

Little Beats: Fetal Monitoring Belt

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Dedication

We dedicate this project to our families, for their constant encouragement, support and patience during this process. We are inspired by their faith in us to persevere and do our best. We also dedicate this research to all mothers, especially those in resource-poor settings, whose health, safety, and access to quality maternal care is so important. We hope this work makes a small contribution to the care of mothers.

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Abstract

The use of third-trimester fetal monitoring is very crucial in the detection of fetal distress, hypoxia, abnormal wall motion, and irregular fetal heart rate (FHR). The traditional techniques, such as Doppler ultrasound and cardiotocography (CTG), are mostly hospital-limited, need trained staff, and cannot be used either in continuous or home monitoring, especially in resource-restricted environments. This paper reports the design and development of a non-invasive wearable fetal monitoring system, which is able to continuously track the fetal movement (FM) and fetal heart rate (FHR) outside the clinical settings.

The suggested solution is deployed in the form of a wearable belt that comprises sensitive sensors such as ADXL345 accelerometers that capture fetal movements (FM) and Ag/AgCl ECG electrodes that capture fetal heart rate (FHR) signals. Other components such as ADS1115 analog-to-digital converters (ADCs) are used to condition the signal, and an ESP32 microcontroller is used to ensure real-time data acquisition and transmission. The device has the principles of passive sensing, where it does not produce radiation or ultrasound, making it safe to use. Sensing, processing, and output functions are supported by a modular architecture.

To analyse signals, abdominal ECG information is preprocessed with filtering, noise removal, and normalization, and then feature extraction in time, frequency and rhythm domains. It uses a two-stage machine learning pipeline with the first stage of the pipeline classifying the validity of the signal, and the second stage similar to a regression model clearly predicts fetal heart rate (FHR) only under the condition that a valid cardiac activity is detected. Random Forest (RF) and Bidirectional Long Short-Term Memory (BiLSTM) are tested to analyze fetal movement, with a higher accuracy of 97% of the collected data than 77% with BiLSTM.

A visualization platform to enable analysis and real-time monitoring is also included in the system. In general, the presented solution proves the possibility of a low-cost, continuous, and home-based fetal surveillance with the help of wearables. The future research will be based on broadening

the range of data, and better generalization of models, and attachment of clinically verified annotations to increase reliability.

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Chapter 1

Introduction

1.1 Project Background

In Pakistan (especially in the rural regions) women lack access to safe and continuous fetal monitoring outside clinical settings especially during the third trimester of their pregnancies when the risk of complications increases significantly [1, 2]. Complications such as a nuchal cord which can sometimes lead to fetal hypoxia [3], fetal growth restrictions [4], Oligohydramnios [5], fetal arrhythmia and other distress complications which can significantly increase risks in the prenatal period. Standard clinical monitoring methods exist, which include conventional Ultrasounds, Doppler ultrasounds, Continuous Electronic Fetal Monitoring (EFM) or Cardiotocography (CTG) which provide the continuous tracing of Fetal Heart Rate (FHR), and uterine contractions. Although methods like these exist and are effective for short-term use, common methods like ultrasound pose risks with prolonged exposure (cavitations, thermal potential) [6], furthermore, they require clinical settings and highly trained personnel or doctors and cannot be used in home settings. Moreover, these methods, though widely accepted, can be overly costly and limited to people living in low resource settings [7], and travelling to medical facilities can sometimes be challenging for women experiencing high-risk pregnancies [8]. There also exist the traditional methods like assessing fetal well-being based on maternal perception of fetal movements, however it is subjective and there are practical limitations for many women and no optimal number of movements is known, it can also be stressful and difficult for many women, furthermore an estimate of 22.1% of pregnancies result in poor perinatal outcomes by maternal perception of reduced fetal movement (RFM), it is not reliable and is unclear how well it detects if the fetus is in distress early enough for treatment [9, 10].

According to a WHO report, 2024 [11], stillbirth rate ranging from 27.5 per 1000 births in Pakistan, emphasizes the need for a portable, non-invasive, user-friendly, and affordable monitoring solution that ensures real time fetal health assessment, especially in rural and low-resource settings. Recent wearable sensor technologies [12], such as healthcare monitoring, fitness and sports and other various technologies use accelerometers, gyroscopes, and electrodes integrated with artificial intelligence (AI) based signal processing. These technologies have created new possibilities for continuous and safe fetal health monitoring outside clinical environment. Continuously tracking the baby’s movement and heart rate can improve prenatal care, by detecting and signaling any fetal distress, for such continuous monitoring wearable systems can be used. The recent use of wearable technologies can help decrease the risk of diseases such as COVID-19, especially in pregnant women, in the future, as the patients would not have to travel to healthcare facilities and can use the device from their home settings. The concept of “Fetal Monitoring 4.0” [13] uses sensors and data analysis for remote maternal-fetal health tracking, aligns with the continuous fetal monitoring approach.

Although there have been advances in fetal monitoring technologies and the use of AI in fetal classification [14], most of the existing approaches still have their limitations, some are limited to clinical settings while some are intermittent assessments of fetal well-being. The wearable technologies already present often center on a single modality of fetal health, such as fetal heart rate [15,16] or fetal movement [17]. Existing wearable fetal monitoring systems require frequent hospital visits, healthcare professionals, and are intermittent. Home-based methods are highly costly and sometimes not user-friendly. Thus, this project designs a safe, non-invasive, radiation-free, affordable, user-friendly wearable fetal monitoring system integrating ac-

celerometer sensors for fetal movement (FM) detection and electrodes for fetal heart rate (FHR) detection to continuously assess fetal health classification during the third trimester, ensuring maternal safety, comfort, and suitability for long-term home monitoring.

1.2 Problem Description

One of the key risk factors for fetal complications in Pakistan is late detection of fetal distress, especially in rural and resource-poor areas where continuous and effective monitoring of pregnancy is often lacking. Often, pregnant women lack consistent access to specialized obstetric services and advanced monitoring equipment, leading to a delayed diagnosis of key issues such as fetal hypoxia (oxygen deprivation), growth retardation or abnormal heart activity. This can lead to poor pregnancy outcomes such as stillbirth and infant complications.

Existing fetal monitoring methods mainly involve periodic clinical monitoring via Doppler ultrasound and cardiotocography (CTG), which require access to hospitals and trained health care providers for their use and interpretation. Although these methods are widely used, they are only suitable for short-term rather than continuous monitoring of the fetus, which is necessary for early detection of fetal distress. Moreover, the expenses incurred from frequent clinical fetal monitoring can be prohibitive for many families, making them less accessible in resource-poor environments.

Alternative methods of fetal monitoring, such as maternal assessment of fetal movements, are widely used in basic antenatal care; but these are subjective and rely on the mother's awareness and experience. This means subtle or early signs of changes in fetal movements or fetal heart rate (FHR) abnormalities may be missed, limiting the effectiveness of this method

in clinical decision-making. This underlines the need for more objective, reliable and technology-based monitoring approaches that are capable of continuous monitoring without the need for strict clinical supervision.

In this work, we present a safe and economical, wearable, non-invasive fetal monitoring system that offers the possibility of continuous monitoring of fetal well-being in rural settings and at home. The system is prioritizing comfort, safety and user-friendliness to allow the expectant mother to take advantage of continuous long-term monitoring without needing to visit the hospital. The system's continuous monitoring of fetal movements and FHR is expected to offer early warning of any abnormal fetal patterns, which may suggest distress conditions. Additionally, the system is intended to provide user-friendly and understandable outputs, thereby making the system accessible to both medical experts and non-technical users, which enhances prompt detection and response in critical circumstances.

The proposed solution of fetal monitoring is given in figure 1.1.

LITTLE BEATS: FETAL MONITORING BELT

— Smart Care. Safe Future. —

An innovative, safe, non-invasive and cost-effective solution for continuous fetal monitoring and better maternal care.

SAFE
Designed with maternal and fetal safety as the top priority.

RADIATION FREE
Uses 100% radiation free technology. Completely safe for mother and baby.

COST EFFECTIVE
Built with affordable components to make quality care accessible to all.

USER FRIENDLY
Easy to wear, easy to use. Designed for both patients and healthcare providers.

NON-INVASIVE
No needles, no pain. Completely external and comfortable to wear.

COMFORTABLE
Lightweight, ergonomic and breathable design ensures maximum comfort for long-term use.

RELIABLE
High quality sensors ensure accurate and consistent monitoring of fetal well-being.

CONTINUOUS MONITORING
Real-time, continuous tracking of fetal heart rate and movement for early detection and timely care.

Continuous monitoring.
Peace of mind for mother.
Stronger start for little beats.

HOW IT WORKS

- 1. SMART SENSORS**
Capture fetal heart rate and movement signals continuously.
- 2. SIGNAL PROCESSING**
Advanced filtering and processing to ensure high quality signals.
- 3. DATA TRANSMISSION**
Secure real-time transmission of data to connected device.
- 4. MONITORING & ANALYSIS**
Doctors and caregivers monitor data anytime, anywhere for informed decisions.
- 5. BETTER OUTCOMES**
Early detection, timely care and improved maternal-fetal health.

KEY BENEFITS

- Improves fetal health outcomes
- Enables early detection
- Supports better clinical decisions
- Reduces healthcare costs
- Peace of mind for mothers and families

WE CARE TODAY, FOR THEIR TOMORROW.

Figure 1.1: Proposed Solution

1.3 Motivation of the Study

This study is driven by the fact, the need for safer, more convenient techniques for fetal monitoring, given the shortcomings of the current techniques. Traditional methods like Doppler ultrasound and cardiotocography (CTG) are commonly employed in hospitals; but they are costly and require healthcare professionals, making them unsuitable for at-home continuous fetal monitoring. Further, risks associated with frequent or long-term exposure to ultrasound-based devices and the absence of low-cost solutions for monitoring indicate a need for alternative solutions.

In many cases, pregnant women in poor resource settings are dependent on subjective measures such as feeling the baby move, which are not reliable and do not facilitate timely diagnosis of complications. The need for such an approach is even greater in low- and middle-income countries such as Pakistan, where stillbirth rates are estimated to be between 30 to 40 per 1,000 births in many areas. Many of these are linked to late detection of fetal distress and lack of continuous fetal monitoring during pregnancy. Unfortunately, pregnant women, particularly in remote and less-developed regions, cannot visit hospitals regularly during pregnancy due to financial and transportation barriers and lack of access to healthcare providers.

Thus, there is an urgent need for an effective home monitoring system that enables mothers to frequently monitor fetal health without relying on regular visits to the clinic. This project is inspired by the desire to create a safe, passive and easy-to-use monitoring system which enables mothers and health-care practitioners to have access to continuous and reliable information about fetal status, leading to early diagnosis of complications and prevention of avoidable stillbirths.

Besides these clinical and societal demands, this project is also moti-

Stillbirth rate (per 1,000 total births)

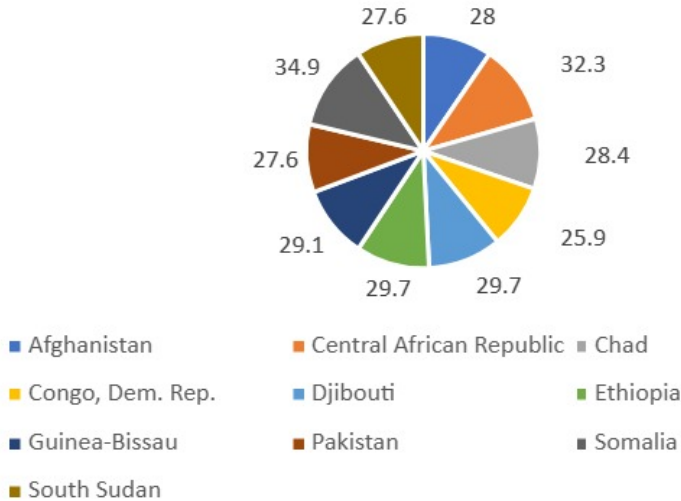


Figure 1.2: Stillbirth Rate Comparison (2000-2025)
Life expectancy trends [18]

vated by the following:

- The increasing use of wearable and IoT technologies in health care, which render remote monitoring more feasible and cost-effective.
- The strain on hospital resources, in which constant monitoring of all pregnant women might not be possible.
- The global recognition of the need for better maternal and child health outcomes, as part of the Sustainable Development Goals (SDG 3: Good Health and Well-being).
- Anecdotes from cases where the late diagnosis of fetal distress has resulted in poor outcomes.
- A passion for developing engineering approaches real-life health challenges, which could have a direct impact on people in the developing

world.

These factors inspired the design of this project aimed at improving the affordability, accessibility and continuity of preventative fetal monitoring.

1.4 Objectives

The main objective of this project is to develop a non-invasive, wearable monitoring system for fetal physiological activity that can safely detect and process the fetal activity through passive monitoring. The system will offer a safe, affordable, and easy-to-use platform for continuous monitoring of fetal health, especially in the home environment and in low-resource settings. To achieve this goal, the project has the following objectives:

- **Design and Development of Wearable Monitoring Belt**

To develop a wearable fetal monitoring belt that is lightweight, comfortable and durable. The belt is equipped with accelerometer sensors and disposable electrodes to non-invasively measure fetal physiological signals, and is safe for both mother and fetus.

- **Measurement of Fetal Movement and Fetal Heart Rate:**

To reliably record fetal movement (FM) and fetal heart rate (FHR) using sensitive sensors (accelerometer and disposable electrodes). The system should pick up abdominal micro-vibrations from maternal abdominal movements, thereby allowing for fetal patterns to be detected.

- **Signal Acquisition Design**

To design a signal acquisition and conditioning system, including suitable sensor interfacing with the microcontroller. This requires

correct data collection, signal distortion reduction and signal integrity during real-time measurements.

- **Signal Processing and Noise Reduction techniques:**

To use suitable signal processing methods for filtering and noise reduction. Such methods will help to remove unwanted maternal activity, breathing, and other noise signals, allowing fetal signals to be extracted from the raw sensor output.

- **Accurate Analysis of Fetal Movement (FM) and Fetal Heart Rate (FHR)**

To apply appropriate machine learning methods, such as Bidirectional Long Short-Term Memory (BiLSTM), Convolutional Neural Networks (CNN) and Random Forest (RF) for fetal signals analysis and classification. These approaches improve the system capability of identifying relevant fetal activity from the background artifacts and noises, such as maternal breathing and movements. Although conventional filtering methods are applied to reduce noise, machine learning methods enhance signal analysis by recognising and extracting important features from the filtered data, which helps to extract the fetal activity from raw sensor data.

- **Real-time Monitoring System**

To create a real-time monitoring system for ongoing fetal monitoring. The framework is intended to offer real-time feedback allowing early detection of anomalies.

- **Develop a Pakistan-Specific Fetal Movement (FM) and Fetal Heart Rate (FHR) Dataset**

To develop a Pakistan-Specific fetal movement (FM) and fetal heart rate (FHR) dataset after getting ethical approvals from the relevant medical institutions, that will help in localizing and improving the performance of future models.

1.5 Project Scope

This project involves the full design, development and initial testing of a wearable fetal monitoring belt that allows for the continuous non-invasive assessment of fetal health during the third trimester of pregnancy. This project aims to overcome the drawbacks of existing fetal monitoring practices by offering a cost-effective, easy-to-use, in-home tool that can be used in poor resource settings.

- **Design and Development of Wearable Fetal Monitoring Belt**

One of the key goals of this project is to design and develop a wearable fetal monitoring belt which incorporates several sensing elements into a single device. This belt is particularly designed for use during the third trimester for continuous monitoring. The belt includes embedded accelerometers for fetal movement detection and Ag/AgCL ECG gel electrodes for obtaining signals from fetal heart activity. It is designed to provide correct sensor positioning on the mother's abdomen to ensure effective signal sensing and comfort. The wearable structure is designed to provide comfort and allow long period usage without hindering expectant mothers' everyday activities. The focus is on developing a non-invasive and safe device that can be comfortably worn and used by pregnant mothers at home.

- **Signal Acquisition and Processing**

The project also focuses on the development of a robust system for capturing and processing signals. It acquires raw physiological signals from the accelerometers and ECG electrodes that are commonly subject to noise, artifacts and maternal interference. The project incorporates basic signal processing steps to mitigate these issues, including filtering, noise reduction and simple feature extraction. Such processing is critical to enhance the quality of the signal and reliably reflect the fetus' movements. The aim is to set up a robust process for the acquisition of useful physiological signals to be used for future analysis and monitoring.

- **Data Acquisition from the Real World with Ethical Considerations**

Real-world physiological data of pregnant women in Pakistan will be collected for this project. This is done in accordance with stringent ethical protocols and with permission from the Ethics Review Committee (ERC). Upholding ethical standards is a fundamental aspect of the project as it includes sensitive mother and child health data. Related information and the secured informed consent, about the study, was provided to the participants about the study before collecting data. Steps are taken to maintain privacy and confidentiality. The data obtained can be used for testing the performance and robustness of the system, since it is obtained under real conditions.

- **Development of a Localized Fetal Dataset**

An important aspect of this project is the development of a localized fetal physiological dataset. There is currently no publicly available Pakistan-Specific dataset, which needs to be taken into account when designing fetal monitoring systems. This project tackles this issue by

gathering and curating data from the local population, and lays a foundation for establishing a dataset that is representative of the region's physiology. This data can be leveraged for future research, model training and to enhance fetal monitoring systems that are more relevant for Pakistan.

- **Comfort, Safety and Monitoring at Home**

The wearable system is prioritising comfort, safety and convenience. The belt is worn comfortably, and is lightweight, non-invasive and portable, allowing for long-term monitoring without discomfort. The passive sensing technology means there is no harmful radiation or signals emitted, which is safe for the mother and unborn baby. Moreover, the system is user-friendly, ensuring ease of use, even for non-experts. This feature is especially valuable for home monitoring, as it eliminates the need for frequent visits to the hospital while allowing for ongoing monitoring of the fetus.

- **Overarching Goals and Future Opportunities**

Overall, this project encompasses the development cycle of a wearable device for fetal monitoring, from hardware development to signal acquisition and preprocessing, to real-world data collection and dataset development. It seeks to deliver a platform for continuous and accessible fetal monitoring, especially in resource-poor scenarios. The project also leaves room for further improvements, including mobile app integration, further classification through machine learning, and remote monitoring through telemedicine systems, as well as big data analysis in the future for predictive health care.

Chapter 2

Literature Review

2.1 Introduction to Fetal Monitoring

Fetal monitoring is an important component of antenatal care, especially during the third trimester, when fetal complications like hypoxia, intrauterine growth restriction and arrhythmias are more likely to occur. Regular monitoring of fetal well-being is important for early identification of distress conditions that can jeopardise fetal health and lead to poor pregnancy outcomes. Currently, fetal monitoring is largely achieved using Doppler ultrasound, cardiotocography (CTG) and maternal assessment of fetal movement. This allows the assessment of physiological parameters including fetal heart rate (FHR) and movement, which are crucial for assessing fetal neurological and cardiovascular health.

The fetal heart rate is an indicator of the autonomic regulation of the fetal heart and fetal movements are an indicator of neurological integrity and well-being. Any variation in these indicators, such as a decrease in variability or lack of movement, can be a sign of fetal distress. But monitoring in the third trimester needs to be more frequent and accurate due to high fetal metabolic demands and vulnerability to low oxygen levels.

While these techniques are routinely used, current clinical monitoring techniques are mainly intermittent and hospital-based, and can't be used for real-time continuous monitoring. In addition, traditional methods only offer intermittent information and typically require skilled healthcare providers and clinic settings for their implementation. This can limit their reach, particularly in resource-poor settings, and hinder their use for continuous home monitoring. These limitations warrant more sophisticated, non-invasive, continuous fetal monitoring tools to detect fetal distress in a timely manner outside the clinic.

2.2 Limitations of Traditional Methods

While conventional fetal monitoring techniques like Doppler ultrasound, cardiotocography (CTG) and subjective maternal perception of fetal movements are commonly employed in antenatal monitoring, they have several key limitations that limit their suitability for continuous, long-term monitoring. Specifically, many of these methods are restricted to the clinical setting and rely on hospital visits for data collection and hence are not suitable for continuous assessment of fetal well-being outside the hospital [19]. Moreover, they can be expensive, require skilled interpretation, and provide unreliable or variable data under certain circumstances, such as maternal obesity, fetal positioning, or may be prone to interference. These constraints may restrict their use for real-time, in-home continuous monitoring, especially in resource poor settings where frequent visits to the clinic may be inaccessible.

In this context, to enhance the accessibility, reliability and continuity of fetal monitoring, this study proposes a wearable fetal monitoring system for non-invasive and continuous monitoring outside the clinic. The system uses accelerometer sensors and surface electrodes to simultaneously measure fetal movements and fetal heart rate (FHR) activity. This multi-sensing approach is proposed to deliver real-time, continuous assessment of fetal health to enable timely identification of possible fetal distress situations without continuous hospital monitoring.

2.3 Wearable Sensor-Based Fetal Movement Monitoring

A number of studies and initiatives have been undertaken to investigate the design and need for fetal monitoring systems based on wearable sensors [17, 20–24], especially for pregnant women at high risk to enable more convenient and continuous monitoring at home. These studies evidence a shift to non-invasive, wearable, sensor-based technologies that overcome the limitations of traditional fetal monitoring in hospital. In a study [20], the authors created a wearable dual-accelerometer-based system to detect fetal movement, with an accuracy of 86.6% and F1-score of 84.2% using machine learning algorithms. They also used the synthetic minority over-sampling technique (SMOTE) to overcome class imbalances and enhance prediction accuracy. Although this research shows the capability of using accelerometers to detect fetal movement, it is only based on a single sensing mode, and does not incorporate fetal heart rate (FHR) monitoring, an important indicator of fetal health.

In a study [21], conducted a review of recent developments in wearable sensors, signal processing and artificial intelligence (AI) applications for pregnancy monitoring. The paper notes that regular visits to the hospital can be cumbersome for pregnant women and the need for continuous monitoring of maternal and fetal health. It also explores different types of wearable sensors and AI algorithms that may help in early detection of complications during pregnancy. While the review highlights the potential of artificial intelligence in detecting fetal distress, it also mentions several challenges such as high computational costs and concerns about privacy and security, which could hinder the widespread use of such systems.

Likewise, [17] also developed an IoT-based fetal movement detection

system that uses both acceleration and gyroscope sensors to detect fetal movements. The platform uses machine learning models, such as a Particle Swarm Optimization (PSO) tuned XGBoost model, to classify fetal movements from maternal body movements with high sensitivity, precision and F1-score in practical test cases. While this study enhances fetal movement detection accuracy and reliability by combining multiple sensors and IoT connectivity, it is only focused on fetal movement. It does not use FHR signals, nor does it offer a way of classifying or predicting fetal distress, two important features of a robust fetal monitoring system, which are key elements of the proposed system in this work.

2.4 Machine Learning Approaches for Fetal Movement Analysis

The study [22], proposed a smart and lightweight wearable device that combines pressure and strain sensors and flexible Band-Aids to increase the comfort and wearability of the device for long-term monitoring. The system aims to accurately classify fetal movements from non-fetal maternal movements, a key issue in practical fetal monitoring applications. Through the use of machine learning models for classification, the proposed method achieved over 90% accuracy, proving that the integration of soft wearable sensors and smart algorithms can help improve the accuracy of fetal movement detection while ensuring comfort and feasibility of the device for users.

Moreover, a recent study at the University of Michigan [23] also examined the use of machine learning for detecting fetal movements from data obtained from multiple inertial measurement units (IMUs). The data set contained linear acceleration and angular velocity (angular rate) signals,

which were used to train and test various machine learning algorithms for classification. By comparing various popular models such as Bi-directional Long Short-Term Memory (BiLSTM), Random Forest (RF), and Convolutional Neural Networks (CNN), the researchers evaluated the ability of these models to learn and extract fetal movement information from multi-modal sensor data.

This study found that using multiple sensors (accelerometers and gyroscopes) outperforms single-sensor methods in terms of accuracy and robustness in detecting fetal movements. The CNN model performed the best among the models considered, thanks to its ability to learn spatial and temporal features from sensor data. But it needed a considerable amount of data for training and validation. In contrast, RF and BiLSTM models performed relatively well with a smaller dataset, and could be more interpretable, but were more vulnerable to noise in the input signals.

In conclusion, the proposed research demonstrates the benefits of multi-sensor data fusion and advanced machine learning models in enhancing fetal movement detection. While these improvements are significant, it is worth noting that this study, like other proposed solutions, only analyses fetal movements and does not include the analysis of fetal heart rate (FHR). Therefore, it does not offer a comprehensive measurement of the fetal status as this requires the analysis of both fetal movement and heart rate for more precise detection of fetal distress.

2.5 Traditional and Clinical Fetal Heart Rate (FHR) Monitoring

Fetal heart rate (FHR) monitors that are commonly used by obstetricians e.g. Doppler ultrasounds have drawbacks in that it is hard to get good qual-

ity data is from women with high body mass index (BMI). Other methods, such as internal fetal monitoring (fetal scalp electrodes) can monitor FHR most accurately but this can only occur when the amniotic membrane is ruptured and the cervical opening is wide enough. This method might also not be used when there are fetal complications. Research indicates that it is more accurate and reliable to detect FHR using abdominal fetal ECG, compared to ultrasound [25].

2.6 Fetal ECG (fECG)-Based Monitoring System and Signal Processing Techniques

There are a number of devices that can be used to monitor fetal heart rate from the fetal electrocardiogram (fECG) signals [16, 26–29]. In the study, [29] the authors developed a wearable device to record (fECG) signals from abdominal electrocardiography (AECG) signals for monitoring the fetal heart rate (FHR) signals at home. The fECG is extracted from the complex AECG which is mainly composed of maternal ECG (MECG) using two algorithms adaptive dual threshold (ADT) and independent component analysis (ICA). Once fECG is recorded, the QRS complex is detected, to detect QRS wavelet adaptive threshold de-noising is used to de-noise the fECG signals and additional algorithms are used for QRS detection. As shown in the study, [28] the author developed a prototype system to detect fetal arrhythmia, where the fetal ECG signals are recorded using abdominal electrodes and displayed on a mobile phone. The author tested it with synthetic signals [30] and it was able to detect at a rate of 88.88%.

2.7 Multimodal Wearable System for Fetal Movement Detection

In the study [15] the authors proposed a wearable system which monitors the occurrence of fetal movement using acoustic sensors, IMU accelerometers, force sensors and piezoelectric diaphragm sensors integrated and embedded into an elastic belt to capture a wide range of fetal movement signals and to reduce the influence of maternal signal, while attaining up to 90% of accuracy in real-time, at-home settings. While this system offers a diverse sensor network and uses machine learning algorithms to process and capture these data and detect fetal movements with improved accuracy, it is only focused on detecting fetal movements, and does not monitor fetal heart rate (FHR) or classify fetal health/fetal distress status (caused by fetal arrhythmia).

2.8 Remote Home-Based and Commercial Fetal Monitoring Systems

There are commercial multimodal advanced CE/FDA-certified NI-fECG based fetal monitoring systems [16, 26, 27], such as Nuvo’s INVU system [26], which are used for remote clinical monitoring, home-based monitoring, and all data interpretation is done by professionals. Women in their third trimester are scheduled for twice-weekly appointments, instead of visiting the clinic, appointments are made and these devices are shipped to their homes, the mother installs the INVU app and can view relevant data through the app, the provider can view all the data in the provider dashboard and notifies the mother if there is concern, after the appointment, mother returns the device. The authors in the study, [31] also assessed the

use of wireless, home-based fetal monitoring system to perform nonstress tests (NST) in high-risk pregnancies, showing that these devices can be used in a non-clinical setting, in the time of crises to remotely record fetal heart rate (FHR) and uterine contractions. While systems such as [26] provide at home fetal monitoring using sensors, data interpretation is still done by healthcare providers.

Current fetal monitoring devices, such as Doppler ultrasound and cardiotocography (CTG) machines, are commonly used in clinical practice but do not provide accessible and affordable solutions for many potential users in resource-limited areas. CTG devices are generally expensive medical grade equipment ranging from around PKR 125,000 to above PKR 295,000 (depending on system configuration and accessories) [32, 33] and are therefore suitable for use in hospitals or well-equipped medical facilities but not for home use. More sophisticated fetal monitoring with the integration of dual fetal and maternal monitoring may cost more than the aforementioned ranges due to more sensing points and better display options.

Besides being expensive to purchase, these systems often require additional services of a health care professional for use and interpretation. While the cost of handheld Doppler devices may be lower, these devices also require skill for interpretation and were not designed for long term continuous monitoring at home. This limits their application, usually only for periodic outcomes such as during antenatal checkups, rather than continuous fetal monitoring.

Due to their high cost, reliance on conventional clinical environment and need for trained expert, traditional fetal monitoring systems are inaccessible in many rural areas and low-income settings. This suggests low-cost, wearable, and home-based fetal monitoring systems offering continu-

ous assessment of fetal health are required.

2.9 Clinical Multimodal Monitoring Systems

There are systems such as The Novii+ Wireless Patch System [16] that used in clinics that reduce maternal discomfort and record important signals. This wireless patch system is combined with several adhesive electrodes and a wireless processing pod to record real-time fetal electrocardiogram (fECG) and maternal electrocardiogram (mECG) and uterine electromyography (EMG) signals. Also, fetal monitoring systems [34, 35] are used to monitor pregnant women’s fetal ECG signals, maternal ECG signals and uterine muscle contraction signals. But these Fetal Monitoring System devices are used in hospitals by medical staff.

2.10 Limitations of Existing Fetal Monitoring Systems

While there are a number of fetal monitoring systems and devices available and on the market, they have limitations, such as portable devices for fetal monitoring only show the baseline fetal heart rate (FHR) and baseline alone can’t predict fetal well-being. When assessing fetal wellbeing, it is important to consider accelerations (which are typically reassuring) and decelerations (which may be due to hypoxia or distress) in relation to fetal movements, as these reflect the cardiovascular responses to fetal movements, rather than simply baseline alone [36]. These systems tend to be Doppler devices that are unsafe to be used without health professionals and can be expensive for people in low-resource and low-income countries, particularly in Pakistan.

2.11 Wearable Sensors for Fetal Monitoring

Furthermore, the recent trends in wearable sensor technologies in the biomedical domain have improved the capacity of researchers to record fetal movements (FM) and fetal heart rate (FHR) signals continuously and non-invasively using the latest accelerometer sensors, gyroscopes and digital signal processing techniques. These techniques are now highly sensitive, and hence, can detect fetal movement with high accuracy [29, 37–40]. The electrodes and accelerometers, being miniaturised, sensitive and low cost, are easily and comfortably incorporated into belts or patches, and can be worn for long periods of time.

2.12 Summary of AI/ML Methods for Fetal Monitoring

Table 2.1 shows the summary of the AI/ML methods for fetal monitoring.

Table 2.1: Summary of AI/ML Methods for Fetal Monitoring

Author	Methodology	AI/ML Method	Performance	Remarks
J. Xu et al. (2022) [20]	Dual wearable accelerometers were used to acquire fetal movement signals. Signals were preprocessed, and statistical, morphological, and wavelet features were extracted. SMOTE was used for class imbalance.	Nine ML algorithms were compared; Extra Trees Classifier achieved the best result.	Accuracy 86.6%, Recall 82.4%, Precision 86.1%, F1-score 84.2%.	Shows feasibility of wearable accelerometer-based fetal movement detection using handcrafted features and classical ML.

Author	Methodology	AI/ML Method	Performance	Remarks
S. Liang et al. (2021) [41]	Accelerometer-based fetal movement signals were processed using Kalman filtering and maternal artifact pre-identification. Feature dictionaries were constructed using dictionary learning.	Dictionary learning with Orthogonal Matching Pursuit (OMP) and adaptive filtering were used.	Positive prediction value 89.74%.	Shows effectiveness of signal processing and machine learning for fetal movement detection.
L. Spicher et al. (2025) [23]	IMU data from four abdominal sensors and one chest reference were filtered and segmented. Features, time-series, and spectrogram representations were evaluated.	Random Forest, BiLSTM, and CNN models were trained on different representations.	CNN performed best, but required larger datasets. RF and BiLSTM were more suitable for smaller datasets.	CNN is effective for larger datasets, while RF and BiLSTM can be useful for shorter or noisy datasets.
M. Qin et al. (2023) [42]	Two three-axis accelerometer sensors were used. Data were processed using Kalman filtering, amplitude thresholding, and OMP-based classification.	Orthogonal Matching Pursuit was used for fetal movement classification after pre-processing.	Recognition Rate 89.74%, Correct Rate 89.74%.	Presents a wearable system for real-time fetal movement monitoring using accelerometer sensors.
Rattanasak A. et al. (2025) [17]	An IoT-enabled wearable device with accelerometer and gyroscope sensors was used. Data from 35 pregnant women were segmented and optimized using PSO, GA, FA, and WOA.	Six ML algorithms were compared. XGB with PSO-based feature selection and tuning achieved the best result.	Sensitivity 90.00%, Precision 87.46%, F1-score 88.56%.	Shows effectiveness of sensor fusion and PSO-based ML optimization for fetal movement detection.

Author	Methodology	AI/ML Method	Performance	Remarks
P. Alwis et al. (2024) [43]	A dataset from 44 pregnant women was collected using a multi-sensor device with four IMUs. Data were segmented and preprocessed for fetal kick monitoring.	An LSTM model with channel attention and sensor fusion was used.	Baseline accuracy 84%, improved to 88% with channel attention.	Shows that channel attention improves LSTM feature learning for fetal movement detection.
K. Barnova et al. (2024) [44]	A review of AI/ML methods in electronic fetal monitoring was presented.	Reviewed supervised learning, neural networks, fuzzy logic, and optimization methods.	–	Summarizes AI/ML methods in fetal monitoring, including advantages, limitations, and future directions.

Chapter 3

Requirement Specifications

This chapter describes a detailed analysis of the requirements of wearable fetal monitoring system. Starting with a review of current methods of fetal monitoring, it discusses the shortcomings of the commonly used methods with respect to accessibility, affordability and real-time monitoring. The new system is then proposed as a better alternative for safe, continuous and home-based fetal monitoring in response to these challenges.

In addition, this chapter outlines the system's functional and non-functional requirements, detailing both the expected behavior and performance of the system. It also provides use cases for the system that define user interactions with the system.

3.1 Existing Fetal Monitoring System

Monitoring the fetus during pregnancy, especially in the last trimester, is important in determining the health of the fetus. A number of monitoring approaches are currently used in hospitals and (to a lesser extent) in homes.

1. Ultrasound and Doppler Systems:

Doppler and ultrasonic sensors are commonly used to monitor in hospital fetal heart rate (FHR) and sometimes fetal movement (FM). Such devices provide accurate clinical information; but they are usually intermittent and require trained operators. They can also not be used for continuous long-term monitoring in the home setting. They generally involve many visits to the hospital, which is not practical and expensive. What's more, the use of ultrasound devices for extended periods and without supervision may pose safety risks, including thermal and cavitation effects.

2. Electronic Fetal Monitoring (EFM) and Cardiotocography (CTG):

Electronic Fetal Monitoring (EFM) and Cardiotocography (CTG) are widely used in the short-term assessment of the fetus in clinical situations. They offer valuable insights into fetal heart rate and contractions, making them a valuable resource for high-risk pregnancy and during labor. But these systems are not continuous, or home-based systems. They need specific equipment, staff and controlled clinical settings, making them difficult to use and access for frequent or regular at home measurements.

3. Maternal Perception of Fetal Movements:

Mothers' perceptions of fetal well-being is one of the earliest and most common means of fetal monitoring. Women rely on subjective assessment of fetal activity (such as kicks and rolls). Although this is a simple technique, it is completely subjective. Fetuses in distress may not show reduced fetal movement (RFM) or the mother may misinterpret reduced fetal movement (RFM). This makes this method unreliable and unsuitable for sole use.

4. Commercially Available Devices:

There are a number of commercially available devices for home monitoring of the fetus (e.g., portable Doppler monitors, such as Sonicade fetal monitors). Although eligible for home fetal monitoring, these devices are again based on ultrasound technology and are not continuous. Although there are other devices that perform well however, they are costly.

3.2 Shortcomings of Current Systems

The evaluation of existing fetal health monitoring systems identifies key limitations to be overcome. Existing systems mainly perform periodic rather than continuous monitoring of the fetus condition, limiting their capacity to assess transient events. Moreover, existing technology is often costly and not optimised for use in resource-poor settings, making it inaccessible to many. Along with being difficult to use without medical training, such systems also need to be interpreted by medical personnel, which also makes them unsuitable for at-home use. Moreover, most current systems do not allow simultaneous monitoring of both FM and FHR, limiting the ability to assess fetal health. These factors underline the requirement for a user-friendly, integrated and continuous fetal monitoring system.

3.3 Proposed System Overview

This work proposes a wearable fetal monitoring system for third trimester that overcomes the shortcomings of the current approaches. Our system uses an accelerometer sensor and ECG electrodes to real-time and non-invasively monitor fetal activity and fetal heart rate.

The system is intended to be used at home, and is suitable for resource-poor settings. This removes the need for repeated visits to the hospital and can detect early and abnormal fetal patterns.

The proposed system offers a number of benefits to combat these issues. It provides continuous fetal activity and fetal well-being monitoring which is infrequently used in current clinical practice. The system is designed to be safe and non-invasive in order to allow long-term monitoring using non ionizing or ultrasound techniques. It is also made from cheap compo-

nents to enable its affordability and availability in resource poor settings. The system's design and user interface prioritise user-friendliness, enabling users, especially pregnant women, to use the system independently. The design also facilitates near-site data collection, allowing for the establishment of a Pakistan specific fetal database, which will help in developing future models. The belt design is comfortable, enabling prolonged use.

3.4 System Requirement Specifications

The system requirements describe the functionality and performance of the system. There are two types of requirements: functional and non-functional.

3.4.1 Functional Requirements:

The system can continuously obtain fetal movement data from sensors (accelerometers) and fetal heart activity from electrodes (ECG). The acquired physiological signals are preprocessed through signal processing methods such as filtering, noise reduction and de-noising. Once preprocessed, relevant features are derived from both time and frequency domains to allow for analysis of fetal activity. The protocol uses real-time presentation of fetal activity and heart rate to monitor the results, and model features extracted for analysis. Furthermore, data is saved for offline analysis and to be used in future datasets. In addition, the system can recognize abnormal patterns and provide early alerts, increasing early detection of potential risks. Data collection can also be exported for use and evaluation in research and clinical studies.

3.4.2 Non-Functional Requirements:

In terms of performance, the system aims to enable real-time data collection and presentation with low delays, enabling timely assessment of the fetus during pregnancy. The system aims to provide low error in both the detection of fetal movements and estimation of the fetal heart rate via integration of sensors and proper signal conditioning. The system is also designed to be safe, performing a fully non-invasive operation without radiation or ultrasound, enabling it for long-term monitoring. Finally, the system aims to be user-friendly, with the ability to be worn and used by non-technical users. Finally the system is designed to be maintainable, enabling sensors and other system components to be changed or repaired as necessary.

Chapter 4

System Design

4.1 System Architecture

The new system is an ambulatory fetal monitoring belt system that records continuous measurement of fetal movement (FM) and fetal heart rate (FHR) in a convenient, non-invasive and safe manner. The focus is on third-trimester monitoring and the system can be used in hospitals and at home. The proposed system uses passive monitoring, as opposed to traditional methods such as Doppler ultrasound or cardiotocography (CTG). This eliminates the need to emit radiation or ultrasound or other signals into the body. Rather, it uses passively existing signals such as mechanical vibrations and electrical cardiac activity.

Maternal safety, comfort and reusability of the system are aimed at while maintaining monitoring of the fetus's well-being. The use of multiple modes of sensing improves the system reliability plus the ability to sense the fetal activity and cardiac activity. The system is designed as a typical embedded system with a modular structure that includes sensing, signal conditioning and processing and output modules.

The system is comprised of the following components shown in table 4.1.

Table 4.1: Hardware Components Used in the Proposed System

System Components
Four Digital Accelerometers (ADXL345)
Nine Disposable Ag/AgCl Electrodes
AD8232 Biopotential Front-End ICs
ADS1115 Analog-to-Digital Converters
TCA9548 I2C Multiplexer
ESP32 Microcontroller
Laptop for Monitoring and Analysis

ADXL345 Accelerometers (Detecting Fetal Movements)

The ADXL345 shown in figure 4.1 is a low-power, high-resolution, 3-axis digital accelerometer that can be used to measure fetal movements, tapping into the micro-vibrations on the mother’s abdomen. Four ADXL345 sensors are used to provide optimal coverage and are positioned at varying locations over the abdomen.

These sensors can pick up micro-mechanical variations as a result of fetal kicking, rolling and micro-movements. The multiple accelerometers increase the reliability of detecting the appearance of any type of fetal movement, regardless of fetal position. They digitally transmit acceleration data to the ESP32 via the I2C bus for processing.

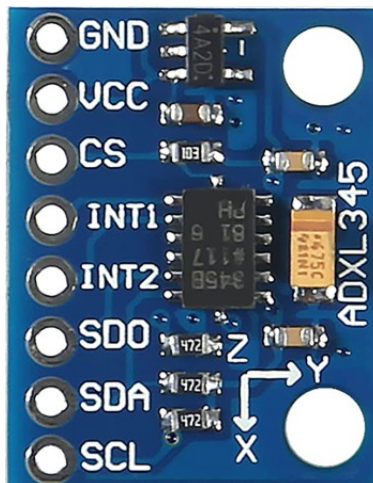


Figure 4.1: ADXL345 Accelerometer

Disposable Ag/AgCl Electrodes for ECG Sensor (Biopotential Signal Acquisition)

Ag/AgCl disposable electrodes shown in figure 4.2 are employed for the acquisition of bio-signals from the abdomen of the mother. These electrodes

are commonly used in biomedical applications because of their excellent conductance, stability and low noise.

The system employs nine electrodes, which are used in a differential mode, and one common reference electrode. The electrodes record abdominal electrocardiogram (AECG) signals, which include both maternal and fetal heart signals. The aim is to separate the fetal electrocardiogram (ECG) signal for fetal heart rate monitoring.



Figure 4.2: Disposable Ag/AgCl Electrodes for ECG Sensor

AD8232 Biopotential Acquisition Module

The AD8232 shown in figure 4.3 is an analog front-end (AFE) module for ECG. In our approach we use four AD8232 modules each with a pair of electrodes.

The modules are configured to operate in differential mode, which improves the signal quality by eliminating common-mode noise and removing artifacts from the mother's ECG and other sources. By using four chan-

nels of the AD8232, the likelihood of acquiring a pure fetal ECG is higher, particularly taking into account the fetal position.

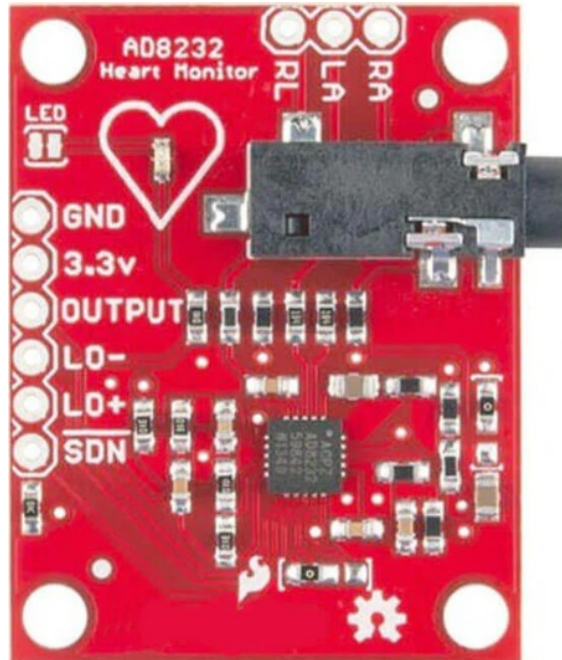


Figure 4.3: AD8232 Biopotential Acquisition Module

ADS1115 Analog-to-Digital Converter (ADC)

The ADS1115 shown in figure 4.4 is a 16-bit high resolution ADC for converting an analog signal to digital via the AD8232 modules. We are using four ADS1115 ADCs. ADCs are set in single-channel configuration to achieve fast sampling rate.

This is required as fetal heart signals need to be sampled well (at approximately 500 Hz) in order to be accurately reconstructed according to the Nyquist sampling theorem. Separate channels of the ADC are preferable to avoid AQ degradation arising from multiplexing.

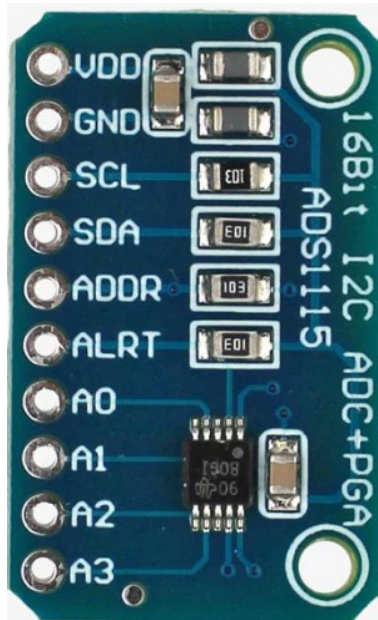


Figure 4.4: ADS1115 Analog-to-Digital Converter (ADC)

TCA9548A I2C Multiplexer

To control multiple I2C devices, the TCA9548 multiplexer shown in figure 4.5 is used. Because there are many ADXL345 sensors and ADS1115 ADCs, potential address collisions may occur. The multiplexer addresses this problem by allocating channels for the devices: The first four channels are used for ADXL345 sensors and the second four channels are used for ADS1115 analog-to-digital converters (ADCs).

This guarantees reliable communication and enables system expandability.

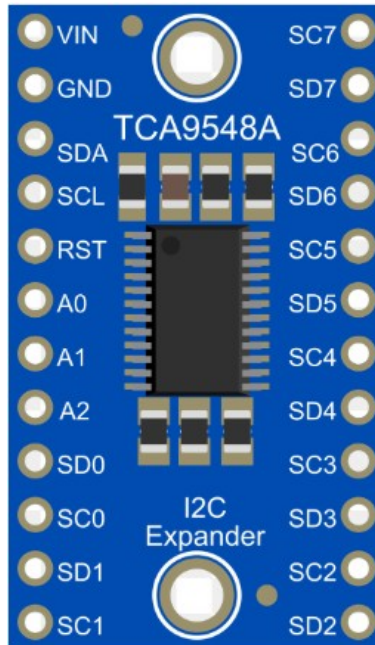


Figure 4.5: TCA9548A I2C Multiplexer

ESP32 Microcontroller (Brain)

The ESP32 shown in figure 4.6 acts as the CPU for the system. It is responsible for:

- Reading all sensors
- Managing I2C communication
- Synchronizing multi-channel inputs
- Performing initial preprocessing
- Sending data to the laptop

The ESP32 module is selected for its powerful processing power, inclusion of Wi-Fi and Bluetooth, low power and affordability.

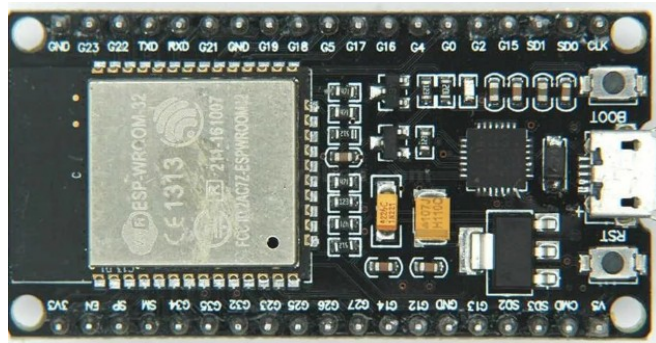


Figure 4.6: ESP32 Microcontroller

Power Supply and System Integration

It's powered using a laptop via USB, which provides reliable power. The wearable belt is designed to house all components in a compact enclosure, and to keep sensors in place during use.

The overall system flow by using the above components is given in figure 4.7.

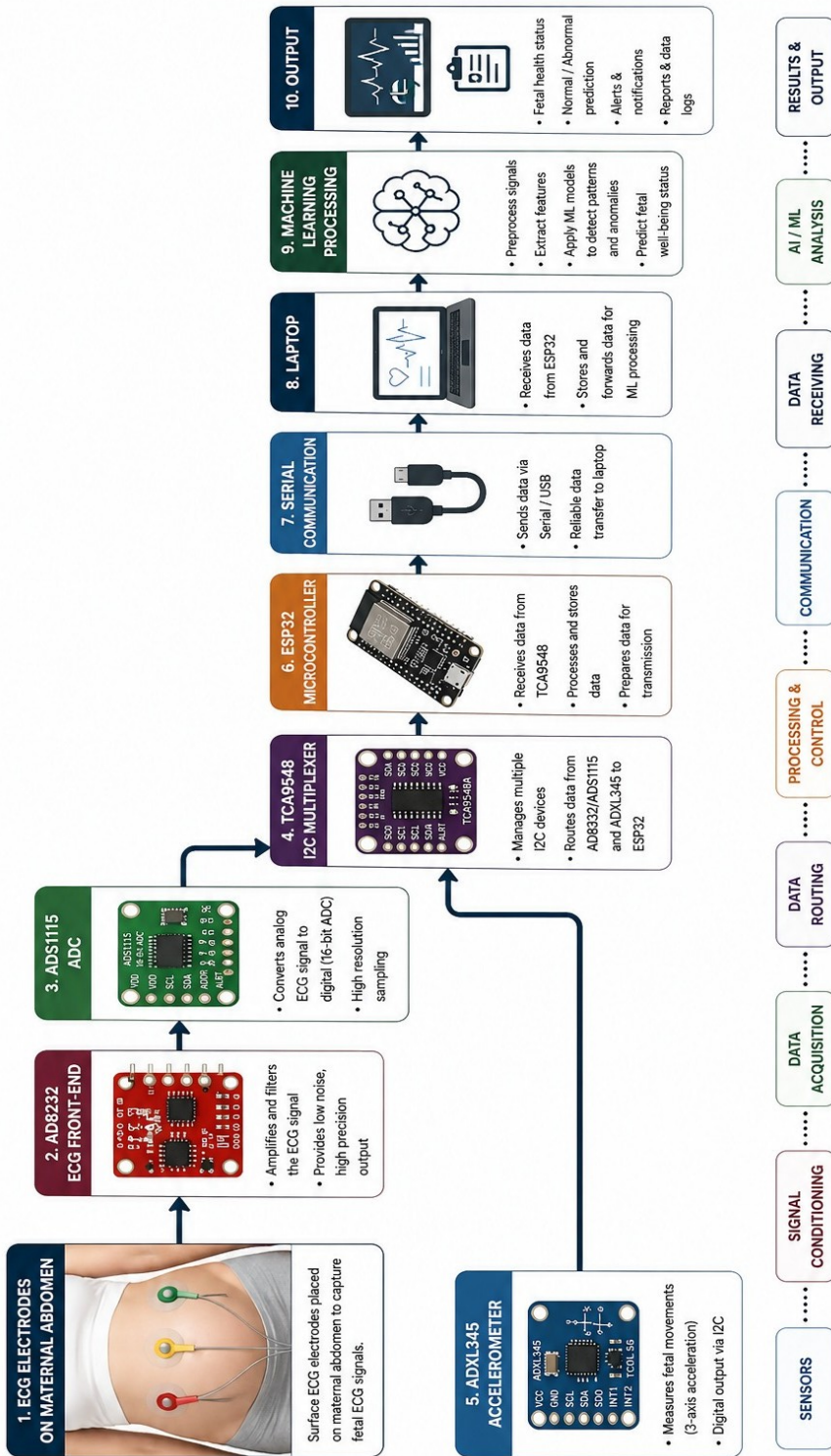


Figure 4.7: Overall System Flow

4.2 Design Constraints

There are a number of constraints and assumptions that affect the system design:

1. Technical Constraints

The main technical constraint in fetal monitoring is the low signal amplitude of fetal signals. Vibrations and electrical signals related to the fetal heart rate (FHR) are much smaller in amplitude than those of the mother, and thus more prone to interference. This results in low amplitude fetal signals being difficult to detect and recover the fetal heart rate (FHR), especially outside the clinic. The system is intended for use on pregnant women in real-world situations, and natural movements (such as breathing, changing position, and walking) cause noise to be injected into the signals. These artifacts can lead to a loss of quality in the signals and the detection of fetal movements and heart rate. Placement of the sensors is another constraint.

Accelerometers and the ECG electrodes can only function well if properly placed on the mother's abdomen. This can yield signals of low quality or unusable quality, hence affecting system performance. Moreover, the fetus may be in different positions in the womb, further adding to the challenge of positioning.

2. Economic Constraints

- Cost is a critical factor, particularly for use in low-resource settings in Pakistan. Currently available fetal monitoring equipment systems are costly and require highly specialised equipment, which is out of reach for many.

- The system is designed to use affordable and easily found components while still maintaining necessary functionality. The use of expensive clinical sensors is eliminated, and instead, low-cost sensors such as ADXL345 accelerometers and AD8232 are used. The aim is to achieve a trade-off between being functional yet affordable while being useful.

3. Safety Constraints

- Another critical consideration in a biomedical system, especially one involved in pregnancy is safety. The proposed system is based on non-contact, passive sensing, meaning that it does not use any type of radiation, ultrasound, or electrical stimulation.
- As a result, it is safe to use for both the mother and the fetus, even over extended periods. Furthermore, all skin-contacting materials, including sensors and wearable textiles, are chosen to be non-irritating and biocompatible materials. The system includes measures to reduce the potential for discomfort, irritation or health complications.

4. Operational Constraints

- The system is designed for non-tech-savvy users, especially pregnant women, at home. Thus, it must be easy to use. It must be straightforward to use, have negligible setup requirements, and yield test results that are readily interpreted.
- The second constraint is convenience and mobility. The belt must be light and comfortable, and enable women to wear it for long periods without discomfort. The device should also be robust, requiring little maintenance and calibration.

4.3 Design Methodology

The design of the proposed system is based on a modular approach using an embedded-systems design methodology rather than a conventional object-oriented software design. Such a design technique is more appropriate for hardware-oriented systems which require real-time data collection and processing.

1. Requirement Analysis

System requirements are the starting point for the design process. The aim is to design a safe, non-invasive and low-cost system that can be used outside the hospital. This system should be able to continuously track the fetal movement and heart rate, while being user-friendly and comfortable.

2. System Decomposition

The system is broken down into three functional blocks to ease its design to acquire the fetal body movement and heart signals via accelerometers and electrodes, responsible for acquiring, processing and conditioning the signal, presents results and provides valuable information to the user. This modular design enhances system organisation, scalability and development.

3. Hardware-Software Co-Design

The system employs hardware components (e.g. sensors, microcontrollers) and software algorithms for data processing and analysis. The ESP32 microcontroller interfaces with both hardware and software, allowing for real-time data collection and communication. Co-design philosophy ensures the hardware and software elements are

well coordinated to achieve efficient operation and enhance the system's reliability and accuracy.

4. Fusing accelerators and electrodes with ESP32 microcontroller:

The system employs hardware components (e.g. sensors, microcontrollers) and software algorithms for data processing and analysis. The ESP32 microcontroller interfaces with both hardware and software, allowing for real-time data collection and communication. Co-design philosophy ensures the hardware and software elements are well coordinated to achieve efficient operation and enhance the system's reliability and accuracy.

5. Signal Processing Design

The physiological signals are known to be noisy requiring the signal processing techniques. Methods like filtering, denoising and peak detection are implemented for signal processing. These techniques are key to extracting fetal signals from maternal signals and other forms of noise. Effective signal processing enables reliable detection of fetal activity and heart rate, essential for fetal health monitoring.

6. Creation of filtering and peak detection methods:

The physiological signals are known to be noisy requiring the signal processing techniques. Methods like filtering, denoising and peak detection are implemented for signal processing. These techniques are key to extracting fetal signals from maternal signals and other forms of noise. Effective signal processing enables reliable detection of fetal activity and heart rate, essential for fetal health monitoring.

7. Testing and Iteration

The system is continually tested and refined during development. Testing starts in controlled environments where sensor responses and signal quality are tested. Based on the findings, adjustments are made to sensor placement, signal analysis software and system settings. This process allows the system to be refined to become a more efficient practical solution. While object-oriented design tools like UML are common in software development, this project is focused on embedded software-hardware integration. Modular firmware is used instead of classes to implement system functionality, which is more appropriate for real-time embedded systems.

4.4 Database Design

- The system does not contain a database management system (DBMS) because it has been developed as a prototype mainly for data collection and dataset creation, not real-time monitoring. Rather than processing data in real time, the system logs sensor data and stores it for subsequent analysis.
- The sensor data (accelerometer and ECG) are saved in raw form to structured data formats (CSV). This allows the inclusion of raw sensor data as well as any transformed values for subsequent analysis and model building.
- The system supports the creation of data sets by recording sensor data at regular time intervals, which can then be used to train and validate machine learning algorithms. This method allows for flexibility in data manipulation and easy integration with data analysis

software.

- While the existing system outputs data to local files, future work can consider connecting to mobile apps, cloud-based storage and electronic medical record (EMR) systems. This would allow for real-time sensor data monitoring, remote access, and easier data sharing with medical practitioners.

4.5 External Interfaces

The system is designed with a minimal number of external interfaces, for ease of use.

Hardware Interfaces

- The main hardware interface in the system is the I2C protocol. This is used to communicate between the accelerometers, ADCs, multiplexer and the ESP32 microcontroller. It is selected because of its simplicity, minimal wiring and ability to communicate with multiple devices on a common bus.
- In addition, a USB connection is established between the ESP32 microcontroller and laptop. This not only supplies power to the system, but also allows serial data transfer enabling real-time data monitoring and visualisation.

User Interface

- The system's user interface is easy to navigate. The data acquisition and display are done through the wearable belt and desktop computer, respectively.

- The system allows users to view real-time plots of the fetal movement and fetal heart rate, which can help them better comprehend the fetal activity. The system is aimed at being as simple to use as possible, so that it can be used even by non-technical users.

Future Interfaces

The system is scalable, and new sophisticated interfaces can be added in future iterations. The ESP32 microcontroller board has Wi-Fi and Bluetooth capabilities that can be used for wireless communication. Future enhancements may include:

- Connectivity to a mobile app for remote monitoring.
- Telehealth connectivity for teleconsulting.
- Data storage and analysis through the cloud.

These features would greatly improve the functionality and utility of the system, offering telemedicine and remote data monitoring.

Chapter 5

System Implementation

This chapter presents the practical implementation of the proposed wearable fetal monitoring system, including hardware integration, signal processing, and machine learning-based classification. The study introduces a wearable device designed to detect fetal movement (FM) and fetal heart rate (FHR) using accelerometer and electrode signals.

5.1 Hardware Implementation

The system is a wearable fetal monitoring prototype that detects fetal movement (FM) and fetal heart rate (FHR) using accelerometer sensors and disposable electrodes that classifies these movements with machine learning algorithms.

The system comprises the following key components:

1. Sensor Module

Four ADXL345 digital accelerometer sensors and nine Ag/AgCl disposable electrodes are used to capture abdominal vibrations, detecting micro-level mechanical motions and converting it into digital signals.

2. Processing Module

An ESP32 microcontroller is used for the following functions:

- Collecting data from all sensors.
- Initial pre-processing.
- Transmitting data to the next processing stage.

3. Communication Module

Sensor data is transmitted via USB serial communication to a laptop for further processing and visualization.

4. Machine Learning Module

Machine learning models on the laptop perform advanced processing and classification. These include:

- Random Forest (RF).
- Bidirectional Long Short-term Memory (BiLSTM).

5. Output Module

The results are displayed on a computer, where:

- Signals are plotted.
- Movement of the fetus is categorized.
- and performance metrics are evaluated.

6. Power Supply

The system uses the following to power up:

- USB power supply ESP32.
- and a battery-powered laptop.

Figure 5.1 illustrates the hardware schematics of the project.

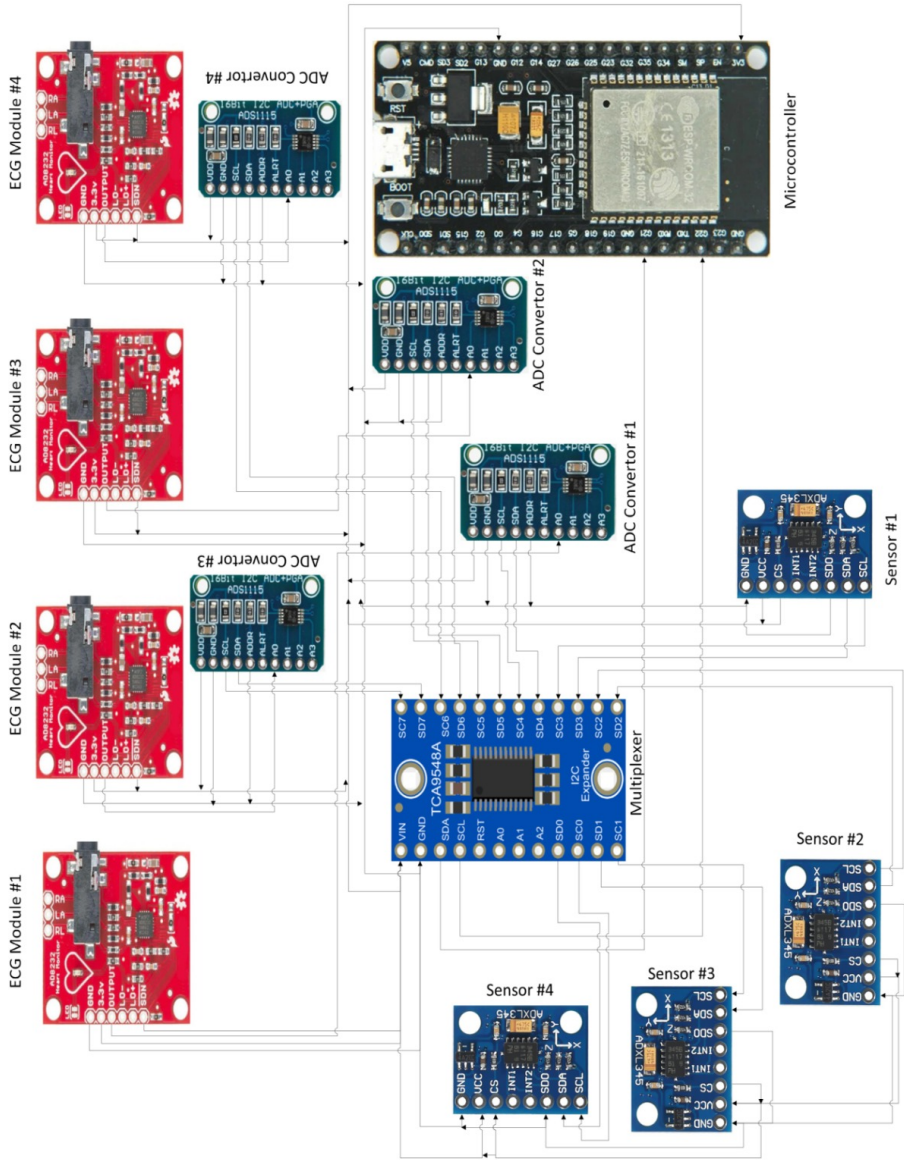


Figure 5.1: Hardware Schematics

System Flow

The system flowchart shown in figure 5.2.

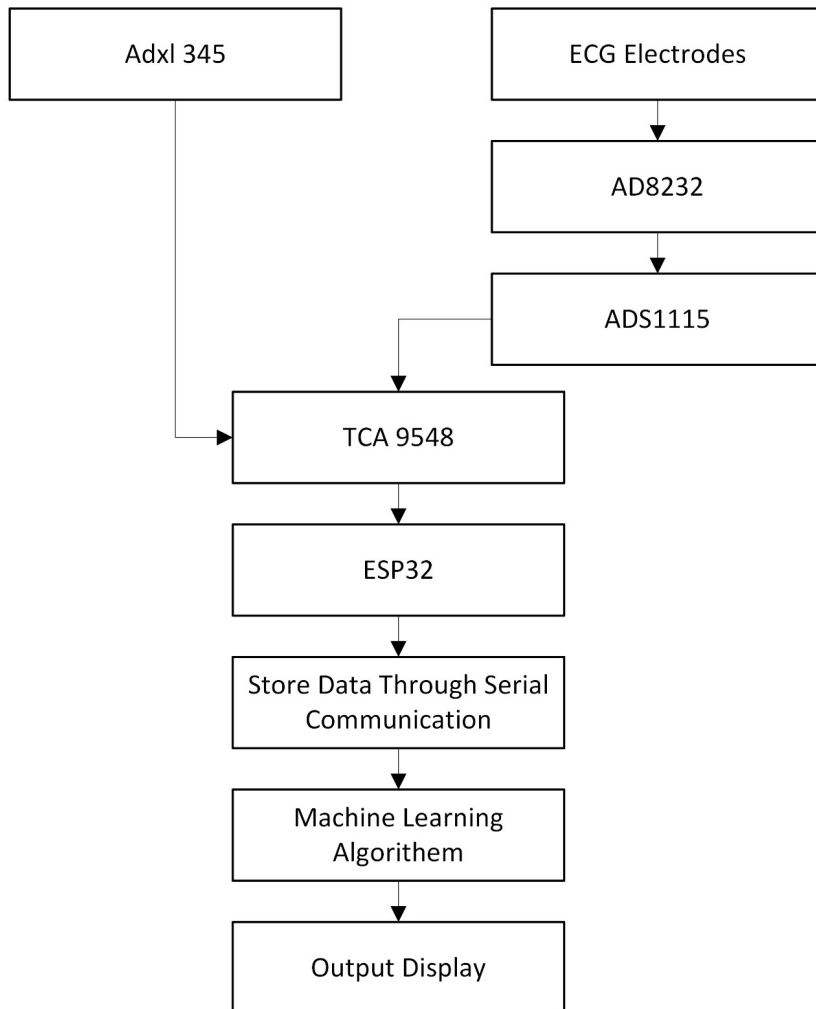


Figure 5.2: Overall System Flow Overview

5.2 Tools and Technology Used

Tools and technologies used are shown in figure 5.1.

Table 5.1: Hardware, Software Tools, and Technologies Used in the Proposed System

Category	Details
Hardware Components	ADXL345 Accelerometers (4 units) ESP32 Microcontroller Multiplexer (for sensor data routing) Wearable Belt Structure
Software Tools	Arduino IDE Python (Machine Learning and Analysis)
Technologies	Embedded Systems Machine Learning Signal Processing Time-Series Analysis

5.3 Hardware Design

The proposed hardware design was developed to non-invasively capture continuous fetal movements. The system consists of the following components as shown in table 5.2.

Table 5.2: Components of the Proposed Fetal Monitoring System

Component	Description
ADXL345 Accelerometers	Four digital sensors for fetal movement detection
Ag/AgCl Electrodes	Nine disposable electrodes for ECG signal acquisition
TCA9548 Multiplexer	I2C multiplexer for managing multiple sensor connections
AD8232 IC	Biopotential front-end for ECG signal conditioning
ESP32 Microcontroller	Data acquisition, processing, and transmission
Laptop (USB Powered)	Real-time monitoring, visualization, and data analysis

The Hardware Behind the Fetal Monitoring Belt is shown in figure 5.3.



Figure 5.3: Hardware Behind the Fetal Monitoring Belt

The illustration in figure 5.4 provides the design of the wearable belt designed in this research to provide comfort, fit, and be wearable for continuous fetal monitoring at home. Figure 5.5 illustrates a generic computer-aided design design of the fetal monitoring belt.



Figure 5.4: Little Beats: Fetal Monitoring Belt

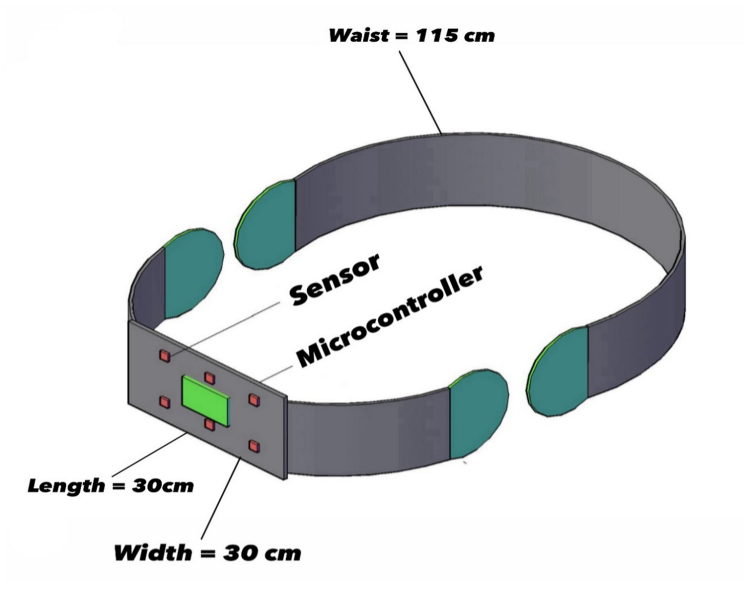


Figure 5.5: Computer-Aided Design

5.4 Sensor Placement

After consultation with the obstetric specialists, the optimal sensor positions were identified to capture fetal movement and fetal heart rate from any fetal orientation navel being the reference point.

- **Accelerometers Placement**

The placement of the accelerometers is shown in table 5.3, and is illustrated in figure 5.4.

Table 5.3: Placement of Accelerometer Sensors on the Maternal Abdomen

Sensor	Position Relative to Navel
Sensor 1	5 cm above the navel
Sensor 2	7 cm below the navel
Sensor 3	3 cm above and 5 cm to the right of the navel
Sensor 4	3 cm above and 5 cm to the left of the navel

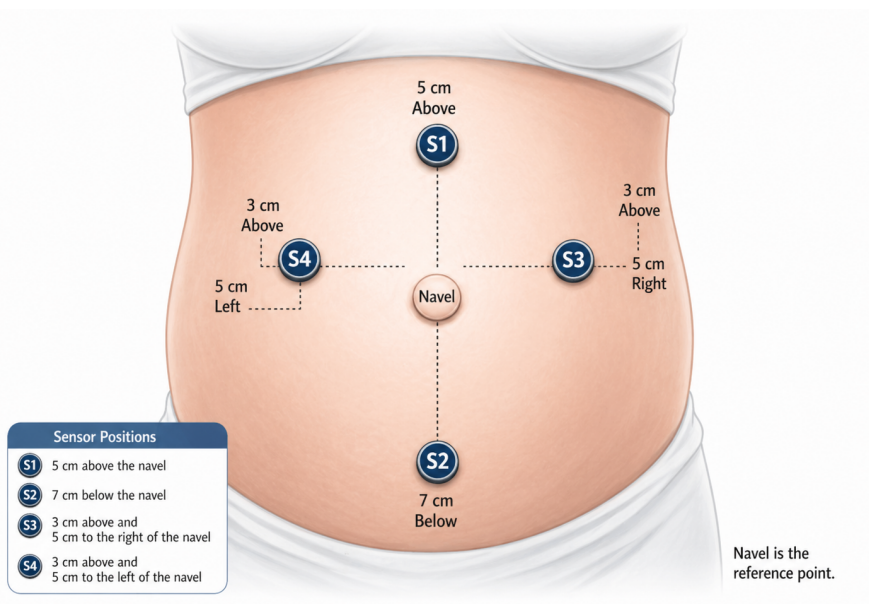


Figure 5.6: Accelerometer Placement for Fetal Movement Monitoring

- **Electrodes Placement** The placement of the electrodes is shown in table 5.4, and is illustrated in figure 5.5.

Table 5.4: Placement of ECG Electrodes for Fetal Signal Acquisition

Electrode	Position Relative to Navel / Body
Electrode 1	7 cm above the navel
Electrode 2	7 cm below the navel
Electrode 3	7 cm to the right of the navel
Electrode 4	7 cm to the left of the navel
Electrode 5	5 cm above and 5 cm to the right of the navel
Electrode 6	5 cm above and 5 cm to the left of the navel
Electrode 7	5 cm below and 5 cm to the right of the navel
Electrode 8	5 cm below and 5 cm to the left of the navel
Electrode 9 (Reference)	Placed on the thigh (common reference electrode)

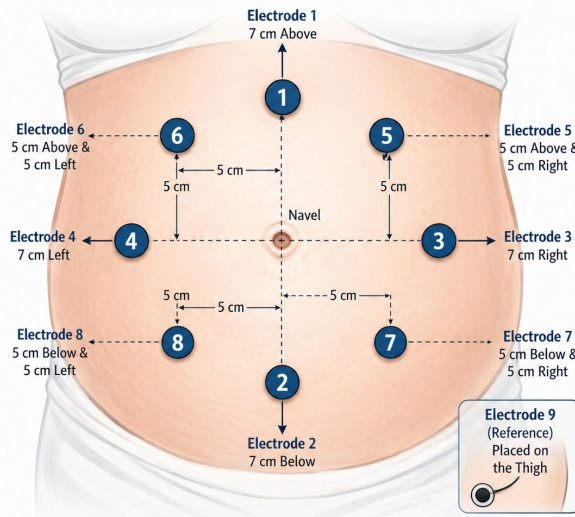


Figure 5.7: Electrode Placement for Fetal Heart Monitoring

5.5 Data Acquisition

The digital readings from the accelerometers and electrodes are routed through a multiplexer to the ESP32 microcontroller. Real-time data is monitored through a USB connection to a laptop. The system is able to detect minor movements, demonstrating its sensitivity.

5.6 Dataset Overview

The research here in involves using time-series signals stored in comma-separated-value (CSV) files. Both data are synchronized and include signals from the abdominal surface (i.e., abdominal ECG/electrode-based signals) and fetal movement sensor. The ECG/electrode signals correspond to electric activity recorded in the abdominal electrodes and the movement signals correspond to inertial (accelerometer) data. The two types of signals were recorded in separate files but with the same naming convention for each recording session.

Two CSV files were saved per data recording: one file for the ECG/electrode signals and one file for the accelerometer/movement signals. The file names for the electrode signals took the form of `XXXXX_ELEC` and the file names of the accelerometer signals took the form of `XXXXX_ACC`. For instance, a recording named `DATA1` would have two corresponding data files: `DATA1_ELEC` for the ECG/electrode signals and `DATA1_ACC` for the accelerometer/movement signals. Such a naming convention enables the fetal heart rate inference based on the ECG data and the fetal movement detection based on the accelerometer data to be independently developed to perform the desired analysis while maintaining the link between the signals from the same recording session.

5.7 Web-Based System Overview

To improve the usability of the system for detecting fetal movement and fetal heart rate, a web-based system has been created. Rather than performing manual command-line Python code to run the model, the web-based system offers an intuitive user interface to upload the required CSV files and get prediction results automatically. This system is able to accept both types of dataset files provided in this study: either an electrode/ECG or accelerometer/movement signal file. The electrode/ECG data files are in the format of `XXXXX_ELEC`, while the accelerometer/movement data files are in the format of `XXXXX_ACC`. Then the system will understand whether the uploaded file is an ECG/electrode file to analyse the FHR or an accelerometer file to detect the fetal movement.

The user interface acts as an intermediary between the user and deep learning models. The user interface allows the user to upload a file, reads the file name and presents the final prediction results. The server receives the uploaded file (in CSV format), verifies the format, reads the signal channels and applies the preprocessing steps. For the ECG/electrode files, the system reads the abdominal ECG channels, preprocesses the data to extract time domain, frequency domain and rhythm features, followed by the stand-alone FHR model for FHR detection. For accelerometer data files, the system uses the fetal movement detection pipeline with the dependent variables related to fetal movement.

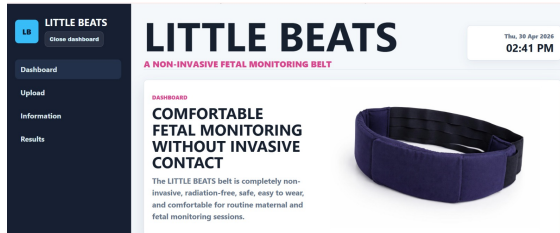
The FHR model in the web system is a two-stage model. Initially, the model determines the presence of a valid fetal rhythm in the ECG. This stage makes sure that if no valid fetal rhythm is detected the web system returns ‘No FHR Detected’ rather than a false BPM value. When a good rhythm is found, the model estimates the FHR in BPM. This feature

makes the web interface more robust, particularly in noisy ECGs that can generate false FHR. Similarly, when testing for maternal heart rate and/or movement, the system provides results only if the model's confidence index and signal quality are high.

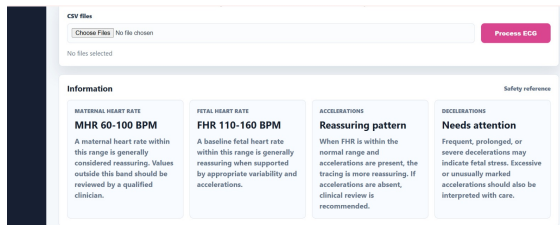
To input the data, the user logs onto the web system and uploads an appropriate CSV file. If fetal heart rate is to be analysed, an electrode file, such as `DATA_ELEC.csv` is selected. If he or she wants to predict fetal movement, an accelerometer data file such as `DATA_ACC.csv` is uploaded. Once the user has entered the data, he/she presses the button for prediction or analysis. The automatic system will automatically process the signal, extract features, run predictions and generate results. The results can include the status of detection of FHR, predicted BPM for FHR, status of detection of MHR (if multiple movement is detected), predicted BPM for MHR, status of detection of movement, and information about certainty.

The web application enhances the flexibility of the proposed method as it enables users to experiment with new recordings without dealing with the underlying code. It also facilitates research by eliminating errors relating to the preprocessing and prediction, as well as the need for code interaction. This interface facilitates a straightforward data input, model prediction and result display process to make the implemented AI system more convenient to conduct experiments and research. Because the system reads data from a CSV file in the same format of the dataset, it can be test on new recordings, provided that the order and names of the columns containing the signals are in the same format as those of the training data.

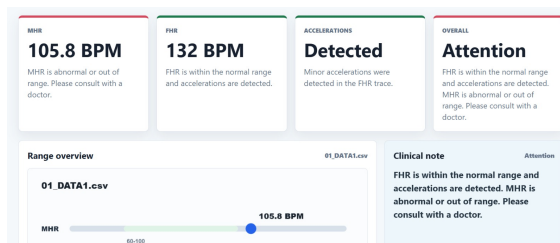
Below is the web interface for Little Beats shown in figures 5.6 (a-d).



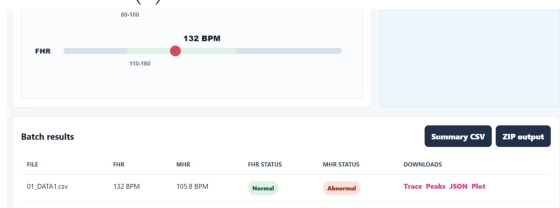
(a) Web Interface Overview



(b) Real-time Monitoring Dashboard



(c) FHR Detection Results



(d) System Output Visualization

Figure 5.8: Little Beats Web Interface and Output Visualization (a-d)

5.8 Dataset Security

The data obtained in this research, using the proposed smart wearable fetal monitoring belt, were managed according to ethical considerations and principles of data security. The data collected from participants (fetal movement (FM) and fetal heart rate (FHR) signals) was handled as confidential information. The data was accessible only to the project team and there was no distribution or disclosure of the data outside the project team without explicit consent.

All subjects were given consent forms detailing the background, objectives and limitations of the study before any data was collected. The participants were allowed to read the details of the study and their consent was sought for participation in the study before data was acquired. Personal identifiers such as names, email addresses and other demographic information were not requested. This ensured complete anonymity of the participants and eliminated any possibility of identification.

Additionally, all data was de-identified at the time it was collected to ensure participant anonymity. The data set only includes signal data relevant to fetal monitoring, and does not contain any identifying information about participants. This ensures the privacy of participants is maintained during the research.

Data was stored securely using systems with restricted access and safeguards. Access controls, secure data storage and simple encryption techniques were applied to ensure that data was not misused, accessed improperly, or leaked. Data was only used for research and analysis in this project.

Also, the research adhered to ethical considerations for biomedical studies. Participants' comfort, safety and dignity were always considered

throughout the study. The wearable system was designed to be non-invasive, comfortably worn for extended periods, and free of any harmful radiation or electricity. To conclude, the study guarantees that all data collected from the fetal monitoring system is confidential, secure and ethically handled, while upholding the privacy and confidentiality of the participants.

5.9 Model Overview

Fetal movement signals are time series and classification is needed to identify patterns of movements and non-movements. Some popular related classifiers include Convolutional Neural Networks (CNNs), which are a type of deep learning neural network designed for image classification, but have been successful for time-series signal classification (despite requiring sizeable data sets) [23], Long Short-Term Memory Networks (LSTMs) are a form of recurrent neural network data (RNN) for time series data, Forest (RF) is a traditional machine learning approach that uses multiple decision trees, or a forest, to avoid overfitting and enhance accuracy. It's commonly used with structured and small data, such as that used in this study.

Two approaches are used in this study. First, Random Forests (RF) were used because of their efficiency with small and imbalanced data. Then the Bidirectional Long Short-Term Memory (BiLSTM) model was used separately and compared with the RF.

In addition to classifying fetal movements, the study also developed a separate fetal heart rate (FHR) detection system from abdominal ECGs. The FHR model was implemented as a noise-aware two-stage model. The first stage was a validity classifier based on Extra Trees to determine the validity of the FHR as valid or invalid (noise or no-detection). In the second stage, when a valid FHR was present, a regression pipeline with Sim-

pleImputer, RobustScaler and KNeighborsRegressor was used to predict the FHR in the number of beats per minute. The validity-based FHR prediction was then conservatively corrected using the initial FHR estimate from this AI model as the primary prediction and the spectral FHR estimate as a minor correction to avoid grossly overestimating the FHR.

The FHR model was trained using weak labels from the ECG signal-processing pipeline, but also using synthetic noise windows to train the model on the no-detection condition. When the model was tested standalone, it did not use teacher assistance to make the prediction; it relied only on the ECG signal, preprocessing, feature extraction, validity classification and BPM regression. This approach prevented the system from producing an FHR value when no valid fetal activity was detected, increasing the robustness of the system for abdominal ECG recordings with noisy fetal activity.

5.10 Preprocessing of Fetal Movement Signals

As raw signals from accelerometer have noise, different motion artifacts, and unnecessary information, preprocessing of the fetal movement data acquired constitutes a critical step. In this study prior to modeling, the continuous multi-axis fetal movement signals were preprocessed to improve signal quality and to make them suitable for machine learning classification. The preprocessing steps include:

1. **Missing Value Handling:** It may occur due to temporary disconnection of the sensors, transmission losses and motion artifacts hence, preserving the timing and order of the data is essential as the Fetal movement (FM) data are time series signals. The missing values were handled using forward filled and backward filled imputation

techniques which ensure that the temporary structure is preserved, future information is prevented from leaking during forward filling and no gaps in the signal.

- Forward filled imputation:

$$x_t = x_{t-1} \tag{5.1}$$

In this approach the missing value at time index t is replaced by the most recent value. The signal will remain stable over short time intervals.

- Backward filled imputation:

$$x_t = x_{(t+1)} \tag{5.2}$$

This approach is used when there is no prior observation, so the missing value is replaced by nearest subsequent valid observation.

2. Imbalanced Class Handling: Prior to the training of the model class distribution of segmented fetal movement windows was examined. The data had high class imbalance with 94.78% samples labeled as No Movement and only 5.22% as Movement, with an imbalance ratio of 18.14. Such imbalance can bias the model towards the larger class and degrade fetal movement detection performance. The class distribution is shown in figure 5.10.

To address this problem, SMOTE (Synthetic Minority Oversampling Technique) was applied for oversampling after flattening the windowed acceleration data, it generates synthetic minority-class samples. After oversampling the dataset increased from 27,680 to 52,468

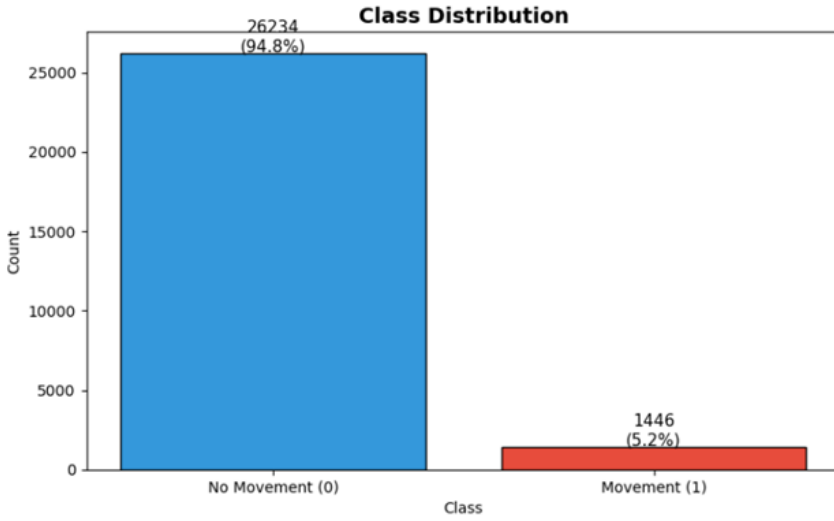


Figure 5.9: Class Distribution

samples, achieving an equal class distribution (50% per class), when the ratio of majority to minority class was equal the data was balanced for training as shown in figure 5.11.

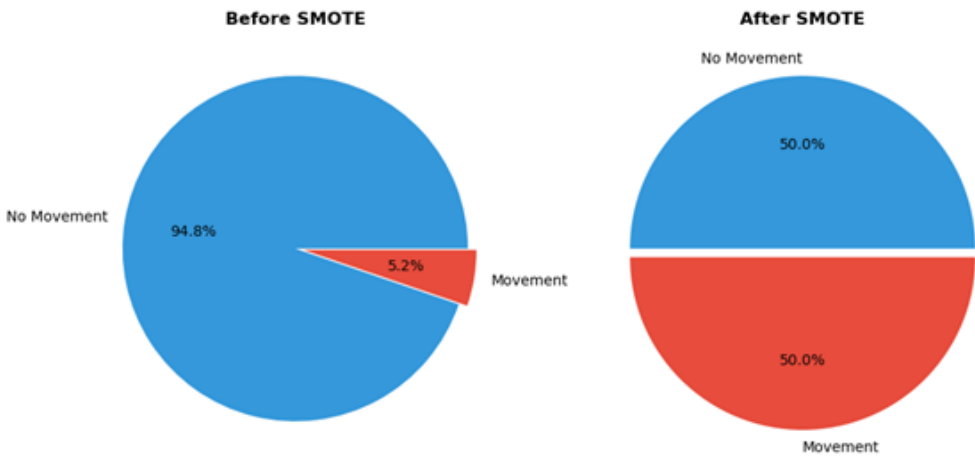


Figure 5.10: Class Distribution Comparison

To normalize (standardize) the data the following formula is used.

$$X_{\text{scaled}} = \frac{X - \mu}{\sigma} \quad (5.3)$$

Where X is original feature value, μ is mean of the feature and σ is the standard deviation of the feature.

3. **Classification Models:** As discussed above, the following two classifiers were implemented in our proposed model.

(a) **Random Forests (RF):** In this study Random Forest (RF), a classical machine learning algorithm based on combining multiple decision trees (a forest), using bootstrap aggregation (bagging) to improve robustness and generalization, was employed as a feature-based machine learning approach for fetal movement detection. Each tree is trained on random samples and features, and the final prediction is obtained by majority voting:

$$\hat{y} = \text{mode}\{h_1(x), h_2(x), \dots, h_T(x)\} \quad (5.4)$$

Where T is the total decision trees and $h_t(x)$ denotes the prediction of "t"-th decision tree.

The signals from accelerometer sensors were segmented using sliding window, statistical features were then extracted from each window, features were then normalized using standard scaling, SMOTE was implemented to handle class imbalance, then the RF model was trained on the balanced feature set and predictions were evaluated using accuracy, precision, recall, and F1-score.

(b) **Bidirectional Long Short-Term Memory (BiLSTM):**

To acquire the changing patterns of fetal movements over time BiLSTM was used. The LSTM networks are a type of recurrent neural network which works on learning patterns over long periods of time in sequential data form, each LSTM cell consists of three main gates; forget, input and output. BiLSTM is a neural network type that processes sequential data in both forward, and Backward direction. It learns patterns from both past and future contexts and improves performance.

$$h_t^{\text{bi}} = \left[\vec{h}_t ; \overleftarrow{h}_t \right] \quad (5.5)$$

Where \vec{h}_t and \overleftarrow{h}_t are forward and backward hidden states and ";" represents concatenation. This allows the network to predict small fetal movements that are contextually dependent on signal patterns that appear before and those that appear after. For classification, a sigmoid activation function was used in the final layer, and the network was trained using the binary cross-entropy that shows how the network learns to minimize error:

$$L = -\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (5.6)$$

where y_i is the true label (0 or 1), \hat{y}_i is the predicted probability, and N is the total number of samples.

The BiLSTM was implemented with two BiLSTM layers along with dropout and dense layers to prevent overfitting and improve generalization. During the training early stopping strat-

egy based on validation loss was used so that the model would stop at the best points. The model learns both short-term fluctuations and long-term temporal patterns in fetal movement making it suitable for classifying tasks on time series classification data.

5.11 Fetal Heart Rate (FHR) Detection Model

The model used for fetal heart rate (FHR) detection in this work is a stand-alone AI-based pipeline that detects fetal cardiac activity and assesses the fetal heart rate (FHR) from 500-Hz sampled four-channel abdominal ECG signals. The model is trained using 70% of the data set and 30% is kept aside for independent testing. To enhance the model's robustness and avoid false alarms, synthetic noise segments were added to the training data to train the model to distinguish between true fetal cardiac activity segments and noise-only segments.

1. Signal Acquisition and Preprocessing Pipeline:

For detecting the FHR, abdominal ECGs are recorded using four channels with a sampling frequency of 500 Hz. The signals undergo a robust preprocessing pipeline to improve signal quality, remove noise and ensure stable features for machine learning algorithms.

The signals are interpolated to replace invalid or missing samples and ensure continuity in the signal to prevent any discontinuities in the extracted temporal features. Next, DC offset is applied to remove constant offsets from the ECG signals.

To remove electrical noise, a 50 Hz notch filter is applied to filter out the main component of the power line, and harmonics, if present. The

signal is then bandpass filtered with cut-offs between 0.7 Hz and 90 Hz, to remove extremely low-frequency drift in the baseline as well as high-frequency interference.

Additional suppression of baseline wander (mainly due to maternal breathing, motion, and electrodes slipping) is achieved by applying a rolling median filter. One-dimensional (1-D) Kalman filtering is used to enhance signal smoothness and eliminate random noise from the signal. The signal is then z-score normalized using the median and median absolute deviation (MAD) for robustness. This approach is well suited for biomedical signals, as it down weights the effect of outliers, while enabling numerical stability. In summary, this preprocessing strategy results in cleaner, stable and physiologically relevant ECG windows that enhance the features extracted, classifications, and regression of FHR.

2. Windowing Strategy and Feature Extraction:

The cleaned ECGs are windowed into 2-second stride overlapping windows of 12 seconds. This overlapping window strategy allows temporal continuity while capturing subtle changes in the fetal heart. For each window, a set of statistical time-domain features are extracted, such as mean, standard deviation, median, interquartile range, percentiles, peak-to-peak amplitude, root mean square (RMS), mean absolute value, maximum absolute value, skewness, kurtosis, derivative RMS, and zero-crossing rate. These include measures of amplitude and dynamics.

Spectral information is captured through bandpower analysis in the fetal heart rate (FHR) and QRS bands. These features aim to capture distribution of spectral power along with increased separability

between fetal activity and noise. Cardiac periodicity is measured using power spectral density (PSD) and autocorrelation features. These features are fetal BPMs, ratio of spectral peaks and autocorrelation coefficient, which jointly reflect rhythm stability of the ECG signal.

3. FHR Detection Framework:

The model is a two-stage system intended to enhance the classification performance and minimise false positives.

- **Stage 1: FHR Validity Classifier** Stage 1 includes an FHR validity classifier to determine if an ECG window contains valid FHR or not. It categorises whether a certain window of ECG is valid (contains the fetal heartbeat) or invalid (noise or non-detectable). It is trained with 700 decision trees, minimal leaf nodes of two samples, maximum features of 0.65, and class weight balancing (valid and non-valid FHR samples) to overcome the class imbalance in the dataset.

- **Stage 2: FHR Estimate (Regression)**

In the second stage, if the first stage detects fetal cardiac activity, it estimates fetal heart rate (BPM). This regression stack contains a SimpleImputer for handling missing data, RobustScaler for scaling the features and a distance-weighted K-Nearest Neighbors (KNN) regressor with five neighbors.

4. Noise Rejection Mechanism:

A key innovation of this FHR estimation system is the noise rejection approach. As regression models always generate real-valued outputs, an additional classification stage is used to avoid false FHR estimation on window segments containing only noise.

If the confidence of the classification is low or the fetus is inactive, the system cancels the regression model response and returns a null value instead of unreliable BPM. This guarantees greater robustness under real human physiological conditions, where composite signals may include motion artifacts, bad lead contact or significant maternal ECG interference.

5. Model Correction Strategy:

To maintain physiological fluency, a conservative correction is used. beats per minute (BPM) predicted by regression is considered as the primary estimate, while spectral estimates of BPM are used only as a corrective measure. This approach avoids unrealistically high fetal heart rate estimates resulting from spectral peaks that can be generated by noise and harmonic effects. Thus, the spectral estimates are utilized for small corrections in the final estimate, keeping the result within the range of physiologically acceptable estimates.

6. Training Strategy and Weak Supervision:

During the system training process, weak labels (i.e., no clinically labelled ground truth FHR data) are generated for the training process due to a lack of access to clinically labelled FHR data. But these predictions are not used at inference time. This approach allows the model to be independent during inference while being weakly supervised during learning to improve its ability to generalize.

7. Inference Pipeline Overview:

At test time, the model runs as a fully independent system. If the model cannot detect any fetal cardiac activity, it returns a null output instead of a false prediction. This makes it suitable for both clinical

and at-home monitoring where signal quality may be poor.

The overall pipeline and model overview are shown in Figures 5.11 and 5.12.

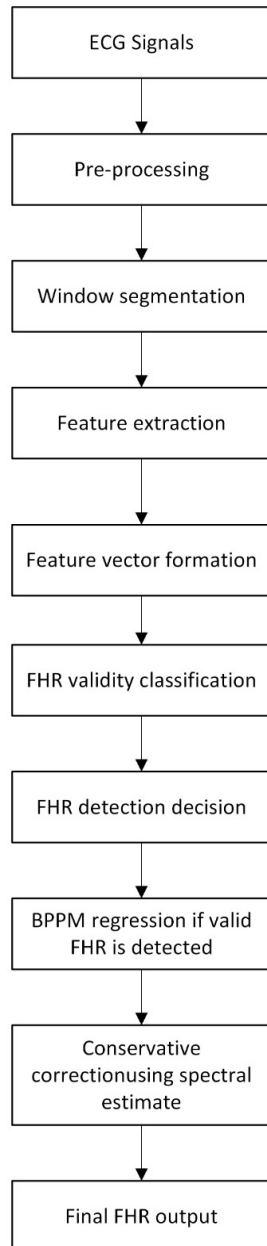


Figure 5.11: FHR Pipeline Overview

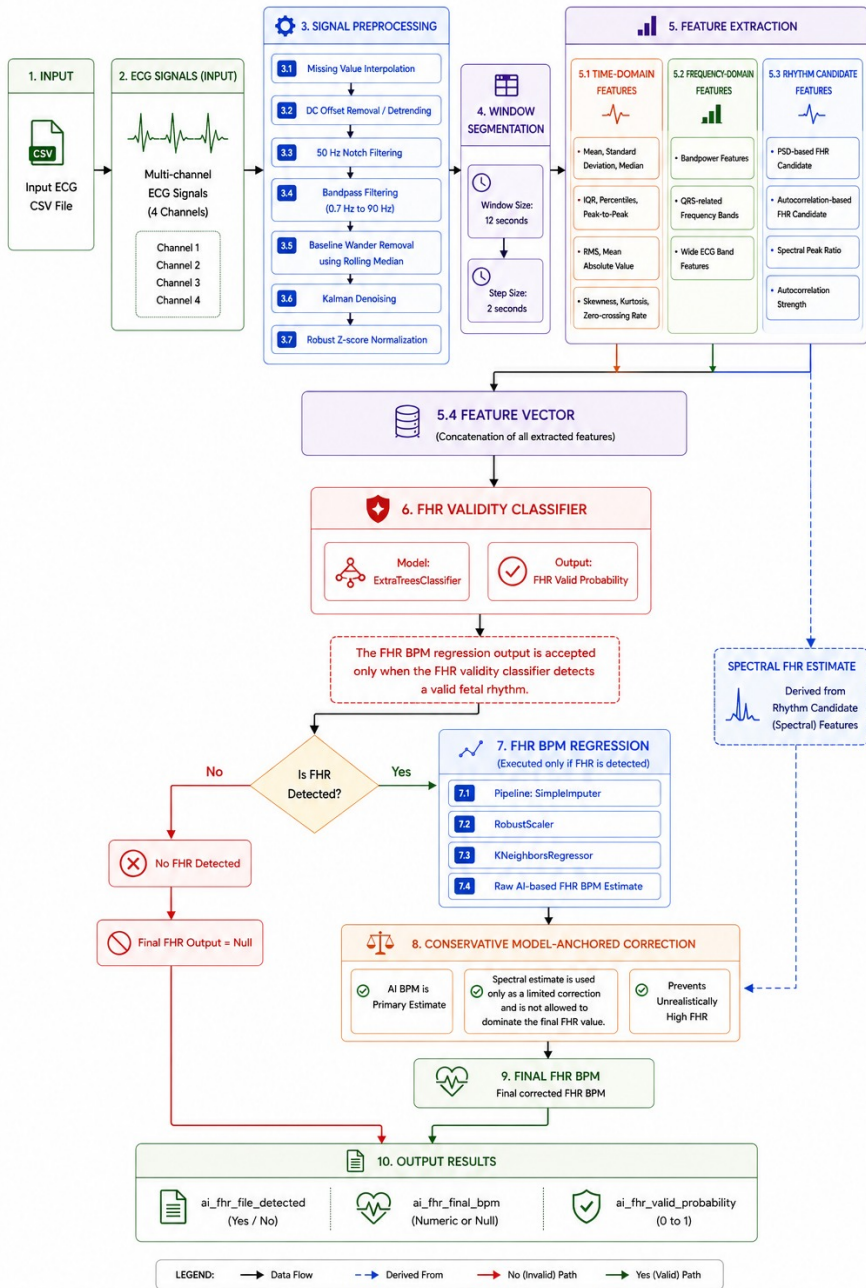


Figure 5.12: FHR Model Overview

Chapter 6

System Testing, Evaluation and Results

6.1 Training Strategy and Evaluation Metrics

The dataset was split into training and testing sets (80-20%) with stratification to ensure the same class distribution. The same training set was used to train both the RF and BiLSTM models with the BiLSTM also employing a validation split and early stopping. Performance was evaluated using accuracy, precision, recall, and F1-score with the F1-score being critical for balancing false positives and false negatives in foetal movement detection. To evaluate classifier performance across thresholds, ROC and Precision-Recall curves were also analyzed.

Evaluation Metrics:

The evaluation metrics is given in table 6.1.

Table 6.1: Fetal Heart Rate Evaluation Metrics

Metric	Formula
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
F1-score	$2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$

Where TP= True Positive, TN= True Negative, FP= False Positive, FN= False Negative.

Two classification models were used to assess the performance of the proposed fetal movement detection framework namely, the Random Forest (RF) and the Bidirectional Long Short-Term Memory (BiLSTM). An equivalent comparison was made between the two models by training and testing against the same segmented fetal movement windows based on our fetal movement dataset.

The overall performance of the Random Forest classifier was very good, as the accuracy was at 97 percent. It was very precise and recalls both classes with a precision of 99 percent No Movement and 94 percent Movement and a recall of 94 percent and 99 percent respectively. The respective F1-scores of 96% (No Movement) and 97% (Movement) engender the presence of a well-balanced classification with fewer false positives and false negatives.

On the other hand, the BiLSTM model had a low overall accuracy of 77%. It was also found to be reasonable to perform in Movement event detection (recall of 85%), but its precision and recall were weaker in both classes. The 75% (No Movement) and 78% (Movement) F1-scores imply that there is indeed a visible trade-off between sensitivity and specificity.

The reports for both the models are given in table 6.2 and 6.3.

Table 6.2: Random Forest Classification Report

Class	Precision	Recall	F1-score	Support
No Movement	0.99	0.94	0.96	5247
Movement	0.94	0.99	0.97	5247
Accuracy			0.97	10494

Table 6.3: BiLSTM Classification Report

Class	Precision	Recall	F1-score	Support
No Movement	0.82	0.70	0.75	5247
Movement	0.73	0.84	0.79	5247
Accuracy			0.77	10494

The confusion matrices further show the performance of RF as better than the BiLSTM model. The reduced number of false negatives in Random Forest results is particularly important for fetal movement detection, where missed movement events may have clinical implications.

The confusion metrics for both the models are shown in figure 6.1 and 6.2.

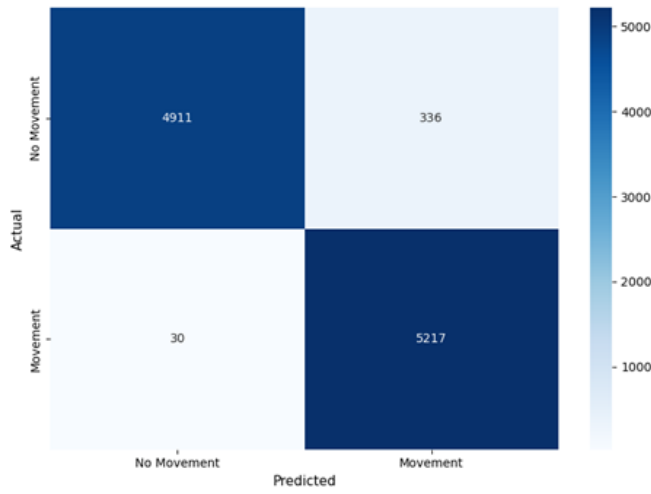


Figure 6.1: Random Forest - Confusion Matrix

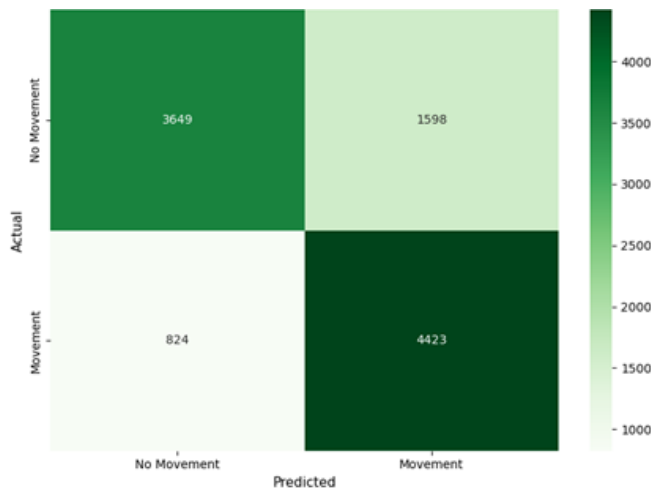


Figure 6.2: BiLSTM - Confusion Matrix

Similarly, the Random Forest performed better than the BiLSTM as shown in their respective Precision-Recall curves and ROC curves in figures (6.3, 6.4, 6.5, 6.6), and a comparison between Random Forest and BiLSTM shows that overall, the RF model performed better than the BiLSTM model as shown in figure 6.7.

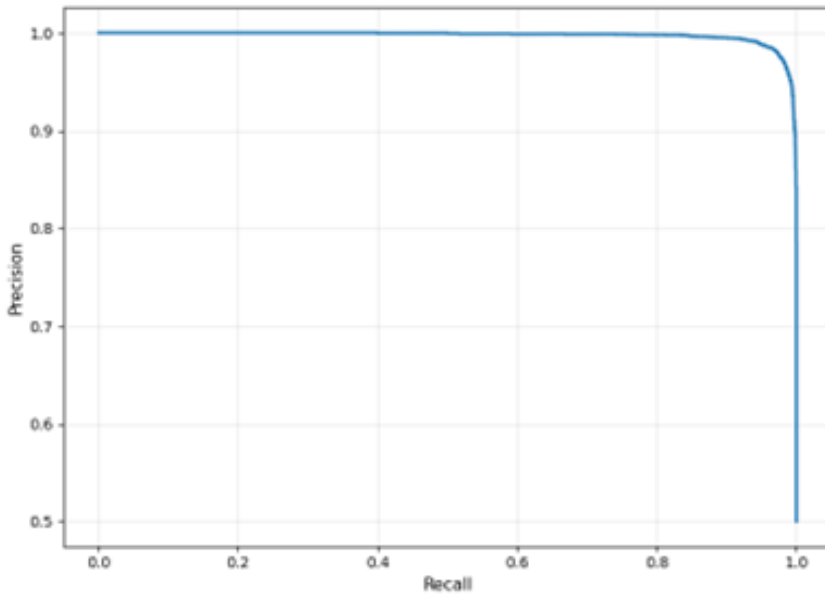


Figure 6.3: Random Forest - Precision Recall Curve

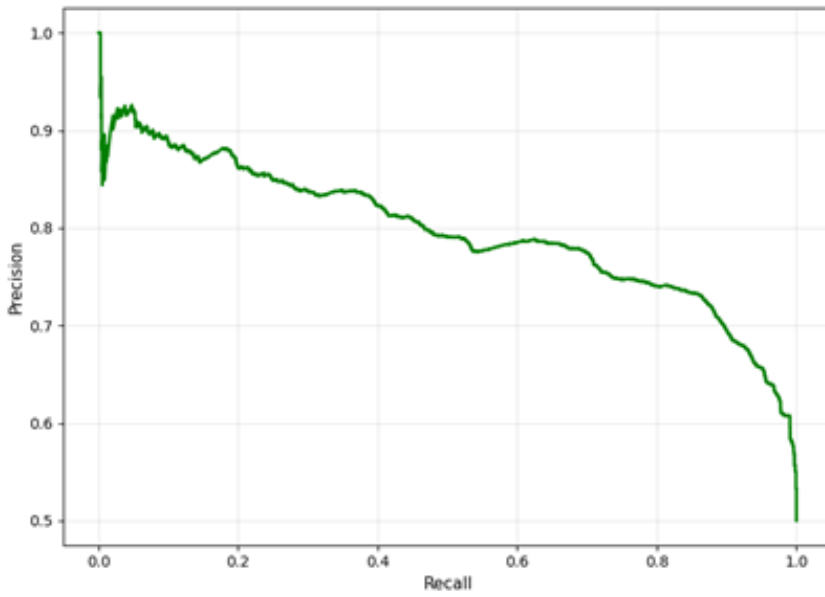


Figure 6.4: BiLSTM - Precision Recall Curve

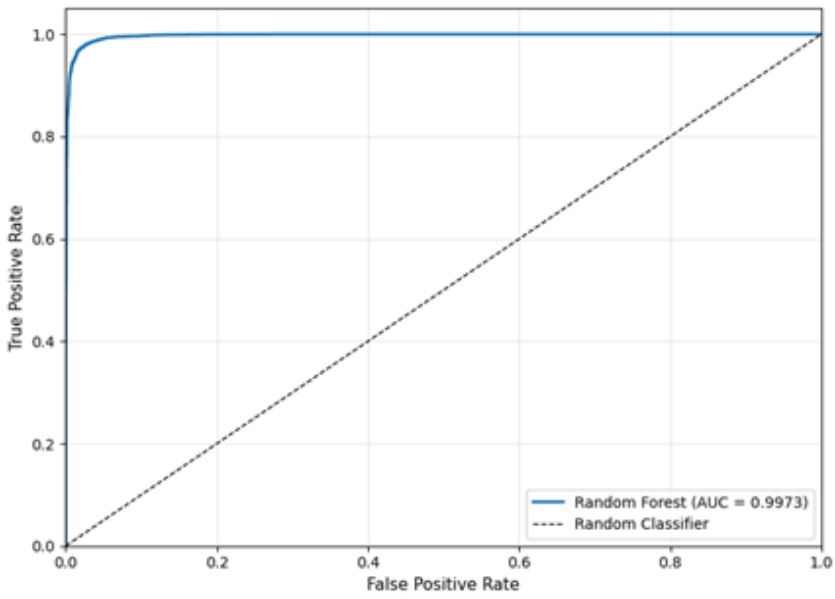


Figure 6.5: Random Forest - ROC Curve

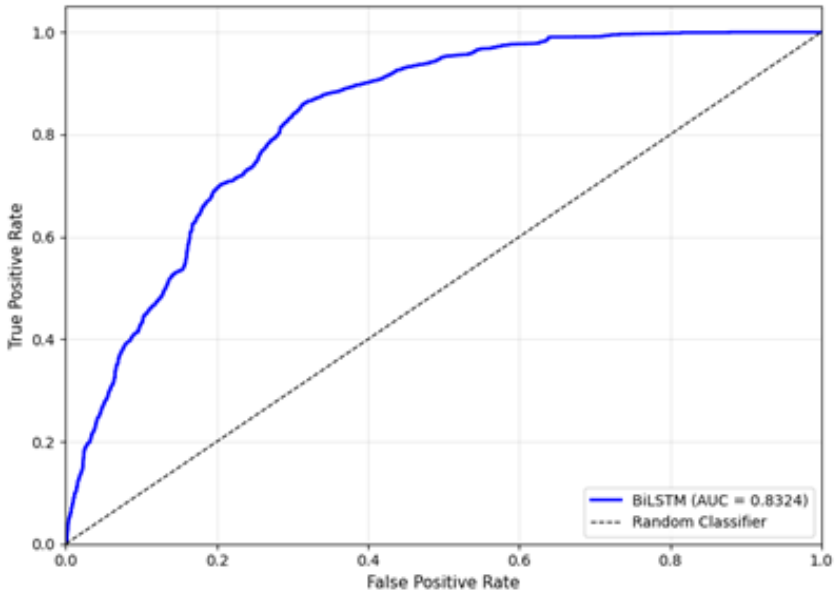


Figure 6.6: BiLSTM - ROC Curve

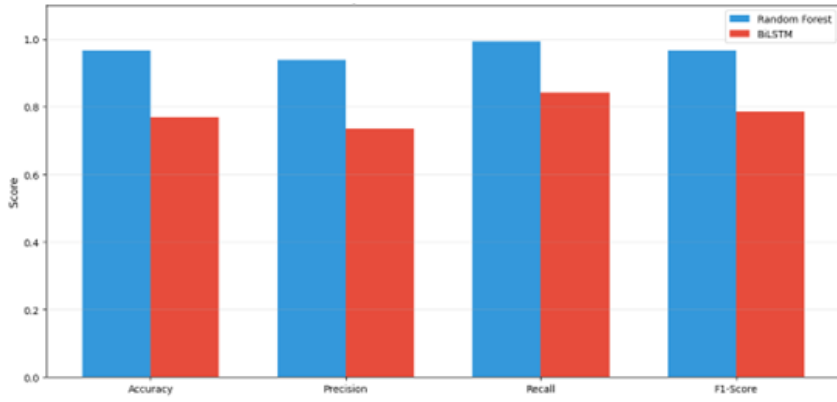


Figure 6.7: Model Comparison - Random Forest vs BiLSTM

6.2 Evaluation and Validation Approach for Fetal Heart Rate Model

Data and Approach to Evaluation

The proposed model for the detection of the fetal heart rate (FHR) was evaluated using a file-based approach. The abdominal ECG recordings were multi-channel CSV files, sampled at 500 Hz. About 70% of the recordings were selected for training, with the remaining 30% held out for independent testing. This separation was done at the file level, rather than at the window level, in order to avoid leakage. Including random windows from the same recording for training and testing could result in overly high performance due to temporal correlations within the recording. Thus, the file level split avoided overlap in testing, allowing to better assess model performance on new data, as it would be used in practice.

Weak Labeling and Training Strategy

The lack of access to clinically-annotated ground-truth FHR data meant that the model was trained with weak labels using a signal processing-based teacher model. During training, a dual-task approach was adopted to address two main challenges: first, to classify the ECG as containing a valid fetal cardiac rhythm or not, and second, to predict the fetal heart rate in beats per minute (BPM) given the presence of a valid fetal cardiac rhythm.

To enhance the resilience of the model, it was also trained using synthetic noise signals. The noise window training set contained examples of various forms of disturbance that may occur in real world signals including random noise, flat lines, baseline offset, spike artifacts, dropouts and

powerline-like interference. The noise patterns helped the model to differentiate between genuine fetal cardiac signals and non-informative or noisy intervals. This allowed the model to learn that it should not predict an FHR when the signal was not informative.

Testing Procedure

The model was tested on the held-out test set without relying on the teacher pipeline and in a single pass of the model. For testing, the ECG signals were initially pre-processed to improve the quality of the signals. Next, the signal was divided into 12 second segments with an overlap of 2 seconds to retain temporal information.

For each window, a rich set of features was extracted, including both time and frequency domain features as well as rhythm-based features. The model then made inferences in a two-stage manner. First, the validity classifier made an initial decision about the presence of fetal heart activity. Interpretation of no valid activity led to a "No FHR Detected" message, and no BPM value was reported. In the latter case, the regression model predicted the fetal heart rate, which was then conservatively corrected to account for possible overestimation due to harmonic or noise artifacts.

Evaluation Metrics

Both classification and regression metrics were used to evaluate the model. FHR detection was implemented as a binary classification problem with two classes, "FHR Detected" and "No FHR Detected". This involved using standard metrics such as accuracy, precision, recall and F1-score metrics.

The main outputs assessed were `ai_fhr_file_detected`, `ai_fhr_valid_probability` and `ai_fhr_final.bpm`. To assess the system's reliability, an all noise-only ECG file was included in the test to

confirm the system’s capacity to reject invalid files.

Evaluation and Analysis

The test results reveal the proposed model was successful in distinguishing fetal activity and in estimating fetal heart rate (FHR) from previously unseen ECG measurements. In the test ECG with a valid segment, the model detected the fetus and output the FHR as 147.46 BPM. However, when evaluated with the noise-only ECG, the model correctly ignored the input and the model did not output any FHR value, demonstrating its capability to handle invalid input data.

For the BPM prediction, we compared the model predicted FHR with the teacher reference. For the unseen test data, the AI prediction of the FHR value was 147.46 BPM while the teacher reference was 158.32 BPM. While there is a difference, the prediction is close and within a satisfactory range, suggesting the success of the proposed approach with weak supervision.

Future Work

Although this approach holds promise, proper evaluation is hampered by the lack of clinically verified FHR annotations. The weak labels (provided by the teacher) mean results are primarily a proof of technical validity. To better validate the approach, future research should include clinically confirmed ground truth labels such as cardiotocography (CTG), Doppler flow, or manually labelled fetal R-peaks.

Also, increasing the size of the dataset and improving the quality of the ECG signals by using advanced fetal ECG separation algorithms will improve the results. And model validation in different populations and clinical settings should be a priority of future work.

In conclusion, the evaluation framework proposed in this paper shows that the FHR detection model can function autonomously when inferring FHR, and discriminate between valid and invalid measurements to achieve reliable FHR estimates under adequate signals. The use of noise rejection algorithms and a two-step prediction approach greatly enhances the system's performance. Although more validation studies are needed for clinical application, these results provide a solid stepping-stone towards wearable non-invasive fetal monitoring. The Little Beats Web Interface FHR Results are given in figure 6.8.

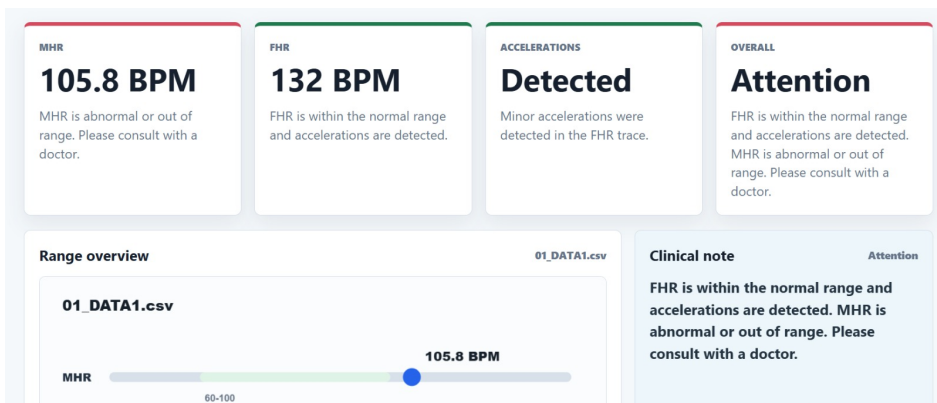


Figure 6.8: Little Beats - Web Interface FHR Results

In the hospital environment, data from subjects was collected using the proposed system. Following the collection of data from each participant, doctors working in the hospital conducted a cardiotocography assessment (CTG) of the participant to provide a benchmark measurement of the fetal heart rate (FHR). This is so that the proposed system could be compared against medical practice.

This measurement was compared with estimated FHR using the proposed model. The two readings were found to be highly correlated. For example, in one of the recorded instances the system's model estimated

a fetal heart rate of 132 beats per minute (bpm) while the clinical observation based on the CTG was 130-140 bpm as shown in figure 6.9. This suggests that the proposed method can successfully approximate clinically observed fetal heart rate measurements in practice.

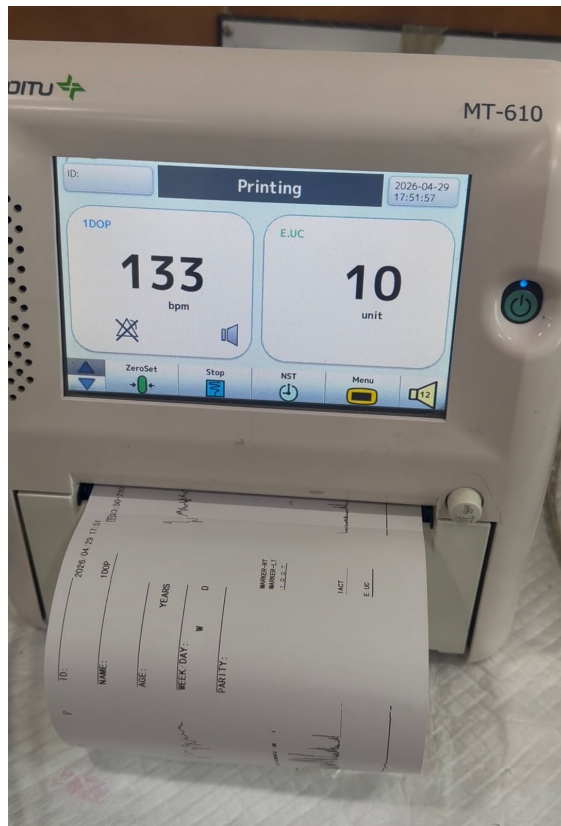


Figure 6.9: Cardiotocography (CTG) recording showing FHR

Chapter 7

Research Challenges and Observations

7.1 Research Challenges

There were a number of technical, ethical and operational considerations behind developing and implementing the proposed fetal monitoring system. The challenges faced are outlined below:

1. Ethics approval and regulatory issues

- Firstly, ethical approval for experiments with human subjects was a complex process. The system was explained in several hospitals, each one was asked to complete specific ethical and compliance related forms documenting all aspects of the system which caused the delay in data collection phase.
- The process involved following medical research guidelines, with a focus on participants safety, privacy and confidentiality. This was a long process and involved regular discussions with administrators and ethics committees.

2. Recruiting and Obtaining Consent

- Recruiting participants and obtaining informed consent was a major challenge. Getting participants to agree to wear the monitoring belt and to enroll in the study was challenging.
- Participants were concerned about safety, comfort and privacy of data. It took skill and stamina to counter these fears, to reassure and encourage voluntary consent. Obtaining informed consent had to be done carefully to ensure participants understood what the aim of the study was, and how it would be carried out.

3. Data Acquisition Challenges

- Acquiring quality physiological data from actual pregnant women was challenging. Different participants states, motion artifacts and improper placement of electrodes interfered with data quality.
- Further complicating matters, participants access was sporadic. At times, considerable time was wasted in the hospital before recording required data due to lack of appropriate participants. The need to juggle hospital visits and coursework was also a challenge.

4. Sampling Rate and Technical Specifications

- Early on in the research project, the system was not able to acquire data at the required speed. Various methods of software optimization to boost the sampling frequency were explored, but the desired sampling rate could not be obtained via software alone.
- As a result, hardware changes were made, such as altering the data acquisition system. While the required sampling rate was ultimately met, this came at the cost of lost data, with around 40% of the fetal heart rate (FHR) data lost due to sampling rate and noise issues.

5. Variable Dataset and Sample Size

- The data collected during the project was highly variable, reflecting variations in patient and fetal physiology, position, and surroundings.

- It was difficult to achieve a large and varied dataset, as the collection of data was reliant on patient co-operation. This reduced the reliability and size of the dataset.

6. Interdisciplinary Coordination

- Being an interdisciplinary project between engineering and medicine, it was important to work with doctors.
- Interactions with doctors were necessary to ensure that the system was safe and acceptable to doctors. Design considerations were also impacted by requirements of the medical practice.

7. System Design Constraints

- Creating a solution which is safe, cheap and efficient can be challenging. Compromises needed to be made between efficiency, cost and user-friendliness.
- Designing a non-invasive and safe device for both the mother and fetus was a critical design constraint for the system.

8. Time and Resource Management

- Managing academic and hospital-based work and data collection was challenging.
- Regular hospital visits, patient wait times and iterative development of the system demanded considerable time and effort. Time management skills were needed to juggle these activities.

7.2 Medical Health Expert's Observations

The medical community has recommended that doctors and nurses keep track of Maternal Heart Rate (MHR) as well as Fetal Heart Rate (FHR)

for better understanding of fetal well being.

Furthermore, doctors stressed FHR should be observed carefully. Rather, it's important to evaluate accelerations and decelerations:

- Decelerations could mean that the heart rate is abnormal.
- Too many or no accelerations may also be abnormal.
- Optimal is occasional and mild accelerations.

Moreover, all fetal postures prescribed in this system are in line with the guidelines from doctors.

7.3 Subject (Participant) Observations

The system was also very comfortable when tested on patients. All subjects reported that they had experienced no issues such as:

- Itching
- Irritation
- Discomfort of any kind

The system was perceived to be better than most current alternatives. They also found it comfortable and convenient to use. After their successful experience, the volunteers recommended that the system should be made available in the market as it would be easier for pregnant women to monitor their fetus well-being.

Chapter 8

Conclusion

The aim of this study was to design and develop a non-invasive and wearable system that could extract information about the well-being status of fetus through fetal movement (FM) and fetal heart rate (FHR) monitoring, and this was successfully achieved. The multimodal sensing, signal processing, and machine learning-based framework implemented in this study offers a holistic and viable solution for wearable and continuous monitoring of fetal well-being, especially in remote and resource-limited environments such as the home.

Regarding the analysis of fetal movement, the results show that the system can effectively classify different types of fetal movements through data collected from the prototype system. The performance comparison between machine learning models showed that the Random Forest (RF) classifier achieved much better accuracy than the Bidirectional Long Short-Term Memory (BiLSTM) model. The BiLSTM model has an accuracy of 77% while the RF model has an accuracy of 97%. This can be explained by the amount and complexity of the data. Traditional machine learning algorithms such as Random Forest are well suited to datasets that are smaller in size and well structured, whereas deep learning models such as BiLSTM are usually robust for large-scale datasets. Although BiLSTM performed poorly, it was able to learn the temporal nature of the signal, and it may be improved with more data in the future. In summary, the fetal movement module shows that it's possible to detect and classify fetal activity by way of wearable accelerometers.

Apart from movement detection and classification, a reliable fetal heart rate (FHR) detection and measurement method was also designed using four-channel abdominal ECGs (500 Hz sampling). The weak amplitude of fetal ECG signals and the overwhelming presence of maternal ECG, motion noise, and environmental noise make it essential to design this model

as a noise-aware dynamic multi-staged model, rather than a traditional regression model. The approach involves a two-stage model design where the FHR validity is determined followed by the estimation of the BPM. This approach allows the FHR signal to be reported only in the case of a valid fetal cardiac signal, preventing false detections of FHR in invalid signal conditions.

An extensive processing chain was developed to improve the input ECG before extracting features. This involved imputation of missing values, detrending to eliminate DC drift, notch filtering to eliminate powerline interference, bandpass filtering to preserve useful ECG components, baseline wander removal, Kalman filter denoising, and robust normalization. This enhanced signal quality and facilitated feature extraction. This used time, frequency and rhythm features extracted from short-time windows of ECG signals to represent the fetal heart activity.

For increased robustness, artificial noise samples were generated and added to the training data, allowing the model to learn how to reject signals containing no fetal activity. This training approach proved quite effective, as the model during testing, correctly ignored the noise-only samples and did not produce erroneous FHR estimates for such inputs. Furthermore, a model-first approach to correction was incorporated, where the regression estimate was used as the primary estimate and spectral features used to make minor adjustments. This strategy reduced the likelihood of FHR overestimation due to spectral peaks related to harmonics and noise.

The model was tested with a train-test split, using 70% of the data for modelling and 30% for testing. The findings suggest that the system is able to correctly detect the presence of a fetal heartbeat and estimate FHR from a previously unseen set of data. But since there were no ground-truth annotations, weak labels automated via signal-processing were used. As

a result, the present results show the technical feasibility instead of the complete clinical validation.

In summary, the proposed wearable device that simultaneously classifies fetal movements and estimates the fetal heart rate is a promising advance towards continuous, non-invasive fetal monitoring. The developed system overcomes several shortcomings of current techniques by providing an economical, convenient, and non-clinical setting solution that is free from radiation and requires no special equipment. Crucially, the system's noise rejection and multimodal sensing capabilities improve its ability to operate in real-world settings.

The next research steps should be to increase the size of the database, to include clinically approved labels, to improve the technique of separating the fetal ECG, and to test the system on a varied population. Ending up with a system that continues to be refined and tested clinically, the proposed strategy will likely play an important role in the area of affordable solutions for maternal health, especially in resource poor settings, as well as potentially helping to detect fetal distress early in pregnancy by providing continuous monitoring.

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Appendix A

User Manual

Appendices are used to present supporting information that is relevant to the thesis. This information is vital to understand the system, but is separated so that the thesis is not obstructed.

- Appendices are labeled in alphabetical order (Appendix A, B, etc).
- Tables, figures, and references in appendices should be numbered and cited the same way as in the chapters.
- Appendices should have a title, which should be listed in the table of contents.

Appendix A: User Manual for Little Beats Fetal Monitoring Belt

A.1 Introduction

This user manual includes comprehensive instructions for proper safe use of the *Little Beats* wearable fetal monitoring belt. The device is meant to monitor and provide information about the fetal movement (FM) and fetal heart rate (FHR) through non-invasive sensing and the belt is meant to be worn by mothers.

The system is to be used for home or non-clinical fetal monitoring in the third trimester. It's based on passive sensing methods, which means it does not use radiation nor ultrasound, leading to being safe for mother and fetus even for long hours of use.

A.2 System Components

The system is comprised of the following components shown in table A.1.

Table A.1: Hardware and System Components of the Proposed Fetal Monitoring System

Component	Description
Wearable Belt	A flexible belt structure designed to hold all sensors securely on the maternal abdomen for continuous fetal monitoring.
ADXL345 Sensors	Three-axis accelerometers used to detect fetal movements through mechanical vibrations on the abdomen.
Ag/AgCl Electrodes	Disposable gel-based electrodes used for acquiring fetal electrocardiography (ECG) signals from the maternal abdomen.
AD8232 Modules	Biopotential analog front-end used for amplifying and conditioning weak ECG signals before digitization.
ADS1115 ADCs	High-resolution analog-to-digital converters used to convert analog physiological signals into digital form for processing.
ESP32 Microcontroller	Central processing unit of the system responsible for data acquisition, preprocessing, and wireless communication.
USB Cable	Provides both power supply and serial communication between the ESP32 and the laptop/PC.
Laptop/PC	Used for real-time data visualization, signal analysis, and storage of recorded physiological data.

A.3 System Requirements

The following system is required: A laptop or computer with a USB port, arduino IDE and Python installed. A secure USB power supply and accelerometers and electrodes.

A.4 Safety Precautions

- It is a non-invasive system and safe to use for extended wear periods when following instructions.

- Make sure skin is dry and free of contamination to prevent skin irritation. Never use the device if any part is damaged.
- Keep still while being monitored to enhance quality.
- Current version of this project is only for research and monitoring and not for medical diagnosis.

A.5 Wearing Instructions

1. Place the belt around the abdomen to fit snugly.
2. Position the sensors in line with the guidelines.
3. Place electrodes in a circular pattern.
4. Make sure the belt is not too tight or uncomfortable.

A.6 Sensor Placement Guidelines

It's important to place the sensors correctly to record signals:

Accelerometers Placement

The accelerometers placement is shown in table A.1.

Table A.2: Placement of Accelerometer Sensors on the Maternal Abdomen

Sensor	Position Relative to Navel
Sensor 1	5 cm above the navel
Sensor 2	7 cm below the navel
Sensor 3	3 cm above and 5 cm to the right of the navel
Sensor 4	3 cm above and 5 cm to the left of the navel

Electrodes Placement

The electrodes placement is shown in table A.2.

Table A.3: Placement of ECG Electrodes for Fetal Signal Acquisition

Electrode	Position Relative to Navel / Body
Electrode 1	7 cm above the navel
Electrode 2	7 cm below the navel
Electrode 3	7 cm to the right of the navel
Electrode 4	7 cm to the left of the navel
Electrode 5	5 cm above and 5 cm to the right of the navel
Electrode 6	5 cm above and 5 cm to the left of the navel
Electrode 7	5 cm below and 5 cm to the right of the navel
Electrode 8	5 cm below and 5 cm to the left of the navel
Electrode 9 (Reference)	Placed on the thigh (common reference electrode)

A.7 Operating Procedure

1. Plug the USB cable from the ESP32 microcontroller to the laptop.
2. Turn on the system.
3. Start the data acquisition program.
4. Start to monitor and record the signals.
5. View fetal movements and heart rate.

A.8 Interpreting System Outputs

The system delivers the outputs:

- Signals of fetal movement (FM) activity
- Fetal heart rate (FHR) in beats per minute (BPM)
- Graphical view of the physiological signals in real time

When a valid fetal ECG is not detected, the system will display:

No FHR Detected

to avoid misinterpretation of noise as signals.

A.9 Troubleshooting Guide

Table A.4: Troubleshooting Guide for the Proposed System

Problem	Probable Source	Solution
Noisy signal	Movement or improper sensor placement	Minimize body movements and readjust the sensors
Noisy signal	Poor contact with electrodes	Securely attach electrodes
No output	USB/software issue	Reconnect and restart the software
Inaccurate readings	Incorrect sensor placement	Ensure proper sensor placement

A.10 Maintenance Guidelines

- Change electrodes for every application.
- Keep it in a dry and clean place.
- Be careful not to pull or strain sensor cables.
- Always check connections.

A.11 Future Improvements

Future releases of the system could include:

- Integration with mobile apps for monitoring.
- Bluetooth wireless data transfer.

- Integration with tele-medicine for remote monitoring.