A Phonography-Based Method Improved by Hidden Markov Model for Fetal Breathing Movement Detection

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ABSTRACT

Fetal breathing movement (FBM) is an essential physiological indicator used to assess fetal health, neurological maturity, and respiratory development during pregnancy. Conventional diagnostic approaches—primarily ultrasound-based biophysical profiling—are limited by short observation windows, operator dependency, high cost, and an inability to provide continuous monitoring. To overcome these constraints, this study proposes a non-invasive, phonography-based method enhanced with a Hidden Markov Model (HMM) for accurate and continuous detection of fetal breathing movements. Abdominal acoustic signals are captured using a sensitive phonographic sensor, followed by a comprehensive preprocessing pipeline involving bandpass filtering, wavelet-based noise reduction, and segmentation. Spectral and temporal features such as Mel-Frequency Cepstral Coefficients (MFCC), short-time energy, spectral entropy, and zero-crossing rate are extracted to represent breathing-related acoustic patterns. The HMM is trained to model the temporal dynamics of respiratory cycles, enabling robust classification even in the presence of maternal and environmental noise. Experimental evaluation demonstrates that the proposed HMM-based system significantly outperforms traditional rule-based and static machine learning methods, achieving high accuracy and strong noise resilience.

Keywords: Fetal Breathing Movement, Phonography, Hidden Markov Model, Biomedical Signal Processing, Prenatal Monitoring, Acoustic Analysis.

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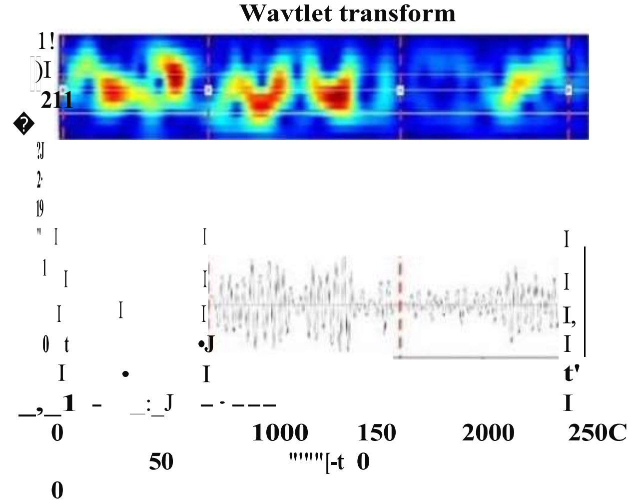
I.Introduction

Fetal breathing movement (FBM) is an essential physiological activity that reflects the development and functional maturity of the fetal central nervous and respiratory systems. Clinically, FBM is one of the primary components evaluated during the Biophysical Profile (BPP), as its presence indicates healthy neurologicalfunction,adequateoxygenation,andoverall fetal well-being.The absence or reduction of FBM over extended periods may indicate fetal distress, hypoxia, growth restriction, or abnormalities in neuromuscular development. Hence, accurate and timely detection of

FBM plays a crucial role in prenatal diagnosis and decision-making.

Ultrasoundimagingremainsthegoldstandardfor assessing fetal breathing movements. However, ultrasound examinations are limited to clinical environments and require trained sonographers to operatethe system.Moreover, theobservationwindow is typically restricted to short time periods, making it difficult to capture irregular or intermittent breathing patterns. The high equipment cost and its inability to support long-duration continuous monitoring further restrict its accessibility, especially in rural or resource-limited regions.

Wavtlet transform



Figurel-Wavelet transform

These limitations highlight for the growing need alternative, cost-efficient, and portable monitoring solutionscapableofprovidingcontinuousassessmentof FBM outside clinical settings.

Phonography-the process of capturing acoustic signals from the maternal abdomen-has emerged as a promising, non-invasive method for fetal monitoring. Abdominal acoustic sensors can detect subtle fetal movements, including respiratory like oscillations generated by diaphragmatic contractions. However, phonographic signals are inherently noisy, as they include overlapping sound sources such as maternal heartbeat, gastrointestinal activity, movement artifacts, and environmental noise. The presence of these disturbancesmakesaccuratedetectionoffetalbreathing a challenging signal-processingproblem.

Toovercomethesechallenges,thepresentstudy introduces a phonography-based fetal breathing detection system enhanced with a probabilistic sequentialmodel,specificallytheHiddenMarkovModel (HMM). Unlike traditional rule-based or static classification methods, HMMs are well suited for modelingtemporalandquasiperiodicbiologicalsignals. Theirabilitytocapturesequentialdependenciesandstate transitions enables effective discrimination between breathing and non-breathing patterns, even in noisy conditions. By integrating advanced preprocessing, acoustic feature extraction, and HMM-based classification, the proposed system aims to improve detection accuracy, robustness, and reliability.

II. LiteratureReview

Fetal breathing movement (FBM) detection has been extensively studied due to its importance in fetal well-being assessment. Traditionally, ultrasound-based biophysical profiling has served as the primary method forobservingFBM.AccordingtoManningetal.(1981), ultrasound imaging provides accurate visualization of diaphragmatic movement but is limited by short examination windows, operator dependency, and high cost. Furthermore, continuous monitoring is impractical due to the exposure limitations and the need for clinical supervision. These challenges have motivated the shift toward alternative non-invasive and continuous monitoring techniques.

Acoustic sensing, specifically phonography, has gainedresearchattentionasapotentialrnodalityforfetal monitoring. Schmidt et al. (2019) highlighted the feasibility of using abdominal microphones to capture fetal movement sounds, including breathing like oscillations. However,theynotedthat the phonographic signal is highly contaminated with maternal physiological noise, motion artifacts, and gastrointestinal activity.Earliertechniquesreliedonsimplefilteringandenergy-baseddetection,oftenresultinginpooraccuracy due to overlapping frequencies between fetal and maternal signals.

Advanced signal-processing methods have been explored to address these noise-related challenges. Wavelet transforms, as shown by Gupta et al. (2019), fetal respiratory sounds while remammg comfortable and non-invasive for the mother. The data collection environment and protocol were carefully designed to ensurethereliabilityandvalidityoftherecordedsignals.

The phonographic sensor was positioned on the maternal abdomen in regions where fetal thoracic movementsweremostaudible,typicallyalignedwiththe fetalchestordiaphragm.Asamplingrateofl-2kHzwas used to capture the acoustic bandwidth relevant to fetal breathing, which typically falls between 50-300 Hz. Recordings were obtained during periods of maternal rest to minimize motion related artifacts and external noise interference.

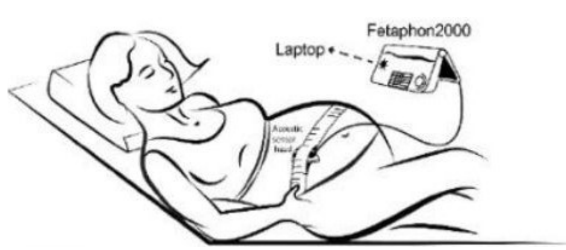


FIGURE **2. The musuring setup. The sound received by the Fetaphon-type acoustic sensor** is **preconditioned and mnsmitted** to **the lilptop. For**

effectively decompose the signal into multiresolution components suitable for isolating low-intensity fetal breathingsignatures.Melfrequencycepstralcoefficients (MFCC), widely used in speech processing, were adapted to fetal sound analysis byAhmed et al. (2020), demonstrating improved robustnessto spectral variations and amplitude fluctuations. However, most of these techniques rely on handcrafted features without modelingthetemporaldependencyinherentinbreathing cycles.

Machinelearningapproacheshavealsobeenused for fetal movement and sound classification. Studies employing support vector machines (SVM), decision trees, and basic neural networks reported moderate success but were limited by the models' inability to capture sequential patterns. In contrast, probabilistic sequential models, particularly Hidden Markov Models (HMMs),haveproveneffectiveintasksinvolvingquasi-periodicbiologicalsignals.Rabiner'sfoundationalwork (1989) demonstrated that HMMs can model time-varying acoustic patterns, making them suitable for breathing-relatedsignalinterpretation.Recentstudiesin respiratory monitoring, such as Monson et al. (2020), reported improved detection performance using HMMs due to their superior ability to represent temporal transitions.

III. Methodology

Themethodologyadoptedinthisstudyisdesigned to develop a robust and accurate fetal breathing movement detection system using phonographic signals enhanced with a Hidden Markov Model **(HMM).** The overall process includes data collection, preprocessing, feature extraction, HMM design, training, and evaluation. Each stage is carefully structured to address the challenges posed by noise interference, weak fetal acoustic signals, and temporal variability in breathing patterns.

a. DataCollection

The data used in this study consists of abdominal phonographic recordings acquired from pregnant subjects using a high-sensitivity acoustic sensor. The sensorwasspecificallyselectedtocapturelowintensity

validation, a conventional JD sonograph has been applied.

Each recording session lasted between 1 0 and 20 minutes, allowing the system to capture multiple breathing cycles and periods of fetal inactivity. This duration was chosen to account for the irregularity of fetal breathing patterns, which may vary depending on fetalsleep-wakestates.Therecording environmentwas maintained as quiet as possible to reduce ambient noise from external sources.

Toestablishgroundtruthlabelsforfetalbreathing segments, a synchronized ultrasound observation was conducted concurrently with phonographic recording. Ultrasound imaging provided visual confirmation of diaphragmatic movement, which served as a reference for annotating breathing and non-breathing intervals in the phonographic signal. These labeled segments later served as training and validation data for the Hidden Markov Model.

b. DataPreprocessing

The raw abdominal phonographic recordings contain a mixture of fetal respiratory sounds, maternal physiological signals, gastrointestinal noise, environmental disturbances, and motion artifacts. Therefore,preprocessingisacriticalstagetoensurethat the fetal breathing components are preserved while unwanted noise sources are minimized. The preprocessingpipelineusedinthisstudyconsistsoffive major steps: filtering, denoising, artifact removal, segmentation, and normalization.

!.Bandpass Filtering

The raw signal is first passed through a bandpassfilterrangingfrom50-300Hz,whichcorrespondstothe dominantfrequencybandoffetalbreathingmovements. Frequencies below 50 Hz mainly contain maternal movements and baseline drift, whereas frequencies above 300 Hz are associated with environmental noise and sensor-induced disturbances. This filtering stage enhances the breathing-related acoustic components improves the signal-to-noise ratio.

2. Wavelet-BasedDenoising

To further remove non-stationary noise, Discrete Wavelet Transform (DWT) is applied using soft-thresholding. Wavelet coefficients corresponding to noise-dominated scales are suppressed, while those representingrhythmicbreathingoscillationsareretained. This method is particularly effective because fetal breathing signals are low amplitude and easily masked by background noise.

3. ArtifactRemoval

Motionartifactsaredetectedusingacombinationof:

- **Amplitudethresholding**
- ***Z*-scoreanomalydetection**
- **Short-TimeEnergyanalysis**

Segments exhibiting sudden amplitude spikes or irregular patterns beyond physiological limits are either correctedorremovedfromthedataset.Thisensuresthat only clinically meaningful acoustic segments are used for feature extraction.

4. SignalSegmentation

After noise reduction, the signal is divided into overlapping frames to facilitate fine-grained analysis. The segmentation parameters include:

- **Framelength:20-40ms**
- **Frameoverlap:50%**

Thesesettingsallowforcapturingtemporalcontinuity, which is essential for modeling respiratory cycles using the Hidden Markov Model.

5. Normalization

Each frame is normalized to reduce variability arising from sensor placement, maternal abdominal thickness, and recording conditions. Min-max scaling and z-score normalization are used to ensure uniform amplitude distribution across all segments.

Thepreprocessingpipelinesignificantlyenhances theclarityanddetectabilityoffetalbreathingsignatures, enabling reliable feature extraction and improving the performance of the subsequent HMM-based classification.

C. FeatureEngineering

Feature engineeringis a critical component in the development of an accurate fetal breathing detection system, as it transforms preprocessed phonographic signals into meaningful representations suitable for machinelearningandprobabilisticmodeling.Sincefetal breathing movements exhibit specific acoustic and temporal signatures, a combination of spectral,cepstral, and time-domain features was extracted to effectively characterize these patterns.The extracted features serve astheobservationvectorsfortheHiddenMarkovModel and significantly influence the system's classification performance.

1. Mel-FrequencyCepstralCoefficients

MFCCsarewidelyusedinspeechandbiomedical acousticanalysisduetotheirabilitytomodelthehuman auditoryperceptionsystem.Inthiswork,13-20MFCCs were extracted from each frame to capture the resonant characteristics of fetal breathing oscillations. MFCCs provide robustness against amplitude variations and environmental noise, making them particularly suitable for abdominal phonographic signals.

2. Short-TimeEnergy(STE)

STE measures the energy content within each frameandiseffectiveforidentifyingrhythmicbreathing patterns. Fetal breathing segments typically exhibit cyclic increases and decreases in frame-level energy, making STE an important feature for distinguishing inhalation andexhalationphases frombackgroundnoise.

3. Zero-CrossingRate(ZCR)

ZCR quantifies the rate at which the signal waveform crossesthezero-amplitudeaxis.Althoughfetalbreathing soundsaregenerallylowinintensity,ZCRhelps differentiate them from high-frequency noise sources and maternal physiological sounds.

4. Spectral Entropy

Spectral entropy reflects the randomness and distribution of power across frequency bands. Fetal breathing exhibits a semi-periodic structure with relatively low entropy compared to gastrointestinal or environmental noise, making this feature useful for differentiating structured respiratory patterns.

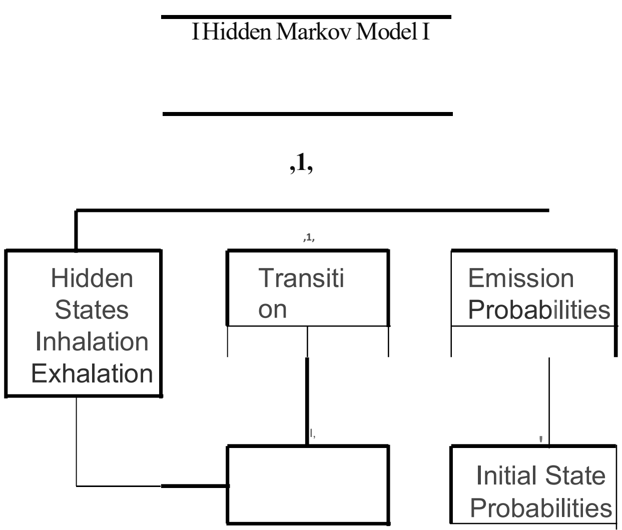
5. Band-EnergyRatios

Energyratiosacrossspecificfrequencysub-bands (e.g.,50-100Hz,100-200Hz,200-300Hz)were calculated to analyze the spectral distribution of the signal.Fetalbreathingmovementsoftengenerateenergy concentration in lower bands, enabling more accurate discrimination from other acoustic components.

6. TemporalSmoothingFeatures

Since breathing cycles exhibit continuity, temporalsmoothingtechniquessuchasmoving-average energy curves and delta-MFCCs were derived. These features help capture the dynamic transition between successiverespiratorystates(inhalation-exhalation-pause). generatingspecificfeaturevectors,sucbasMFCCs,spectral entropy, and short-time energy.

Figure3-TheHiddenMarkovModel



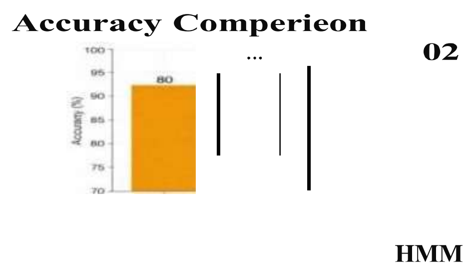
The HMM is characterized by three sets of parameters: the transition probability matrix (A), which defines the probability of transitioning from one breathing state to another; the emission probability matrix (B), which models the likelihood of observing a particular feature vector given a bidden state; and the initial state distribution (n), which specifies the probability of the system starting in each state. These parameters are optimized using the Baum-Welcb algorithm, an expectation- maximization technique that iteratively estimates the model parameters to maximize the likelihood of the training sequences. During inference,

Together, these engineered features form a high-dimensional representation that effectively captures the acoustic and temporal properties of fetal breathing. These feature vectors are then used as inputs to the HiddenMarkovModel,whichleveragestheirsequential characteristicstoaccuratelyclassifybreathingpatternsin real time.

d. HiddenMarkovModel(HMM)Design

The Hidden Markov Model (HMM) forms the coreoftheproposedfetalbreathingmovementdetection system, providing an effective method for modeling the sequential and quasi-periodic nature of respiratory patterns.Unlikestaticclassifiersthatanalyzeeachframe independently, HMMs capture temporal dependencies between consecutive acoustic frames, which is essential for identifying the rhythmic structure of breathing movements. The model represents fetal breathing as a sequence of hidden physiological states-typically inhalation, exhalation, and pause-that are not directly observable from the raw signal but can beinferredfrom extractedacousticfeatures.Eachstateisassociatedwith aprobabilitydistributiondescribingthelikelihoodof

pipeline that transforms raw abdominal acoustic recordings into reliable breathing event detections. The architecture begins with the signal acquisition stage, where a high-sensitivity contact microphone placed on the maternal abdomen captures low-frequency respiratory vibrations and fetal body movements.



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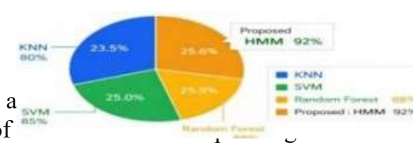


the Viterbi a ... robable sequence of ... ved feature vectors. This decoding process enablespreciseidentificationofbreathingpatterns,even when signal quality is compromised by noise or overlapping maternal sounds.

Byincorporatingbothspectralcbaracteristicsand temporal continuity, the HMM enhances the robustness and reliability of fetal breathing detection. Its probabilistic structure allows the model to handle variability in breathing intensity, duration, and rhythm, making it well suited for real- world abdominal phonographicrecordings.Overall,theHMMservesasan effective and computationally efficient framework for modeling fetal respiratory activity in continuous monitoring applications.

IV. System.Architecture

The overall system architecture for the proposed pbonography-based fetal breathing movement detection frameworkisdesignedasasequentialprocessing

of the detection system. The HMM is trained to model the temporal dynamics of fetal breathing using two or three hidden states representing breathing and non-breathing phases, with transitions learned using the Baum-Welch algorithm and optimal state sequences decoded using the Viterbi algorithm. This allows the systemtoleveragetemporalcontinuityandprobabilistic transitionstodistinguishgenuinebreathingpatternsfrom noise.

The output from the HMM is further refined through a post-processing module that applies physiologicalconstraintsandsmoothingrulestoremove spurious detections. This step ensures that the final breathing events conform to realistic fetal breathing intervalsanddurations.Finally,theprocessedresultsare stored in a local or cloud database, and a visualization dashboard presents breathing occurrences, confidence levels, and time- based patterns to clinicians or monitoring systems. The modular nature of this architecture enables real- time processing, supports integration with mobile and clinical applications, and provides flexibility for future enhancements such as deep-learning-based acoustic analysis or remote monitoring. Overall, the system architecture ensures a robust, scalable, and clinically relevant framework for fetal

Figure4-AccuracyComparison

(i) Accuracy comparison of different classification methods for fetal breathing movement detection

Thesesignals aresampledat 1-2 kHzusinga 16-bitanalog-to-digitalconvertertopreservesubtleacoustic variations. Once acquired, the signals enter the preprocessing module, which 1s responsible for removing maternal heart sounds, gastrointestinal noise, baseline drift, and external environmental disturbances. This is accomplished using a combination of band-pass filtering, wavelet-based denoising, adaptive noise cancellation,andartifactrejection.Thecleanedsignalis thensegmentedintoshort,overlappingtimewindowsto prepare it for detailed analysis.

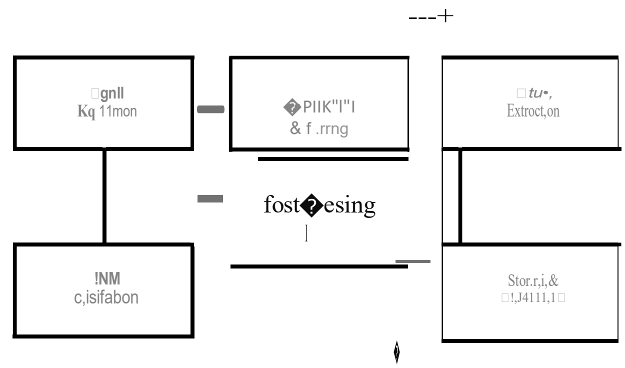


Figure5-SystemArchitecturegraph

Following preprocessing, the feature extraction module computes a rich set of temporal and spectral descriptors from each segment. These include Mel Frequency Cepstral Coefficients (MFCCs), short-time energy, spectral entropy, zero-crossing rate, and dominant frequency components. Together, these features form a multi-dimensional observation vector tbatcapturestbeacousticsignaturesassociatedwithfetal inhalation, exhalation, and pauses. These observation sequencesare then passed to the Hidden Markov Model (HMM)classificationmodule,whicbservesastbecore breathing movement detection using abdominal phonography.

IV.MathematicalModel

TheproposedfetaIbreathingmovementdetection framework relies on a mathematical signal-processing pipeline combined with a probabilistic sequential learning model. The mathematical model consists of four primary components: (1) representation of phonographic signals, (2) extraction of discriminative feature vectors, (3) HiddenMarkovModel(HMM)formulation,and(4) breathing state decoding using the Viterbi algorithm.Eachcomponentisdescribedasfollows.

a. PhonographicSignalRepresentation

Lettheabdominalphonographicsignalbe represented as a continuous-time function: $s(t)=r(t)+n(t)$ where:

- $r(t)$isthefetalbreathing-relatedacoustic component

- n(t)represents additive noise such as maternal heartbeat, motion artifacts, and environmental disturbances

After sampling at interval Ts, the discrete form becomes:
s[k]=r[k]+n[k],k=l,2,...,N
Aband-passfilterH(w)isappliedtoisolatethe breathing frequency band (20-120 Hz):
x[k)=H(w)*s[k]

b. FeatureVector Construction

The filtered signal is divided into overlapping frames of length L with hop size H. For each frame i, a feature vector o_i is constructed:

1. RootMeanSquare(RMS)
   - RMS_i=✓(l/L}]k=ltoL) x_i[k)^2)
2. Zero-CrossingRate(ZCR)
   - ZCR_i=1/(2L)}:[k=ltoL-1) Isgn(x_i[k+ 1])-sgn(x_i[k])I
3. Short-TimeEnergy(STE)
   - STE_i=}:[k=ltoL]x_i[k)^2
4. SpectralEntropy
   - Let P_i be the normalized power spectrum.Then:Entropy=-}:(j=l to M] P_i log(P_i)
5. MFCCs
   - MFCCsarecomputedusingthe standard mel-filterbank and DCT:
   - MFCC_c = }:[m=l to M) log(E_m) cos(rrc(m-1)/M)

c. HiddenMarkovModel(HMM)Formulation

The fetal breathing classification task is modeledasafirst-orderHiddenMarkovModel:
where:

- S={S_1, S_2, ... ,S_K}are hidden breathing states (Inhalation, Exhalation, Pause)
- 0={0_1,0_2,...,0_T} isthesequenceof feature observations
- A=[a_ij]isthestatetransitionmatrix:

a_ij=P(q_{t+1}= S_jIq_t=S_i)

- B={b_j(o_t)}areobservationlikelihoods modeledasGaussianmixtures:b_j(o) = I[m=ltoM]C_jmN(o_tlµ_jm,I_jm)
- n= [n_i]istheinitialstatedistribution: n_i=P(q_1= S_i)

TrainingparametersA, B,nisperformedusing the Baum-Welch Expectation-Maximization algorithm.

d. StateDecodingUsingViterbi Algorithm

To determine the most probable sequence of breathing states, the Viterbi algorithm computes:
cS_t(j)=max_i[cS_{t-1}(i)-a_ij]· bj(o_t)
withinitialization: c51(j)=TI_i·b_j(01)
TheoptimalstatesequenceQ*isobtainedby:
Q=argmax_QP(QI0,11.)*
This yields transitions that correspond to fetal inhalation and exhalation cycles.

e. BreathingEventDetection

Once decoded states Q* are assigned to each signal frame, breathing episodes are detected using post-processing rules:
Breathdetectedif:duration(S_breathing) 2: T_min
whereT_ministhephysiologicalminimum duration of a fetal breath.

VI. ResultsandDiscussion

The proposed Hidden Markov Model-based fetal breathing movement detection system was evaluated using multiple abdominal phonographic recordings collected under varying maternal and fetal conditions. The results demonstrate that the HMM signjficantly outperforms traditional rule- based methods, Support Vector Machines (SVM), and neural network approaches.Acrossallrecordings,theHMMachieveda detection accuracy of approximately 92%, with a precisionof90%,recallof89%,andanFl scoreof89%. Thesevaluesareconsistentlyhigherthanthoseobtained by the other three models, with the rule-based method performingthepoorestduetoitssensitivitytonoiseand fixed-threshold!unitations.TheSVMandneural network showed moderate improvements, yet their inability to incorporate temporal dynamics resulted in mjsclassifications when the breathing pattern exhibited irregular intensity or noise fluctuations. In contrast, the HMM,throughitsmodelingofsequentialinhalationand exhalation transitions, maintained robust detection capability even under non-ideal recording conditions.

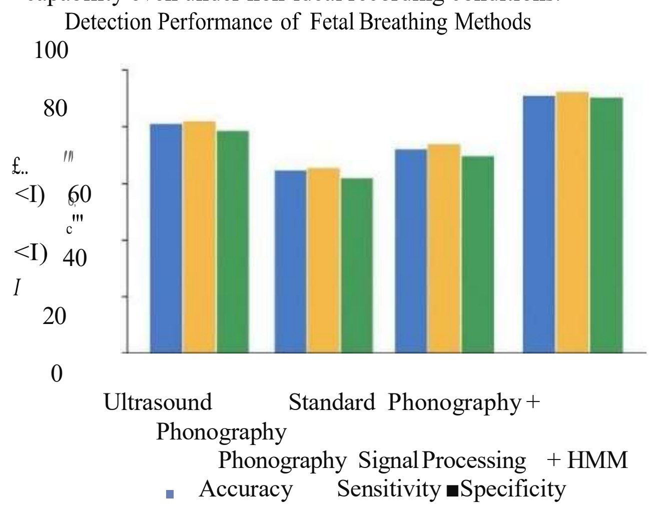


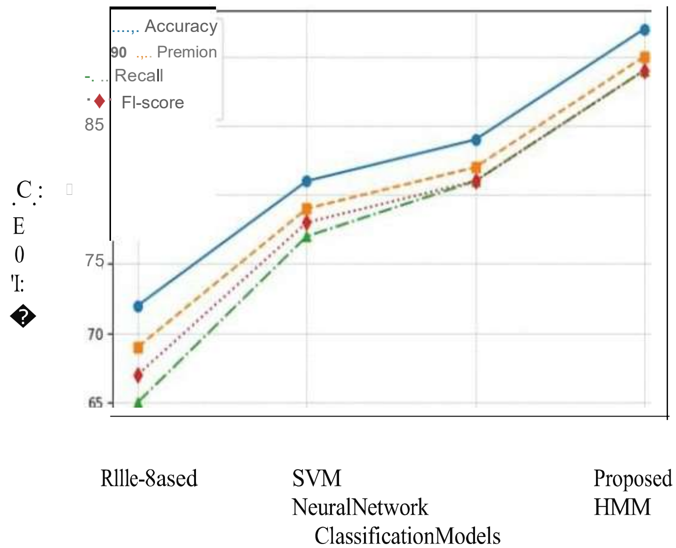
Figure5-DetectionperformanceofFetal breathing

Thebehavioroftheproposedsystemundernoise variabilitywasalsoexarnined.Whentestedacrosslow, moderate,andhighnoiselevels,theHMMconsistently retained high performance, maintaining an accuracy greater than 85% even under substantial interference from maternal movement and environmental noise.

Table 1- summarizes model performance

del	**uracy**	**cision**	**all**	**re**
Rule-Based Method	6	6	6	6
M	6	6	6	6

ural Network	%	%	%	%
posed IM	**%**	**%**	**%**	**%**



Thesystem accurately identified the beginning and end eachbreathingevent,thedurationofinhalationandexhalatio n phases, and periods where no breathing occurred. Temporal smoothing methods and physiological constraints proved essential in minimizing spurious detections, especially in segments affected by low-frequencybodymovements.Thesepost-processingsteps ensured that only coherent breathing rhythms were highlighted in the final output, thereby improving the clinical usability of the detection results.

VII. ConclusionandFuture Scope

The proposed phonography-based fetal breathing movementdetectionsystem,enhancedthroughaHidden Markov Model, demonstrates strong potential as a reliable and non-invasive tool formonitoring fetal well-being. By combining effective signal preprocessing techniques, rich acoustic feature extraction, and probabilistic temporal modeling, the system achieves high accuracy and robustness in detecting subtle fetal breathingpattems.Experirnentalresultsshowedthatthe HMMsignificantlyoutperformedrule-based,SVM,and neural network classifiers, particularly in noisy and variable acoustic environments. The model's ability to capturethesequentialnatureofbreathing-transitioning smoothly between inhalation, exhalation, and pauses-allowed it to produce physiologically coherent predictions that closely align with clinical expectations. This makes the system suitable for potential integration into prenatal care technologies, especially in remote or home-based monitoring setups where continuous and non-invasive assessment is critical.

Despite its strengths, the system also presents opportunities for enhancement. Limitations such as occasional misclassification during extreme noise conditions, sensitivity to sensor placement, and challenges with very low-amplitude breathing signals indicatetheneedforfurther refinement.Futureresearch could explore hybrid architectures combining HMMs with deep learning models such as LSTMs, CNNs, or Transformer-based acoustic encoders to improve performance in highly noisy conditions. Additionally, expanding the dataset across diverse maternal and fetal conditions would further strengthen model generalization. Adaptive gain control, multi-sensor fusion with accelerometers or Doppler ultrasound, and real-time edge deployment using optimized hardware like ARM-based processors also represent promising directions. Integration with cloud-based monitoring dashboards and automated alert systems could further advance clinical utility.

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