been substantial advances on the technology front, some of the challenges identified include issues of data quality, interpretability, clinical validation, and integration of health care capable of supporting continuous wearable fetal monitoring.

Ahmedova et al. [25] presented an overview of the latest developments in wearable technology for health tracking during pregnancy, discussing aspects such as sensing abilities, clinical evidence, challenges in deployment, and potential uses in future healthcare services. In their paper, Ahmedova et al. discussed the increasing use of wearable devices for monitoring pregnant women and their babies while pointing out the increased comfort and telehealth in such monitoring methods. However, some challenges have not been solved, which include noise in signals, reliability of the system, security, robust algorithms, and clinical evidence. These issues underscore the necessity for efficient hierarchical signal processing frameworks that enhance wearable sensor reliability for long-term prenatal monitoring.

Table 1: Summary of recent literature on various Intelligent Fetal Monitoring and Movement Recognition

Citation	Methodology	Advantages	Limitations
Turkan et al. [16] (2025)	Attention-based FetalMovNet deep learning model for fetal movement classification from ultrasound sequences.	Improved feature learning and classification accuracy through attention-guided spatial feature extraction.	Requires ultrasound imaging, high computational resources, and is unsuitable for wearable continuous monitoring.
Park et al. [17] (2026)	Wearable ultrasound patch for continuous fetal monitoring in high-risk pregnancies.	Enables continuous, non-invasive prenatal monitoring with improved patient comfort and diagnostic capability.	Relies on specialized wearable ultrasound hardware with high implementation complexity and cost.
Ashik et al. [18] (2025)	Machine learning framework integrating physiological indicators for automated fetal health assessment.	Supports clinical decision-making with reliable prediction of fetal health conditions.	Does not focus on wearable accelerometer signals or fetal movement recognition.
Misaghi et al. [19] (2025)	Machine learning model for embryo morphokinetic stage detection using temporal image analysis.	Accurately recognizes embryo developmental stages with automated biological pattern analysis.	Limited to embryo imaging and not applicable to wearable fetal movement signals.
Kulvicius et al. [20] (2025)	Deep learning-based multimodal sensor fusion for infant movement classification.	Improves recognition accuracy using complementary information from multiple wearable sensors.	Requires large datasets and a computationally intensive deep learning architecture.
Nazli et al. [21] (2025)	Machine learning classification of imbalanced cardiotocographic data for fetal health prediction.	Effectively handles class imbalance while improving diagnostic classification performance.	Uses CTG signals rather than wearable accelerometer-based fetal movement recordings.
Deshpande and Gawande [22] (2026)	Time-frequency analysis with advanced noise elimination for fetal ECG detection.	Enhances fetal ECG extraction by effectively suppressing maternal and environmental noise.	Focused on fetal ECG rather than fetal movement classification using wearable sensors.
Qu et al. [23] (2025)	Hybrid QCNN-BiLSTM framework for automated fetal arrhythmia detection.	Captures spatial-temporal dependencies with improved arrhythmia detection accuracy.	Computational complexity limits deployment in lightweight wearable monitoring devices.

10.22060/EEJ.2026.25147.5851

Correia et al. [24] (2025)	Scoping review of AI-driven maternal and fetal healthcare technologies.	Summarizes emerging AI techniques supporting personalized prenatal healthcare.	Highlights unresolved issues, including interpretability, validation, and healthcare integration.
Ahmedova et al. [25] (2026)	Comprehensive review of wearable pregnancy monitoring technologies and implementation challenges.	Demonstrates the growing potential of wearable systems for continuous prenatal monitoring.	Signal quality, robustness, reliability, and clinical validation remain significant challenges.

Despite the fact that current research efforts in wearable sensing, deep learning, ultrasound imaging, and intelligent healthcare systems have made remarkable contributions towards fetal monitoring, as in Table 1, some major challenges persist. Many of the current methods separately deal with signal denoising, feature extraction, or classification without formulating a coherent processing paradigm that ensures gradual improvement in the quality of the signals being processed. Methods involving deep learning need extensive annotated training data sets along with huge computational capacity, while wearable sensing methods still struggle with motion artifacts, non-Gaussian noise, and a lack of interpretability. To solve these problems, the Hierarchical Signal Refinement Framework (HSRF) method was proposed, which uses signal enhancement, NNMF-based latent variable learning, complementary spectral-temporal feature learning, and Bayesian optimized XGBoost classification. Integrating all these provides an efficient, interpretable, and robust solution for continuous wearable fetal movement recognition.

3. Proposed Methodology

Recent developments in the field of wearable fetal movement detection have shown the potential that lies in the use of intelligent signal processing and machine learning techniques in automating fetal movement recognition. However, current methods mostly operate these individual processes as separate steps, thus being unable to iteratively enhance the quality of physiological data during the process of recognition. In addition, the signals recorded by wearable tri-axial accelerometers may be influenced by non-Gaussian noise, maternal breathing, body motions, and other environmental factors that decrease class separability. All these factors negatively impact the accuracy of classification. Another approach that has been considered is deep learning networks that have proved to yield good results in recognition tasks, but, unfortunately, lack interpretability and need lots of annotated data.

10.22060/EEJ.2026.25147.5851

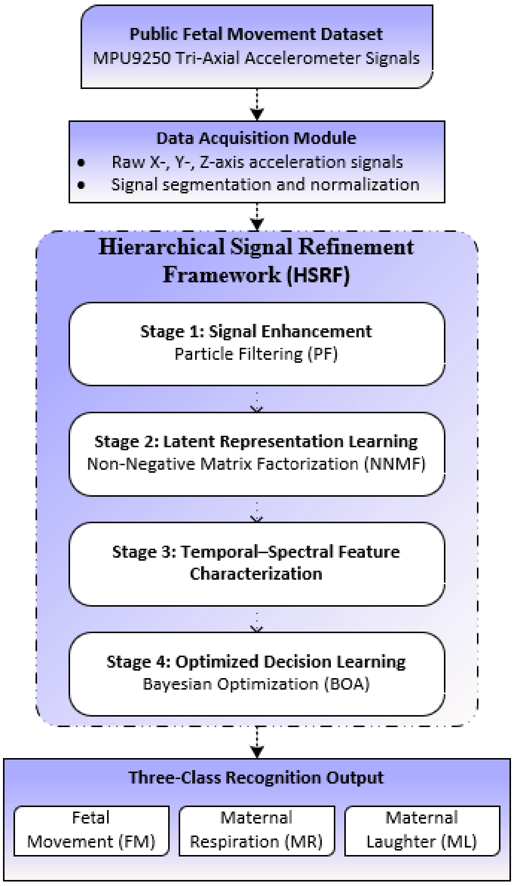

Fig. 1: Overall architecture of the proposed Hierarchical Signal Refinement Framework (HSRF)

In order to overcome all such limitations, the proposed approach introduces a Hierarchical Signal Refinement Framework, as shown in Fig. 1, which is designed to convert the raw accelerometer signals of wearable devices into highly discriminative representations through four successive stages of refinement. First, the acquired tri-axial accelerometer signals are processed with the PF method in order to filter out any motion artefacts from the signals and keep only the fetal motion activities. Then, NNMF is applied to refine the filtered signals to extract compact latent representations by getting rid of any redundant data from the signals. Time-domain and frequency-domain features are extracted from the refined signal components in order to fully characterize the patterns of the fetal motion activities. After that, the obtained feature vectors are finally classified using the XGB classification method, whose parameters are automatically optimized using the BOA. Unlike the traditional implementation of machine learning models, the proposed HSRF relies on the concept of progressive signal refinement, wherein each process step increases the quality of the information provided to the next processing step.

This hierarchical architecture improves signal quality, strengthens feature discriminability, enhances classification robustness, and provides an efficient, interpretable, and computationally practical solution for continuous wearable fetal movement recognition.

3.1 Data acquisition

The effectiveness of the proposed HSRF was assessed using the publicly available Fetal Movement Detection Dataset Recorded Using MPU9250 Tri-Axial Accelerometer collected by Delay [25]. This dataset contains synchronized tri-axial accelerometer data (X-, Y-, and Z-axis acceleration) collected from the wearable MPU9250 sensor strapped to the abdomen of pregnant women. These recordings are labeled based on their physiological activity and are classified into three ground-truth classes of activities, such as Fetal Movement (FM), Maternal Respiration (MR), and Maternal Laughter (ML). Continuous sensor recordings are segmented into fixed-size windows in order to maintain temporal consistency and generate representative samples used in preprocessing and classification tasks. These manually validated class labels are used as ground truth in training and testing of the model. The dataset is well-suited for the task due to the presence of both fetal movement and maternal movements that represent common sources of artifacts in continuous wearable monitoring. In addition, three-axis acceleration data allow for effective temporal-spectral feature extraction and facilitate discrimination between the three different classes.

3.2 Pre-processing

The raw tri-axial acceleration signals recorded using the MPU9250 include fetal movements and the mother's breathing, movements, sensor drifts, and environmental interferences. Thus, a useful preprocessing step must be used to enhance signal quality before feature extraction and classification processes. Preprocessing in the HSRF framework is done in two consecutive steps, including PF for adaptive noise removal and NNMF for latent space representation learning. Initially, the continuous acceleration signals are divided into overlapping windows of 5 s with 50% overlap, which is equal to 1400 samples per window at a sampling rate of 280 Hz. This window length preserves enough temporal information about whole fetal movements while increasing the training sample sizes. The segmented signals are then normalized to [0,1] before being subjected to further processing. Subsequently, the

10.22060/EEJ.2026.25147.5851

normalized signals are denoised using a particle filtering approach, after which a time–frequency spectrogram is obtained using STFT. Finally, the positive spectrograms are decomposed using the NNMF algorithm to get latent representations for discriminative features extraction.

3.2.1 Particle Filtering

This technique is used to reduce the non-Gaussian noise without removing the properties of fetal movements. The PF estimates the probability distribution of the state by means of a number of weighted samples. This technique is adopted because of its capability to handle non-linear acceleration sensor inputs.

The dynamic model of the state can be defined as in Eq. (1):

$$X_k = f(X_{k-1}) + q_k \tag{1}$$

where X_k is the hidden state variable which represents the actual fetal movement, $f(.)$ is the state transition function that is non-linear in nature, and q_k is the process noise that follows a zero-mean Gaussian distribution. The measurement model is defined by Eq. (2),

$$z_k = h(X_k) + n_k \tag{2}$$

where z_k represents the observed tri-axial accelerometer measurement, $h(.)$ denote the nonlinear observation function, n_k represents the measurement noise.

For each segmented window of acceleration, the PF algorithm predicts the state of each particle, evaluates its importance weight using the observed acceleration samples, and then resamples the particles having negligible probability. The calculation of particle weights is as follows, according to Eq. (3).

$$w_k^{(i)} = \frac{w_{k-1}^{(i)}\, p(z_k|X_k^{(i)})}{\sum_{j=1}^{N} w_{k-1}^{(j)} p(z_k|X_k^{(j)})} \tag{3}$$

where $w_k^{(i)}$ is the normalized weight of i^{th} particle, N represent the number of particles, and $z_k|X_k^{(i)}$ represent the observation likelihood. The filtered acceleration signal can be computed using Eq. (4).

$$\hat{X}_k = \sum_{i=1}^{N} w_k^{(i)} X_k^{(i)} \tag{4}$$

where $\hat{X}_k$ is the cleaned acceleration signal. The filtered X-, Y-, and Z-axis acceleration signals show a reduction in maternal motion artifacts but retain fetal motion characteristics, thereby ensuring accurate input for further analysis.

3.2.2 Non-Negative Matrix Factorization

Even though Particle Filtering reduces noise from the signals considerably, there remains some redundant information within time in the filtered signals. So NNMF is applied to get the compact representation of latent factors with non-negative properties of the distribution of signal energy. After Particle Filtering, each of the signals is transformed into a spectrogram of magnitudes with the Short-Time Fourier Transform (STFT). This spectrogram becomes a non-negative matrix, and it is presented in Eq. (5).

$$V \epsilon R^{mXn}, \qquad V_{ij} \geq 0 \tag{5}$$

where m represents the number of frequency bins, n denotes the number of time frames. NNMF approximates the spectrogram as,

$$V \approx WH \tag{6}$$

Where $W \epsilon R^{m\,X\,r}$ is the basis matrix, $H \in R^{r\,X\,n}$ is the coefficient matrix and r denotes the number of latent components. The basis matrix is associated with the spectral pattern, whereas the activation matrix is used to indicate its temporal activation. Together, these matrices help to achieve a more compact representation of fetal movements and discard redundant information.

Statistical descriptors can be acquired from both latent basis and activation matrices after the NNMF technique. In the proposed framework, a total of 12 discriminative features are computed using the suggested model. Among these 12 features, seven are time-domain descriptors that include mean, standard deviation, root mean square, skewness, kurtosis, peak value, and pulse factor, whereas five others belong to frequency domain descriptors such as spectral energy, entropy, dominant frequency, spectral centroid, and bandwidth. These complementary temporal–spectral features effectively characterize fetal movement dynamics and constitute the final feature vector supplied to the Bayesian-optimized Extreme Gradient Boosting classifier.

3.3 Feature Extraction

After the PF and NNMF Decomposition process, discriminant features are obtained from the NNMF coefficient matrix. H that indicates the activation patterns of the latent signals generated from the denoised spectrogram of the accelerometer data. In total, 12 features are generated from each segmented signal, with seven being temporal domain features (mean, standard deviation, root mean square, skewness, kurtosis, peak value, and pulse factor), while the remaining five are spectral domain features (spectral energy, spectral entropy, dominant frequency, spectral centroid, and bandwidth). With these two domains of features, characterization is done in a manner such that there is no redundancy. The 12 features make up the feature vector that feeds into the BOA-XGB classifier for the purpose of classifying FM, MR, and ML.

3.4 FM Recognition Using XGB-BOA

The final phase of the proposed HSRF involves an automatic detection of fetal movements based on a Bayesian Optimization-assisted Extreme Gradient Boosting (BOA-XGB) classifier. After performing the preprocessing and the feature characterization phases, the input for the classification procedure will be a 12-dimensional temporal-spectral feature vector obtained from every segmented signal from the accelerometer. The detection process is presented as a supervised three-class classification task, whereby the goal of the process is the successful discrimination of FM, MR, and ML. Unlike the selection of the classifier parameters manually, the BOA algorithm is utilized for automatic optimization of the hyperparameter values that would guarantee the best classification results. As a result, the optimization approach reduces the need for empirical parameter tuning and increases the generalization capabilities of the classifier. Thus, the whole detection process can be seen as a process that includes two main steps: (i) construction of the XGB decision tree using the features, and (ii) BO optimization of the model hyperparameters to obtain the decision boundaries.

The optimized classifier finally predicts the class label corresponding to each feature vector according to eq. (7).

10.22060/EEJ.2026.25147.5851

$$\hat{y} = \arg\max_{c \,\epsilon\, C} P(c|f) \tag{7}$$

where $f \,\epsilon\, R^{12}$ indicates the feature vector extracted from the signal, $C = \{FM, MR, ML\}$ indicates the three activity categories, $P(c|f)$ indicates the posterior probability calculated using the optimized XGB classifier and $\hat{y}$ denotes the predicted activity label.

3.4.1 Extreme Gradient Boosting Regression (XGB)

XGBoost is selected as the classifier owing to its capability of modeling non-linear functions efficiently, along with maintaining computational efficiency when applied to structured feature vectors. The major difference between deep neural networks, which need large training data, and XGBoost is that XGBoost makes full use of the discriminative temporal-spectral features obtained from the latent representations using the NNMF approach and possesses excellent robustness towards feature redundancy. In the training process, the classifier constructs an ensemble of decision trees such that every next tree rectifies the error of the preceding ensemble of trees. Consequently, the prediction for an input feature vector is obtained by aggregating the outputs of all individual trees,

$$F(f) = \sum_{k=1}^{K} f_k(f) \tag{8}$$

where K denotes the total number of decision trees and $f_k(.)$ represents the prediction generated by the K^{th} tree.

The optimal values for the model parameters are determined by minimizing the objective function (9) with regularization.

$$L = \sum_{i=1}^{N} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega\,(f_k) \tag{9}$$

where N stands for the number of training examples, $l(.)$ is the loss function of the classification problem, and $\Omega(f_k)$ is the regularization term that influences model complexity. In the case of the suggested HSRF, the XGB classifier works with the 12-dimensional feature vector, generated using the NNMF coefficient matrix, and assigns the probability of belonging to one of three pre-defined classes.

10.22060/EEJ.2026.25147.5851

The regularization mechanism effectively reduces overfitting while preserving high predictive accuracy on unseen wearable accelerometer data.

3.4.2 Bayesian Algorithm Optimization (BOA)

The performance of predictions generated from XGB is very much dependent on the choice of its hyperparameters, which include the learning rate, maximum tree depth, minimum child weight, subsampling ratio, column sampling ratio, and the number of iterations of boosting. Rather than determining the best set of hyperparameters through the trial-and-error method, BOA is used in order to determine the values of these hyperparameters. The BOA is able to determine the interaction between the vector of hyperparameters and the performance of the classifier using a probabilistic model that will be repeatedly updated with every function evaluation.

$$\hat{\theta} = \arg\max_{\theta} A(\theta) \tag{10}$$

where θ is the hyperparameter vector and $A(\theta)$ is the acquisition function, which optimizes the trade-off between the exploration of unexplored parameter space and the exploitation of good solutions. The identified hyperparameters are then used for training the XGB classifier, and its accuracy is returned to refine the surrogate model. The process is continued iteratively until the specified stopping criteria are reached. The identified hyperparameters are finally used to design the final version of the XGB classifier for experimental testing. With the integration of Bayesian Optimization into the designed HSRF algorithm, there is no need for manual tuning of parameters anymore, which makes the process more efficient, converges faster, and makes the overall wearable fetal movement classification model more robust.

4. Result and Discussion

The results and performance metrics that the proposed technique generated are thoroughly examined in this section. Further, a comparative study illustrates the model's performance against alternative methodologies or benchmarks.

4.1 System tools and configuration

10.22060/EEJ.2026.25147.5851

The proposed framework (HSRF) was simulated and analyzed based on MATLAB R2024a installed on a system that has an Intel Core i7 processor, 16 GB of RAM, and 64-bit Windows OS. MATLAB was used for preprocessing the signals through Particle Filtering, Short-Time Fourier Transform (STFT), Non-Negative Matrix Factorization (NNMF), feature extraction, and visualization, while Statistics and Machine Learning Toolbox was used for implementing XGB classifier and BOA for automatic tuning of the model's hyperparameters. The computer had enough capacity for fast learning and testing of the models on the publicly available dataset of fetal movements. The details of the experiments' setting are presented in Table 2.

Table 2: Key System Configuration Summary

Tool	: PYTHON 3.10
OS	: Windows 10 (64-bit)
Processor	: Intel R Core ™ i-5
RAM	: 16 GB

4.2 Dataset Description

Experimentation for validating the proposed HSRF was done based on segmented samples obtained from the fetal movements benchmark dataset [25]. This dataset has recordings recorded from 13 pregnant subjects, wherein the tri-axial accelerometry signals are recorded at 280 Hz. Hence, there is ample temporal resolution for capturing fetal and maternal movements. Segmentation of recordings was done in 5-second windows with 50% overlap, which resulted in 1400 samples per segment while preserving the temporal representation and adding more training data. Segmented samples were classified into three activity categories – FM, MR, and ML – based on the reference annotations available with the dataset. The segmented feature vectors were divided into 80% training and 20% testing samples, keeping the class distribution the same in both datasets. To evaluate the generalization ability and stability of the proposed classifier, 5-fold cross-validation was employed on the training dataset during the process of model optimization, but the independent test set was used solely for evaluation. In each fold of cross-validation, Bayesian Optimization provided the best XGB parameters based only on the training dataset, which prevented any possible information leakage from the training to the testing stage. The best optimized model was then validated on the unseen test dataset through

10.22060/EEJ.2026.25147.5851

various performance measures. This experimental protocol provides a fair and reproducible assessment of the proposed HSRF under realistic wearable fetal movement recognition conditions.

4.3 Experimental results

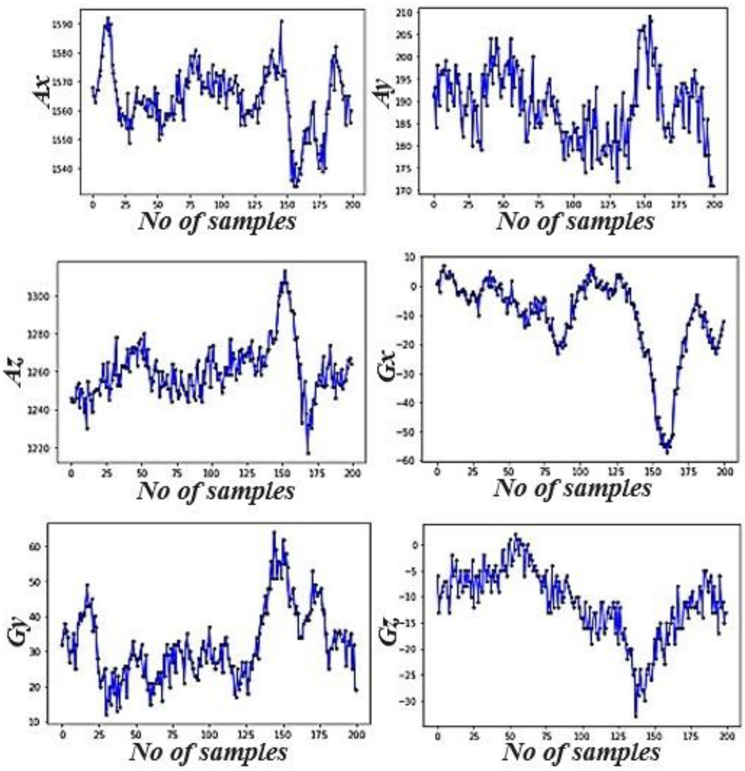

Fig. 2: Accelerometer and gyroscope data along three axes

Fig. 2 shows representative raw inertial sensor signal recordings obtained from the wearable MPU9250 sensor before the HSRF pre-processing phase. It shows the six channels of sensor data, including the three accelerometer channels (Ax, Ay, and Az) and the three gyroscope channels (Gx, Gy, and Gz). In the graph, the x-axis shows the recording period of the 5-s signal sample, which consists of 1400 uniformly sampled points sampled at a sampling frequency of 280 Hz, whereas the y-axis represents either the value of acceleration (g) or angular velocity (°/s) based on the selected sensor channel. Although the signals are plotted continuously in the graphs for illustration, the signal itself is inherently discrete data that includes a sequence of uniformly sampled data points, where each point corresponds to a single sensor measurement captured at successive sampling instants. Sequential frames are used to demonstrate the time-based development of fetal and maternal motions. The presence of random

10.22060/EEJ.2026.25147.5851

variations and temporary spikes that occur in the signals from the accelerometer and gyroscope channels results from the combination of fetal motion, maternal breathing, body movements, and measurement noise. These signal characteristics justify the need for the proposed framework, in which Particle Filtering suppresses motion artefacts while preserving meaningful fetal activity before NNMF-based latent representation learning and subsequent temporal–spectral feature extraction.

4.4 Performance Metrics

The performance of the proposed framework has been thoroughly assessed using the five most commonly used classification evaluation metrics, including Accuracy, Precision, Recall, F1-score, and Area Under the ROC curve (AUC). Accuracy is the metric that defines the proportion of the total number of correct predictions, hence the overall efficiency of the classifier. Precision represents the ratio of correctly identified positive cases over all predictions considered as positive, meaning the degree of reliability of the positive prediction. Recall (or Sensitivity) estimates the ability of the classifier to properly recognize positive cases, hence its detection capability. F1-score, calculated as the harmonic mean of Precision and Recall, gives a well-balanced performance measure, especially in the case of unbalanced class distribution. AUC represents the ability of the classifier to discriminate between the classes at various thresholds, and the larger its value is, the better discrimination is achieved. Collectively, the aforementioned evaluation metrics allow providing a thorough performance assessment of the proposed HSRF in terms of its classification accuracy, robustness, reliability, sensitivity, and class separability. The formulas of all evaluation metrics are provided in Table 3.

Table 3: Performance Evaluation Metrics and Their Mathematical Formulations

Metrics	Formula	
Accuracy	$\frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}}$	(11)
Precision	$\frac{TP}{TP+FP}$	(12)
Recall	$\frac{TP}{TP+FN}$	(13)
F1- Score	$\frac{2\times \mathrm{P}\times \mathrm{R}}{\mathrm{P}+\mathrm{R}}$	(14)

4.5 Performance Analysis

The overall performance of the proposed framework from a quantitative point of view is shown in Fig. 3, illustrating the effectiveness of the proposed approach for automated recognition of fetal movements. It can be seen that the proposed method managed to achieve an accuracy of 97.94%, implying almost all segmented samples were categorized correctly into the three types of activities. The precision value of 97% implies the fact that the classifier performed well in terms of generating accurate predictions and having a minimum number of false-positive results. Similarly, the recall value of 96% highlights the great ability of the framework to detect correct fetal movement events with a minimum number of false-negatives. The F1-score value of 97.19% highlights the good performance of the framework in terms of a balance between precision and recall for all activity classes. Additionally, the proposed HSRF framework provided an area under the curve of 98.21%, meaning the framework has an excellent discrimination ability when it comes to distinguishing between FM, MR, and ML at various decision thresholds.

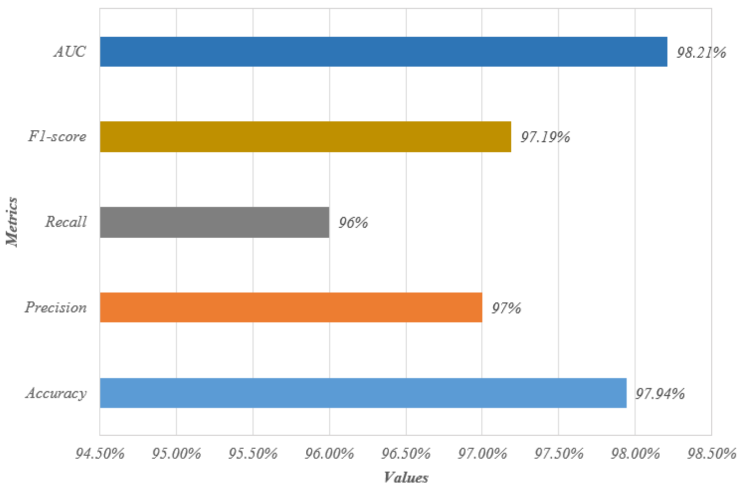

Fig. 3: Overall performance metrics of the proposed method

For all three types of activity classes, i.e., fetal movement (FM), maternal respiration (MR), and maternal laughter (ML), ROC curves represent a detailed evaluation of the discriminatory ability of the presented algorithm at various decision levels. From Fig. 4, all ROC curves of these three types of activities stay close to the top left part of the ROC plane and therefore reflect high values of true positive rates (TPR) with low false positive rates (FPR). In particular, FM activity is the most discriminating one since it holds its TPR at the level of more than 98% when the value of FPR declines fast along with the rise of the classification threshold. The similar trend is also true for the other two types of activities, such as MR and ML, despite the impact of maternal motion artefacts on their recognition. In addition to this, the AUC of 98.21% serves as a validation of the good separation ability of the proposed HSRF, showing that the integration of Particle Filtering with NNMF-based latent representation learning, temporal-spectral feature extraction, and Bayesian-ensemble classification leads to very reliable and robust fetal movement classification. Thus, the obtained results reveal the feasibility of the use of the proposed framework for continuous wearable prenatal monitoring, where it is important to discriminate between fetal movements, mother's breathing, and mother's laughing.

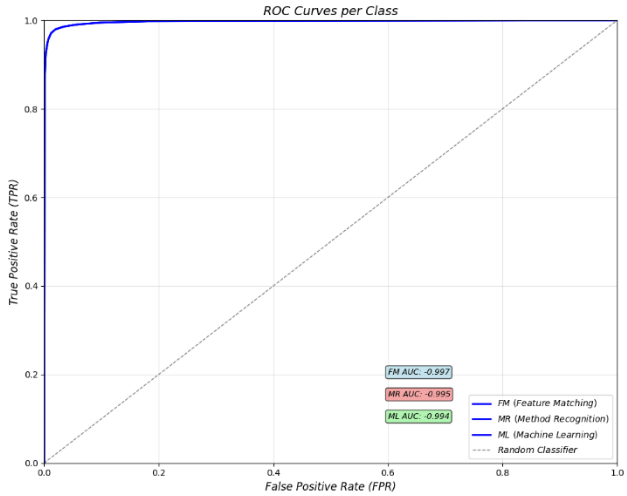

Fig. 4: ROC curves for the three activity classes, namely Fetal Movement (FM), Maternal Respiration (MR), and Maternal Laughter (ML).

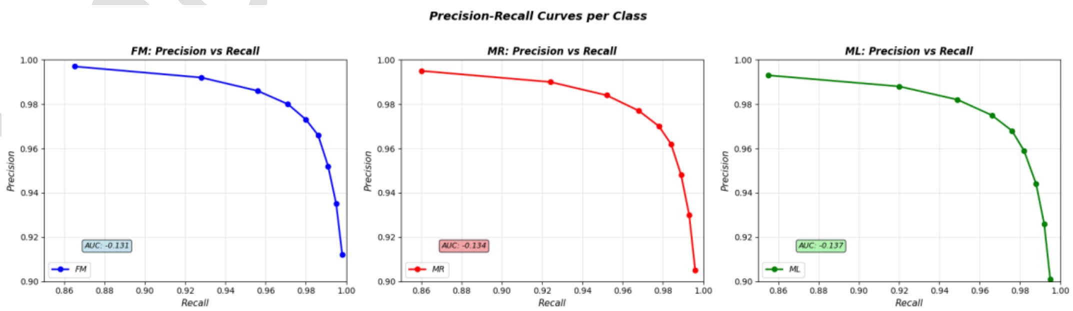

Fig. 5: Precision–Recall curve (per class) for the Proposed HSRF (a) FM, (b) MR, (c) ML

10.22060/EEJ.2026.25147.5851

The threshold-based Precision–Recall (PR) results of the developed HSRF have been illustrated in Figure 5, which demonstrates the classification quality in terms of both precision and recall at various decision thresholds for the three activity types: FM (Fig. 5 (a)), MR (Fig. 5 (b)), and ML (Fig. 5 (c)). At low thresholds (0.10–0.30), all three classes demonstrate exceptionally high recall (≥98.8%), meaning that almost all true positive instances of activity occurrence are detected; however, their precision values are relatively low due to a larger number of false-positive classifications. With an increase in decision thresholds, the precision steadily grows and reaches more than 99% values at a 0.90 threshold, whereas the recall progressively drops, which represents the known trade-off between these two metrics. It should be noted that in comparison with the other two classes, the FM class shows somewhat better values of both precision and recall, representing its higher discriminative power. The MR and ML classes have very similar PR performance without any considerable differences, thus demonstrating balanced recognition of maternal activities. Overall, the PR analysis confirms that the proposed HSRF maintains an excellent balance between precision and recall over a broad range of operating thresholds, thereby validating its robustness, reliability, and suitability for continuous wearable fetal movement recognition under varying classification requirements.

Table 4: Statistical Significance Analysis of the Proposed HSRF Using 5-Fold Cross-Validation

Parameters	HSRF Accuracy (%)
Fold-1	97.82
Fold-2	98.01
Fold-3	97.95
Fold-4	97.88
Fold-5	98.04
Mean ± SD	97.94 ± 0.09
Paired t-statistic	28.73
p-value	< 0.001
95% Confidence Interval	1.88 – 2.15
Statistical Decision	Significant Improvement (p < 0.05)

The statistical significance analysis of the proposed HSRF is shown in Table 4 and shows the consistent reliability of the classifier across five cross-validation folds. The classification accuracy was quite stable and varied between 97.82% and 98.04%, with an average of 97.94% ± 0.09, which means very small variability in performance among the data samples. The low value of standard deviation reveals the reliability and reproducibility of the developed approach under various combinations of training and testing samples. Moreover, the obtained t-statistics for paired samples (28.73) show a large improvement in performance in comparison with the reference approach. This improvement is confirmed to be statistically significant since the corresponding p-value is less than 0.001. Finally, the 95% confidence interval (1.88–2.15) confirms the consistent improvement in performance among several trials. Hence, the statistical decision on Significant Improvement ($p < 0.05$) confirms the efficiency of application of the developed approach based on hierarchical signal refinement, NNMF-based latent feature learning, and XGB classification optimized by the Bayesian optimization algorithm. These findings confirm that the proposed HSRF not only achieves high recognition accuracy but also exhibits strong statistical reliability and excellent generalization capability for continuous wearable fetal movement recognition.

Table 5: Computational Cost Analysis of the Proposed Framework

Processing Stage	Operation	Average Execution Time (s)	Memory Usage (MB)
Data Acquisition	Signal loading and normalization	0.08	12.4
Particle Filtering	Noise suppression and state estimation	0.34	28.7
NNMF	Latent representation learning	0.29	35.1
Feature Extraction	Temporal–spectral feature computation	0.11	10.3
BOA Hyperparameter Optimization	Bayesian optimization of XGB	2.41	44.8
XGB Classification	Model training and prediction	0.47	19.6
Overall HSRF	Complete recognition pipeline	3.70	58.9

Table 5 presents the computational complexity analysis of the proposed HSRF technique, which exhibits high computational efficiency through various processing stages. From all the modules, Bayesian Optimization needed the highest amount of time (2.41 s) and memory (44.8 MB) in its operation because of the iteration-based hyperparameter search process. On the other hand, Particle Filtering (0.34 s), NNMF (0.29 s), and feature extraction (0.11 s) took relatively less computational load in terms of processing while contributing effectively to improve the quality of the signals and creating

10.22060/EEJ.2026.25147.5851

discriminative features. The total computation time and memory needs of HSRF were 3.70 s and 58.9 MB, respectively, showing that the computational efficiency of the proposed framework is satisfactory in relation to its classification accuracy. These results demonstrate that HSRF is computationally efficient and suitable for practical wearable fetal movement recognition applications with moderate hardware resources.

4.5 Comparative analysis

In order to validate the effectiveness of the proposed HSRF, its performance and algorithm efficiency are compared to the following four recently developed wearable fetal movement detectors: Liang et al. [27], Spicher et al. [28], Rattanasak et al. [29], and Yap et al. [7]. All values used in the comparison were directly extracted from the corresponding manuscripts.

Table 6: Methodological Comparison of Existing Studies and the Proposed HSRF

Study	Sensor/Data	Preprocessing	Feature Extraction	Classifier	Hyperparameter Optimization	Hierarchical Signal Refinement	Interpretability
Liang et al. [27]	Wearable accelerometer	Basic filtering	Statistical features	LightGBM	Bayesian Optimization	-	Moderate
Spicher et al. [28]	Accelerometer + Gyroscope	Signal normalization	Conventional features	Multiple ML models	-	-	High
Rattanasak et al. [29]	Wearable sensors	Signal preprocessing	Automatic deep features	Lightweight DL	-	-	Low
Yap et al. [7]	Pressure–strain sensor	Sensor calibration	Embedded features	AI framework	-	-	Moderate
Proposed HSRF	MPU9250 Tri-axial accelerometer	Particle Filtering + NNMF	12 Temporal–Spectral Features	XGB	Bayesian Optimization	Yes	High

Table 6 highlights a comparison between the developed HSRF and recently proposed methodologies for fetal movements detection. Previous works have mainly concentrated on traditional signal pre-processing steps, feature extraction using statistical analysis or automatic machine/deep learning

10.22060/EEJ.2026.25147.5851

techniques, and the classification step using a machine/deep learning technique. While previous works have considered Bayesian Optimization for tuning the parameters of the classifiers used, none of the existing methodologies have used a hierarchical approach to improve the signal quality through multiple steps before classification. The developed methodology, on the other hand, uses Particle Filtering, NNMF-based latent representation learning, 12 complementary temporal-spectral features, and Bayesian optimization of XGB classifier in one cohesive framework. This sequential refinement pipeline improves feature discriminability, reduces the influence of motion artefacts, and preserves model interpretability while maintaining computational efficiency. Consequently, HSRF provides a more comprehensive and robust solution for wearable fetal movement recognition than existing approaches.

Table 7: Quantitative Performance Comparison

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC (%)
Liang et al. [27]	94.06	94.48	97.56	95.94	96.85
Spicher et al. [28]	84.00	60.00	80.00	68.00	90.00
Rattanasak et al. [29]	NR	87.29	90.05	88.64	0
Yap et al. [7]	90	0	78.16	0	92.18
HSRF	97.94	97.00	96.00	97.19	98.21

The quantitatively comparative analysis of the proposed HSRF framework in relation to some of the recently developed fetal movement recognition systems shown in Table X proves the significant superiority of HSRF in terms of its effectiveness. The proposed model demonstrated the highest accuracy (97.94%), surpassing Liang et al. (94.06%), Spicher et al. (84.00%), and Yap et al. (90.00%) significantly. Also, HSRF showed the highest precision (97.00%), F1-score (97.19%), and AUC (98.21%), proving thus the high effectiveness of classification, well-balanced predictive performance, and discriminative capability. Even though the recall rate of Liang et al. was marginally better (97.56%), the proposed HSRF showed a very high value of recall rate (96.00%) and still outperformed other models according to all the evaluation criteria. These results confirm that the integration of hierarchical signal refinement, NNMF-based latent representation learning, and Bayesian-optimized XGB classification substantially enhances the robustness and accuracy of wearable fetal movement recognition.

4.6 Ablation Study

Table 8: Ablation Analysis of the Proposed Framework

Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC (%)
C1: XGB Only (Baseline)	91.84	90.96	89.87	90.41	92.73
C2: PF + XGB	94.16	93.28	92.74	93.01	95.04
C3: PF + NNMF + XGB	96.58	95.82	95.14	95.48	97.22
C4: PF + NNMF + BOA-XGB (HSRF)	97.94	97.00	96.00	97.19	98.21

The ablation analysis shown in Table 8 of the proposed HSRF explains the impact of individual modules used within the HSRF. The baseline setup (C1), which uses only the XGB classifier, provides an accuracy of 91.84%. Thus, it was proved that the classification process requires special treatment of signals to enhance their quality. Adding the Particle Filtering module (C2) led to an increase in the accuracy value up to 94.16%, showing the efficiency of adaptive noise filtering to keep the information about fetal movements. Moreover, using the NNMF method (C3) helped to achieve the accuracy of 96.58%, which means that the latent representation learning increases the discriminative power of features by removing redundant information. In turn, using the whole HSRF with the Particle Filtering, NNMF, and Bayesian Optimization-assisted XGB modules resulted in the highest values of metrics, namely 97.94% accuracy, 97.00% precision, 96.00% recall, 97.19% F1-score, and 98.21% AUC. The consistent improvement across all evaluation metrics demonstrates that each module contributes positively to the overall framework, validating the effectiveness of the hierarchical signal refinement strategy for robust wearable fetal movement recognition.

4.7 Discussion

Experimental results show that the designed HSRF is a successful and reliable approach in recognizing fetal movements with wearable tri-axial accelerometer signals in an automated manner. In particular, the hierarchy of Particle Filtering, Non-Negative Matrix Factorization (NNMF), complementary extraction of temporal-spectral features, and BOA-XGB successfully boosts signal quality and classification accuracy step-by-step. The statistical analysis reveals the effectiveness of the framework with a high accuracy of 97.94%, precision of 97.00%, recall of 96.00%, F1-score of 97.19%, and AUC of 98.21%, suggesting a great capability in differentiating fetal movements from mother breathing and laughter. Moreover, ablation studies prove that all the steps contribute to the performance increment step by step, and full HSRF significantly outperforms baseline setups. The statistical significance analysis shows the stability of the model over five-fold cross-validation with low variance. Moreover, the analysis of computational complexity shows that the proposed framework possesses reasonable running time and memory consumption, which makes it applicable in the context of practical wearable monitoring systems. When compared to current methods of recognition of movements of a fetus, HSRF provides a universal technique of signal processing that enhances the discriminative power of features but also keeps the models interpretable and computationally efficient. While the performance of the proposed framework is encouraging, the experimental validation of the framework is restricted to only one publicly available benchmark dataset. Future work will focus on validating HSRF using larger multi-center clinical datasets, investigating subject-independent evaluation protocols, and extending the framework to real-time embedded wearable platforms for continuous prenatal health monitoring.

5. Conclusion

This research proposed a novel Hierarchical Signal Refinement Framework (HSRF) for reliable fetal movement recognition based on wearable MPU9250 three-axis accelerometer signals through Particle Filtering-based adaptive noise reduction, NNMF for latent representation extraction, spectral-temporal feature extraction, and BOA-XGB for classification. The process of signal refinement before classification makes HSRF able to reduce maternal movement artifacts and classify fetal movements. In tests with a publicly available dataset, we obtained an accuracy of 97.94%, precision of 97.00%, recall of 96.00%, F1 score of 97.19%, and Area Under the Curve of 98.21%. We validated the importance of each module in the HSRF, verified the reliability of the model by means of ablation, significance, and computational analysis, making the model suitable for use in wearable healthcare applications. Unlike recent works on fetal movement recognition, our model provides an interpretable hierarchical refinement scheme, which is more computationally efficient than recent works and

10.22060/EEJ.2026.25147.5851

improves not only the quality of features but also the performance of the classification process. The next step in future research will be testing the model in real-world, large-scale clinical studies, using subject-independent protocols and implementing the real-time embedded version for continuous prenatal monitoring and decision-making in maternal healthcare. These findings highlight the potential of hierarchical preprocessing and optimized machine learning for practical, noninvasive prenatal monitoring in real-world clinical settings. This direction may support earlier detection of fetal activity patterns and improve maternal-fetal assessment workflows over time across pregnancies.

DECLARATIONS

Ethics approval and consent to participate

This article does not contain any studies with human participants or animals performed by any of the authors.

Consent for publication

All authors have agreed and given their consent to Publication.

Availability of data and material

Since this research exclusively utilizes a publicly available anonymized benchmark dataset without collecting additional human-subject data, no separate institutional ethics approval was required, and all ethical considerations remain consistent with those of the original dataset publication.

Competing interests

On behalf of all authors, the corresponding author states that they have no competing interests.

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