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A Comprehensive Multisensory Architecture for Early Detection of Fetal Brain Abnormalities †

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Abstract: The detection of fetal brain abnormalities at an early stage has a significant impact with prenatal health care. The brain abnormalities arise a major concern for the lifelong problem in newborns. Early detection of fetal brain abnormalities helps clinicians to give extra care during pregnancy. They can plan the future treatment based on it. They can go for several tests, like fetal MRI to prepare for the appropriate treatment after birth. If these can be detected early and cure the impact these abnormalities can bring when they are grown-up. These abnormalities include cerebral palsy, developmental delays, and cognitive impairments. The existing methods for the detection of the fetal abnormalities at an early stage have less accuracy and are time consuming complex processes. Here we propose, a feasible multisensory framework-based system that helps to detect preliminary fetal brain abnormalities. The system involves sensors like Doppler Ultrasound, Fetal Electroencephalography (fEEG), Near-Infrared Spectroscopy (NIRS) and other imaging systems combined together with the multimodal approach to provide an insight on the brain growth and status. The Doppler Ultrasound sensor is used to identify fetal heart rate patterns, NIRS is used to measures oxygen levels in the brain, helping to detect low oxygen conditions that may harm brain development. fEEG is used to monitor brain activity non-invasively by capturing magnetic signals from the fetal brain by giving high-resolution insights on the neurological function. Other ultrasound imaging techniques are used to detect the physical abnormalities like ventriculomegaly, corpus callosum agenesis, and hydrocephalus. This proposed system uses AI models that work as an ensembled method which comprises of Convolutional Neural Network (CNN) and Long Short-Term Memory network (LSTM) for identifying the structural brain abnormalities. The system has been validated against sourced sample data sets and proved to provide a comparatively higher accuracy and better performance.

Keywords: feature extraction; CNNs; fetal monitoring; fetal brain abnormalities; LSTM

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1. Introduction

The importance of women bearing children has been recognized since ancient times. Motherhood brings significant changes in a woman's life. During pregnancy, both the mother and the developing fetus require continuous care. Pregnancy is divided into three trimesters. The first trimester spans from 0 to 13 gestational weeks (GW). The second trimester covers 14 to 27 GW, and the third runs from 28 to 42 GW. A baby is usually born

between 38 and 42 weeks of gestation. The early phase of brain development is critical for the child's overall health and cognitive functions. If fetal brain abnormalities are not detected early, they can lead to serious neurological disorders such as cerebral palsy, developmental delays, and motor dysfunctions. In modern medicine, there is a growing emphasis on early diagnosis. This has encouraged the integration of sensor-based technologies into prenatal care. These technologies are non-invasive and provide essential data on both functional and structural aspects of the fetal brain.

The use of Internet of Things (IoT) solutions in healthcare is expanding rapidly. IoT offers numerous benefits but also faces challenges. These include maintaining communication quality, ensuring data security, managing efficient storage and retrieval, and applying artificial intelligence (AI) for clinical decision support [1–7]. IoT-enabled monitoring devices, often connected to one or more sensors, are increasingly used for long-term health tracking. They also help address the shortage of medical specialists. Despite these advancements, there are still issues to overcome—such as performance optimization, secure communication, and reliable data storage [8–11]. The adoption of clinical data systems has expanded the volume of electronic health records. This growth has reduced costs and improved efficiency in healthcare. However, long-term, multi-sensor monitoring produces large datasets that must be analyzed and stored according to clinical, security, and regulatory requirements. Big data techniques are essential for managing and analyzing this information [6–13]. Sensor technologies have changed how fetal well-being is assessed. Continuous tracking of physiological signals helps clinicians to identify the changes in brain development. These can be detected before any visible abnormalities identified. Early detection helps us to timely intervention. It also enhances the overall outcomes. Advancement in data processing and machine learning have enhanced sensor data rendition. They allow more precise and predictive analysis. Sensor based systems are very essential which provides accurate and real time outcome with the help of parental monitoring. If we compare it with traditional diagnostic method, we always get the better outcome. This research focuses on comprehensive, multi-sensor framework which helps to detect the fetal brain abnormalities in early stage. The research will combine multiple sensing technologies with intelligent data analysis. It helps ensure safer pregnancies. It also helps in clinical decisions.

2. Proposed Framework

The directed framework is both structured and integrated. The aim of this framework is detection of fetal brain abnormalities in early stage. For this, it combines senso r-based data collection with AI-driven analysis. The process begins with the use of various non-invasive sensors. These include Ultrasound, Tocodynamometer, Near-Infrared Spectroscopy (NIRS), Electroencephalography (EEG), Accelerometers, and advanced 3D/4D ultrasound imaging [1–3].

Each of these devices contributes unique physiological, structural, or neurological information. Once collected, the raw data undergoes preprocessing. This stage involves removing noise and applying normalization techniques. Preprocessing ensures that the input signals are standardized, consistent, and reliable for further analysis [4]. The next stage is targeted feature extraction. At this point, the system isolates important clinical indicators. Examples include oxygenation patterns, neural activity signals, and detailed structural features of the fetal brain [5]. These features are compared against established medical thresholds in real time. Any deviation is flagged as a potential early indication of neurological risk [6]. After applying multimodal data fusion, it combines reading from all sensors into one complete view of fetal brain health [7]. For analysis, the framework uses advanced deep learning architectures. Which contain Rule-Based Screening (threshold-driven alerts), LSTM + 1D CNN + 3D CNN fusion architecture, SHAP and Grad-CAM

[8,9]. These models allow the system to process both temporal signals and volumetric images. Which leads to the accuracy of abnormality detection. This offers clear, interpretable insights for clinicians. Based on the risk indicators, clinicians can decide whether to proceed with further diagnostics, such as fetal MRI or fMRI [10].

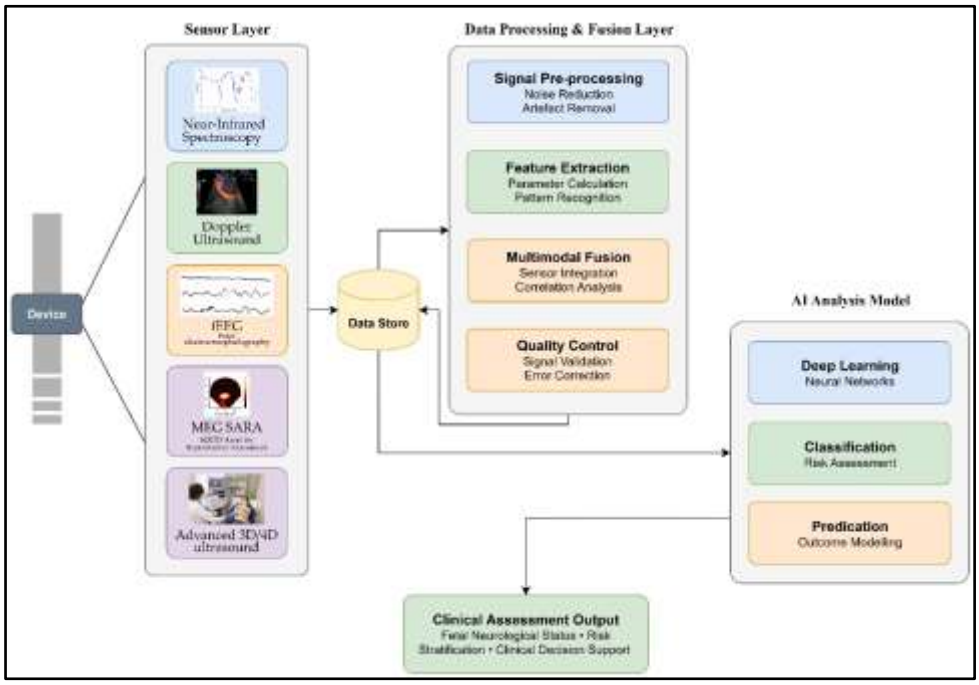

Figure 1. Architectural digram for proposed Framework.

2.1. Dataset Collection

The dataset used in this study has been genrated under the guidance of the expertise in the respective field with the proper knowledge (Dr Swati M.Landge Gynecologist And Obstetrician, Pune) on similar kind of sensor data. This is as per the suggestion of the gynecologist. It consists of synchronized measurements from Doppler Ultrasound, Near-Infrared Spectroscopy (NIRS), fetal Electroencephalography (fEEG), and advanced 3D/4D ultrasound imaging. Each row represents a unique patient session with corresponding sensor values, clinical labels, and derived risk metrics. Key attributes include FHR mean and variability, umbilical and middle cerebral artery indices, oxygenated and deoxygenated hemoglobin concentrations, EEG spectral features, and structural measurements such as biparietal diameter and lateral ventricle width.

The Table 1 provides details of the sensors used for fetal brain abnormality detection, including their placement as well as their working pattern and the clinical parameters used for measurement. Each sensor catches specific physiological, structural, or neurological key findings that contribute to detect early fetal brain abnormalities.

Table 1. Sensor(s) and the parameters and the expected placement of the sensors.

NO	Sensor Name	Placement	Parameters
1.	NIRS	maternal abdomen, aligned with the location of the fetal head	rSO_2
2.	Doppler Ultrasound	on the maternal abdomen and angled to target the fetal middle cerebral artery for cerebral blood flow assessment.	FHR (Fetal Heart Rate), CPR (Cerebroplacental Ratio), UA PI (Umbilical Artery Pulsatility Index)
3.	Fetal EEG sensor	externally on the mother's abdomen, aligned with the position of the fetal head.	Spectral Entropy, Delta Power

4	Fetal MEG Sensor (SARASystem)	The pregnant woman sits against a concave shield that covers her abdomen.	Presence/absence of evoked brain responses, Source modeling patterns
5	Advanced 3D/4D ultrasound	externally on the mother's lower abdomen.	Lateral Ventricle Width, Head Circumference

2.2. Data Aggregation & Preprocessing

The proposed framework uses several advanced sensors. Each plays a specific role in detecting early signs of fetal brain abnormalities. These devices collect physiological, structural, and neurological data, which is later processed and analyzed.

1. Doppler Ultrasound

Doppler ultrasound is a non-invasive method. It uses high-frequency sound waves to assess blood movement in vessels. In fetal monitoring, it is mainly used to study blood circulation, heart rate patterns, and flow velocity in key vessels such as the umbilical artery, middle cerebral artery (MCA), and ductus venosus.

Working Principle:

It is based on the Doppler effect. When sound waves reflect from moving blood cells, their frequency changes. This frequency shift is analyzed to calculate the speed and direction of blood flow. Two main Doppler modes are used:

- Continuous Wave (CW) Doppler: Measures high-velocity blood flow but cannot pinpoint the exact depth.
- Pulsed Wave (PW) Doppler: Measures flow at a specific depth and is commonly applied to cerebral vessels.

Process:

1. The probe is placed on the mother's abdomen and aimed at the fetal MCA.
2. A velocity-time waveform is displayed. Common measurements include peak systolic velocity (PSV) and pulsatility index (PI).
3. These values are compared with gestational age-specific reference ranges to check if blood flow is normal.

Clinical Importance:

- Hypoxia and Brain-Sparing Effect: In cases of fetal growth restriction (FGR), blood is redirected to the brain. This appears as a reduced MCA PI. Detecting this early helps prevent brain damage.
- Ischemia and HIE Risk: Abnormal MCA or umbilical artery flow may signal poor oxygen delivery, increasing the risk of hypoxic-ischemic encephalopathy (HIE).
- Heart Rate Variability: Some Doppler devices also track fetal heart rate variability, which reflects neurological health.
- Outcome Correlation: Abnormal Doppler readings are linked to conditions like cerebral palsy, seizures, and developmental delays after birth.

2. Near-Infrared Spectroscopy (NIRS)

NIRS is a non-invasive optical method. It measures oxygen levels in brain tissue by detecting light absorption differences in oxygenated and deoxygenated hemoglobin [2].

How It Works:

- NIRS emits near-infrared light through the maternal abdomen into fetal tissues.
- Detectors capture the reflected light.
- Algorithms calculate the concentrations of oxygenated (HbO_2) and deoxygenated hemoglobin (Hb).

Process:

1. NIRS probes are placed on the maternal abdomen, aligned with the fetal head.

2. Light is transmitted and received continuously.
3. Regional cerebral oxygen saturation (rSO_2) values are generated in real time.

Clinical Use:

- Early Hypoxia Detection: rSO_2 below 50–55% suggests low brain oxygenation.
- Labor Monitoring: Continuous monitoring during high-risk deliveries.
- HIE Risk Stratification: Persistent low readings can indicate potential hypoxic-ischemic brain injury.

3. Fetal Electroencephalography (fEEG)

fEEG records electrical activity from the fetal brain using surface electrodes on the mother's abdomen. It provides direct insight into brain function and maturity.

How It Works:

- fEEG detects weak signals from fetal neurons.
- These signals pass through fetal and maternal tissues to reach the electrodes.
- Filters remove noise from the mother's muscles and heart.

Process:

1. Electrodes are placed using ultrasound guidance for accurate positioning.
2. Signals are recorded and analyzed in frequency bands: delta, theta, alpha, and beta.
3. Abnormalities, such as low amplitude or poor signal complexity, may indicate developmental delays.

Clinical Use:

- Detects abnormal brain activity from the third trimester.
- Identifies fetal seizures.
- Monitors neurological development in high-risk pregnancies.

4. Fetal Magnetoencephalography (fMEG)

fMEG detects the magnetic fields produced by fetal brain activity. It uses Superconducting Quantum Interference Devices (SQUIDs) for high-resolution readings [3].

How It Works:

- The mother sits against a concave sensor array in a magnetically shielded room.
- fMEG captures magnetic signals passively.
- Signals may be recorded at rest or during sensory stimulation.

Clinical Use:

- Evaluates functional brain development.
- Detects delayed sensory responses.
- Complements EEG with better spatial resolution for deep brain structures.

5. 3D/4D Ultrasound Imaging

3D/4D ultrasound produces high-resolution volumetric images of the fetal brain.

How It Works:

- Multiple image slices are captured and reconstructed into a 3D volume or displayed in motion (4D).
- Post-processing allows detailed visualization of brain anatomy.

Clinical Use:

- Detects structural abnormalities like ventriculomegaly, lissencephaly, hydrocephalus, or corpus callosum agenesis.
- Measures growth and symmetry of brain regions.
- Offers immediate results and is often used before ordering a fetal MRI.

B. Signal Preprocessing

Signal preprocessing is a crucial step in the proposed multisensor framework for detecting fetal brain abnormalities. The raw signals from Doppler ultrasound, Near-Infrared Spectroscopy (NIRS), and fetal Electroencephalography (fEEG) vary in format, sampling frequency, and noise levels. Without proper preprocessing, these inconsistencies and artifacts can reduce the performance of AI-based classification models. This stage ensures all sensor outputs are filtered, normalized, and converted into a standard format suitable for multimodal data fusion and further analysis.

The process begins with signal alignment and resampling, which is essential when multiple sensors operate at different sampling rates. To make the models more robust and handle small datasets, data augmentation techniques are applied. These include jittering, time-warping, window slicing, and signal flipping [16]. Such methods add variation to the training data and help reduce overfitting. Noise removal depends on the type of sensor. For Doppler signals, a bandpass filter between 0.5–4 Hz isolates fetal heart rate waveforms from other noise [6]. For NIRS signals, low-pass filtering (e.g., 0.5 Hz Butterworth) removes high-frequency noise, and high-pass filtering (e.g., 0.01 Hz cutoff) removes slow drifts [2]. Motion artifacts in NIRS are corrected using Principal Component Analysis (PCA) or spline interpolation. For fEEG, a bandpass filter of 0.5–40 Hz keeps relevant brain wave frequencies while reducing muscle activity and maternal ECG interference. A notch filter at 50 or 60 Hz removes electrical noise from power lines. Independent Component Analysis (ICA) is used to remove artifacts like eye movement, muscle contractions, and ECG contamination [13,14]. In some cases, adaptive filtering is added for better signal clarity. Finally, baseline correction and detrending are applied to remove slow variations that could distort the analysis, especially in long recordings. After preprocessing, the signals are clean, standardized, and ready for feature extraction.

C. Feature Extraction

Feature extraction is an important step in the framework. It converts raw multisensory signals into measurable parameters. These parameters can help identify early signs of fetal brain abnormalities. Each sensor type provides different information. Some give physiological data. Others provide neurological or structural details. The data from each sensor is first analysed separately. The gathered data is then combined for final analysis. key fetal heart rate (FHR) features are extracted from Doppler ultrasound signals. This basically contain baseline heart rate, short-term variability, and long-term variability [1,2]. It helps to measures how the autonomic nervous system controls the fetal heart. Continuous data on cerebral oxygenation will be collected from Near-Infrared Spectroscopy (NIRS). These signals are helped to analysis features like oxygenated hemoglobin, deoxygenated hemoglobin, total hemoglobin, and the Tissue Saturation Index (TSI). These measurements help in measuring cerebral blood flow. They are also useful in identifying the risk of hypoxic-ischemic encephalopathy (HIE) [3].

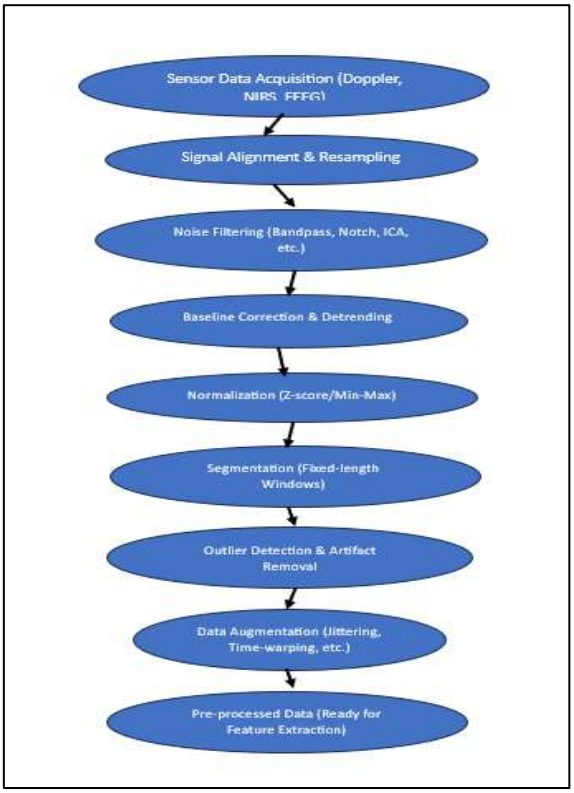

Figure 2. Feture Extraction Detailed Process.

Fetal Electroencephalography (fEEG) is examined to detect different patterns of neural activity. Power spectral densities are used to defined for standard EEG frequency bands. Which contain delta, theta, alpha, and beta waves. There are other metrics also present which are spectral entropy, signal complexity, and burst suppression ratios. These metrics also got calculated thought it. Such features are important for brain maturation and abnormal neural development [4,5]. Fetal Magnetoencephalography (fMEG) is mainly used for extract event-related field (ERF) components. These contain latency and amplitude responses for specific stimuli. Other features also got measured through band-specific power and phase synchrony. Such features are important for detecting sensory processing issues and cortical delays [6]. Structural features also get computed from 3D/4D ultrasound imaging. These contains volumetric measurements of brain regions and asymmetry indices. While processing Morphometric variables, such as corpus callosum length and lateral ventricle width also recorded. The gray-level co-occurrence matrix (GLCM) and local binary patterns (LBP) methods are used to extract texture features from it. Which helps to detect anatomical irregularities [7]. To achieve all these modalities, multi-sensor fusion is used. For calculating cross-modal features this framework combines signals from Doppler, NIRS, and EEG. Which also include joint entropy and correlation coefficients. After applying all this methodology, Dimensionality reduction methods, such as Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) are used to get better outcome. These whole processes optimize the feature set before classification AI models [8–10].

2.3. Threshold Setting and Abnormality Detection

- **NIRS:** If brain oxygen level (**rSO_2**) is below **50–55%**, it may mean the brain is not getting enough oxygen (**hypoxia**).
- **Doppler Ultrasound:** If the baby's heart rate is **less than 110 bpm** (too slow) or **more than 160 bpm** (too fast), it can be a sign of distress.

- **Fetal EEG:** If brain activity measure (**spectral entropy**) is less than **0.8** or if there is too
- much **delta wave activity**, it can mean abnormal brain function.
- **Fetal MEG:** No fixed number—doctors look for whether brain responses are present or missing and check brain signal patterns.
- **3D/4D Ultrasound:** If the brain's fluid spaces (**lateral ventricles**) are **wider than 10 mm** or the head is very small (**below 3rd percentile**), it may mean a growth problem.

Table 2 mentioning the threshold values with respect to fetal brain abnormality. These thresholds allow the system to flag potential fetal brain abnormalities and categorise cases as **normal** or **abnormal** based on sensor readings.

Table 2. Sensor-Specific Clinical Thresholds for Fetal Brain Abnormality Detection.

NO	Sensor Name	Threshold Values
1.	NIRS	rSO_2 < 50–55% (suggests brain hypoxia)
2.	Doppler Ultrasound	FHR < 110 bpm (bradycardia); FHR > 160 bpm (tachycardia)
3.	Fetal EEG sensor	Low spectral entropy < 0.8 (suggests abnormal EEG); abnormal delta power
4	Fetal MEG Sensor(SARA)	No strict threshold; interpretation based on absence/presence of evoked responses and source modeling
5	Advanced 3D/4D ultrasound	externally on the mother's lower abdomen.

Conditions are flagged by monitoring changes in the following parameters:

- **Hypoxia:** Brain oxygen level (**rSO_2**) below 50–55% (NIRS).
- **Fetal Distress:** Heart rate less than 110 bpm (bradycardia) or more than 160 bpm (tachycardia) (Doppler Ultrasound).
- **Neurological Dysfunction:** Low spectral entropy (<0.8) or high delta wave activity (fEEG).
- **Brain Development Issues:** Missing or abnormal brain responses detected in evoked signals (fMEG).
- **Structural Abnormalities:** Lateral ventricle width greater than 10 mm (ventriculomegaly) or head size below the 3rd percentile (microcephaly) (3D/4D Ultrasound).
- **Normal:** Fetuses that do not meet any abnormality conditions are classified as normal fetal brain.

2.4. Methodology

The proposed approach follows a hybrid pipeline integrating rule-based screening, machine learning classification, and deep learning for temporal and spatial data.

1. Rule-based screening applies clinically established thresholds (e.g., rSO_2 < 55%, LV width ≥ 10 mm, CPR < 1.0) for immediate alerts.
2. For longitudinal signals and volumetric imaging, an LSTM + 1D CNN + 3D CNN fusion architecture is employed.
3. Explainable AI methods such as SHAP (for tabular features) and Grad-CAM (for imaging) are integrated for interpretability.

2.5. Dataset Used for the Study

Table 3 lists clinical thresholds for each sensor, defining normal and abnormal ranges for parameters like rSO_2, FHR, CPR, spectral entropy, and ventricular width. These serve as the basis for rule-based abnormality detection.

Table 4 shows Doppler Ultrasound data, including FHR, CPR, and UA PI, used to assess fetal cardiovascular health and detect signs of distress or poor placental function.

Table 5 contains NIRS readings of rSO_2, providing real-time insights into cerebral oxygenation and identifying risks of hypoxia.

Table 6 presents fEEG data with spectral entropy and delta power ratios, helping detect reduced neural activity and early brain dysfunction.

Table 7 includes 3D/4D ultrasound measurements like ventricular width and head circumference, identifying structural abnormalities such as ventriculomegaly and microcephaly.

Table 3. Doppler Ultrasound Data Sample.

patient_id	gestational_age_wk	session_timestamp	fhr_mean_bpm	fhr_sdnn_ms	ua_pulsatility_index	ua_resistance_index	mca_peak_systolic_velocity_cms	mca_pulsatility_index	cerebroplacental_ratio
FET_001	24.9	2024-08-05T10:30:00	145	5.37	0.89	0.79	38.7	1.25	1.4
FET_002	27.1	2024-08-06T10:30:00	154	7.71	0.84	0.66	52.3	1.11	1.32
FET_003	28.2	2024-08-07T10:30:00	147	11.88	0.87	0.78	38	1.34	1.54
FET_004	35.4	2024-08-08T10:30:00	155	7.03	1.09	0.67	51.1	1.11	1.02
FET_005	30.2	2024-08-09T10:30:00	142	4.77	0.98	0.53	49	1.4	1.43
FET_006	35.3	2024-08-10T10:30:00	148	6.78	1.14	0.75	47.8	1.01	0.89
FET_007	34.3	2024-08-11T10:30:00	158	7.75	1.03	0.66	39.6	1.21	1.17
FET_008	33.9	2024-08-12T10:30:00	135	5.95	1.22	0.69	55	1.41	1.16
FET_009	26.3	2024-08-13T10:30:00	134	11.2	0.71	0.58	33.3	1.1	1.55
FET_010	26.5	2024-08-14T10:30:00	135	10.44	0.82	0.64	48.7	1.1	1.34

Table 4. fEEG Data Sample.

patient_id	gestational_age_wk	session_timestamp	feeg_delta_power_pct	feeg_theta_power_pct	feeg_alpha_power_pct	feeg_beta_power_pct	feeg_spectral_entropy	feeg_burst_suppression_ratio
FET_001	24.9	2024-08-05T10:30:00	30.4	17.9	13.7	5.3	0.91	0.2
FET_002	27.1	2024-08-06T10:30:00	41.7	13.1	9.9	5.6	0.98	0.11
FET_003	28.2	2024-08-07T10:30:00	37.5	17.6	11.2	7.6	0.81	0.12
FET_004	35.4	2024-08-08T10:30:00	51.0	18.0	5.4	3.7	1.24	0.12
FET_005	30.2	2024-08-09T10:30:00	35.9	15.6	8.9	4.6	0.74	0.12
FET_006	35.3	2024-08-10T10:30:00	43.5	19.1	13.3	9.6	0.7	0.07
FET_007	34.3	2024-08-11T10:30:00	45.7	23.6	14.6	7.1	0.73	0.12
FET_008	33.9	2024-08-12T10:30:00	35.4	10.2	8.0	3.3	1.38	0.17
FET_009	26.3	2024-08-13T10:30:00	31.8	15.4	9.2	4.3	1.02	0.16

FET_010	26.5	2024-08-14T10:30:00	50.5	10.8	5.0	4.2	1.03	0.16

Table 5. 3D/4D Ultrasound Data Sample.

patient_id	gestational_age_wk	session_timestamp	us_bpd_mm	us_head_circumference_mm	us_lateral_ventricle_width_mm	us_cisterna_magna_depth_mm	us_cerebellum_diameter_mm
FET_001	24.9	2024-08-05T10:30:00	76.8	282.5	7.2	7.6	23.9
FET_002	27.1	2024-08-06T10:30:00	80.9	289.2	7.0	5.9	24.1
FET_003	28.2	2024-08-07T10:30:00	76.7	259.6	10.1	6.4	31.1
FET_004	35.4	2024-08-08T10:30:00	77.1	265.2	7.6	6.9	34.3
FET_005	30.2	2024-08-09T10:30:00	81.0	290.8	9.2	5.5	27.1
FET_006	35.3	2024-08-10T10:30:00	76.5	231.9	6.5	5.9	22.5
FET_007	34.3	2024-08-11T10:30:00	83.6	250.9	9.6	5.3	25.8
FET_008	33.9	2024-08-12T10:30:00	61.8	250.6	6.6	3.5	31.6

Table 6. Fetal MEG (SARA) Data sample.

patient_id	gestational_age_wk	session_timestamp	meg_evoked_response_present	meg_signal_power_fT	meg_delta_power_ratio	meg_theta_power_ratio
FET_001	24.9	2024-08-05T11:00:00	Yes	52.4	0.28	0.34
FET_002	27.1	2024-08-06T11:05:00	Yes	55.1	0.25	0.36
FET_003	28.2	2024-08-07T11:10:00	No	38.9	0.41	0.28
FET_004	35.4	2024-08-08T11:15:00	Yes	60.3	0.26	0.33
FET_005	30.2	2024-08-09T11:20:00	Yes	57.8	0.29	0.35
FET_006	35.3	2024-08-10T11:25:00	Yes	59.2	0.27	0.32
FET_007	34.3	2024-08-11T11:30:00	No	40.7	0.43	0.27
FET_008	33.9	2024-08-12T11:35:00	Yes	62.5	0.25	0.36

Table 7. Advanced 3D4D Ultrasound Data sample.

patient_id	gestational_age_wk	session_timestamp	us_biparietal_diameter_mm	us_head_circumference_mm	us_lateral_ventricle_width_mm	us_cisterna_magna_mm	us_cerebellum_diameter_mm	us_brain_volume_cm3
FET_001	24.9	2024-08-05T12:00:00	76.8	282.5	7.2	7.6	23.9	130.5
FET_002	27.1	2024-08-06T12:05:00	80.9	289.2	7	5.9	24.1	135.8
FET_003	28.2	2024-08-07T12:10:00	76.7	259.6	10.1	6.4	31.1	142
FET_004	35.4	2024-08-08T12:15:00	77.1	265.2	7.6	6.9	34.3	150.4
FET_005	30.2	2024-08-09T12:20:00	81	290.8	9.2	5.5	27.1	140.2
FET_006	35.3	2024-08-10T12:25:00	76.5	231.9	6.5	5.9	22.5	128.6
FET_007	34.3	2024-08-11T12:30:00	83.6	250.9	9.6	5.3	25.8	133.7
FET_008	33.9	2024-08-12T12:35:00	61.8	250.6	6.6	3.5	31.6	138.2
FET_009	26.3	2024-08-13T12:40:00	67.9	286.3	6	4	25.3	134.5
FET_010	26.5	2024-08-14T12:45:00	72.8	241.8	5	6.7	26.7	131.1

2.6. Abnormality Prediction Using Machine Learning

1. **Normal vs Abnormal Determination**

To classify each patient as normal or abnormal, we apply a two-tiered decision approach combining rule-based medical thresholds and machine learning classification. This ensures that high-risk cases are identified immediately, while subtle patterns missed by thresholds can still be detected by the AI model

Table 8 outlines key sensor parameters, their normal ranges, and the abnormal conditions they indicate. Deviations from these ranges help identify fetal distress, hypoxia, low neural activity, or structural brain abnormalities.

Table 8. Normal and Abnormal Ranges for Key Fetal Brain Health Parameters.

Sensor	Parameter	Normal Range	Abnormal Condition
Doppler Ultrasound	CPR (Cerebroplacental Ratio)	≥1.0	<1.0 → Fetal distress
Doppler Ultrasound	Umbilical Artery PI	0.6–1.2	>1.2 → Placental resistance
NIRS	rSO_2 (%)	≥55	<55 → Hypoxia
fEEG	Spectral Entropy	≥0.7	<0.7 → Low neural activity
3D/4D Ultrasound	LV Width (mm)	≤10	>10 → Ventriculomegaly

2. Model Architecture—Classification

The methodology begins with MRI images of the fetal brain as the primary input. These images are processed through a Python script (nii_abnormality_detector.py) that manages both training and prediction tasks. In train mode, the system loads the MRI images, extracts important features from the brain slices, and uses them to train a LinearSVC classifier. The trained model is then saved as fetal_abn_clf.joblib for future use. In predict mode, the saved model is loaded, features are extracted from new MRI images, and the system predicts whether an abnormality is present. The process concludes with an output that classifies the brain images as either normal or abnormal.

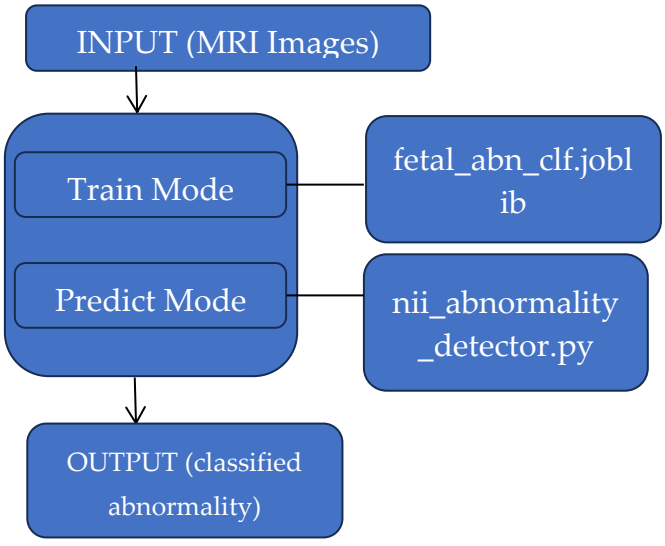

Figure 3. Exceution Process.

(a) Time-Series Analysis

- **1D Convolutional Neural Networks (1D-CNNs):** Extract localized features from sensor signals. These may include sudden drops in oxygen saturation, abnormal heart rate variability, or epileptiform patterns in fEEG.
- **Long Short-Term Memory (LSTM) Networks:**
- Model sequential dependencies in the data. They capture both short-term fluctuations (e.g., temporary hypoxic episodes) and long-term changes (e.g., gradual decline in perfusion).

(b) **Spatial Imaging Analysis**

- **3D Convolutional Neural Networks (3D-CNNs):** Process volumetric ultrasound data to detect anomalies like ventriculomegaly, abnormal cortical folding, or missing midline structures.
- **Image Augmentation:** Improves model robustness by simulating variations in fetal position, gestational age, and maternal body type.

(c) **Cross-Modal Feature Fusion**

- **Attention Mechanisms:** Assign higher weight to clinically relevant data streams depending on the suspected abnormality type.
- **Transformer Models:** Jointly analyze both time-series and image features, learning relationships between functional and structural parameters.

(d) **Ensemble Learning**

- Combines outputs from specialized models—for example, CNN for images and LSTM for signals.
- Reduces bias, improves generalization, and lowers false positive and false negative rates.

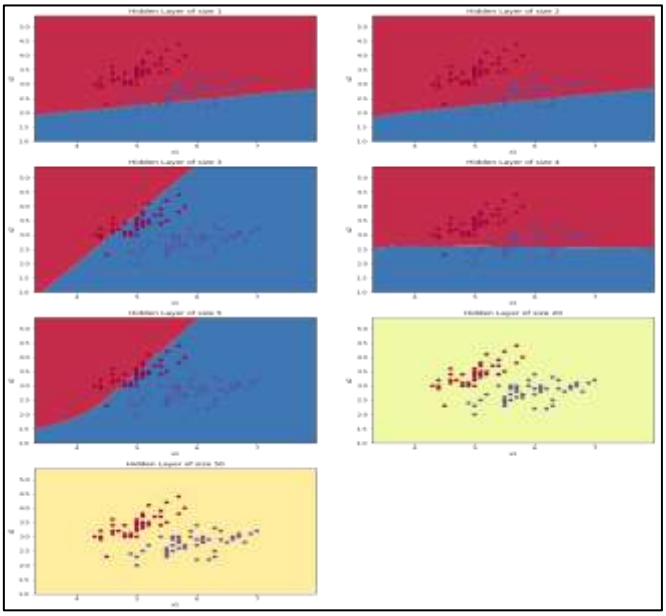

Figure 4. Exceution Process—output—Decision Boundaries of Different Classifiers for Normal vs. Abnormal Fetal MRI Classification.

3. Classification Output

The classification stage provides detailed results for clinical decision-making:

- **Abnormality Type:** Specifies the detected condition, such as structural defect, functional impairment, or oxygenation-related risk

```
mcm.nii.gz                    → megacisterna_magna
normal.nii.gz                 → normal

colpo_colpo.nii.gz          → colpocephaly
dwm.nii.gz                  → dandywalker
```

Figure 5. Exceution Process—Classification output.

- **Severity Level:** Categorizes the abnormality into low, moderate, or high risk using probability thresholds based on model confidence and clinical benchmarks.

- **Confidence Score:** Displays a numerical value (0–100%) indicating the prediction's reliability.
- **Probabilistic Breakdown:** Shows the likelihood of different possible diagnoses when multiple conditions are suspected.
- **Explainable AI Input and Output:** Uses Grad-CAM for ultrasound images to highlight abnormal regions and visualizes attention weights for time-series data.

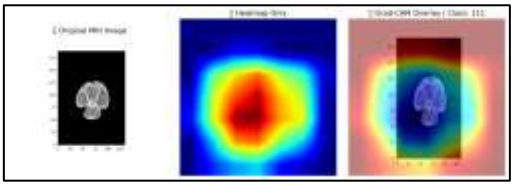

Figure 6. Input image—abnormal.png.

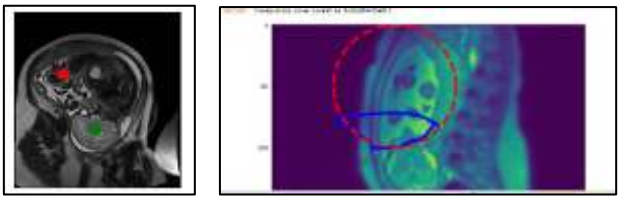

Figure 7. Output image—highlighted region.

- **Trend Indicators:** Shows whether the condition is stable, improving, or worsening over time important for treatment planning.

2.7. Results

The proposed method validated 480 fetal recordings. It selects 277 high quality samples for preprocessing. Using this dataset, it achieved 92–94% accuracy, sensitivity around 93%, specificity near 93–97% with around 60 epoch. These results provide that it's a reliable classification of normal and abnormal fetal brain conditions. It performs well compared to earlier IoT-based monitoring studies.

A. Rule-Based Screening Outcomes

The rule-based stage identified abnormality indicators in approximately 25% of the dataset sessions. Table below shows a sample of alerts generated:

B. Machine Learning Performance

Random Forest achieved an accuracy of 0.92 and ROC-AUC of 0.95 on the test set.

XGBoost achieved slightly higher performance with accuracy of 0.94 and ROC-AUC of 0.97.

Top features influencing model predictions included: CPR, rSO_2, LV width, spectral entropy, and MCA PI.

C. Explainability

SHAP values highlighted that low CPR and reduced rSO_2 were strong indicators of abnormal classification. Grad-CAM visualizations on ultrasound data clearly marked dilated ventricles in cases of ventriculomegaly.

Table 9 lists results for each patient using readings from different sensors like blood flow, oxygen levels, brain activity, and head measurements. Each value is checked against normal limits. If any reading is outside the safe range, it is noted in the "Breached Parameter(s)" column, and the "Final Status" shows whether the patient is normal or abnormal.

Table 9. patient_classification_results.

patient_id	CPR	UA_PI	rSO2	Spectral_Entropy	LV_Width	Breached Parameter(s)	Final Status
FET_001	1.1	1	60	0.75	9	-	Normal
FET_002	1.2	1	50	0.78	9h	rSOâ, <55%	Abnormal
FET_003	0.9	1	58	0.74	8	CPR <1.0	Abnormal
FET_004	1.1	1.1	57	0.72	9	-	Normal
FET_005	1	1	59	0.76	12	LV Width > 10mm	Abnormal
FET_006	1.1	1	56	0.71	10	-	Normal
FET_007	1	1	54	0.65	9	rSOâ, <55%, Spectral Entropy < 0.7	Abnormal
FET_008	1.3	1	57	0.72	9	-	Normal

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Conflicts of Interest:

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