A NOVEL APPROACH FOR DETECTION OF FETAL HEALTH USING CARDIOTOCOGRAPHY AND DEEP LEARNING MODELS

MINI PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

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ABSTRACT

Cardiotocography provides information on fetal heart rate and uterine shrinkages, which is highly helpful in determining if the foetus is normal, questionable, or pathologic, it is used to measure the fetal heart rate in the foetus throughout pregnancy to assure physical health. Due to human error, several cardiotocography measures make incorrect inferences and predictions. The time required to read the cardiotocography measurements in the conventional manner is prone to many human errors. It is crucial to monitor the foetus's status at various stages and to provide it with the right medication for its wellbeing. It records the fetal heart rate and uterine contraction continuously, where obstetricians evaluate health of foetus. Excellent results have been obtained by training deep learning models for intelligent fetal monitoring using CTG records that are identically distributed and extensively annotated. However, the collecting and annotation of CTG signals necessitates specialized personnel and a significant amount of time for the construction of these training sets. Multi center studies have been shown in the past to enhance model performance. However, because datasets differ in their distribution, models trained on cross-domain data could not transfer effectively to target domains. In order to intelligently analyze antenatal CTG signals, this paper conducted a multi-center investigation using Deep Semi-Supervised Domain Adaptation (DSSDA). Cardiotocography is a clinical procedure used to assess and track the degree of fetal discomfort. Despite the fact that CTG is the most often used tool for monitoring fetal health, the presence of positive false result towards interpretations visually significantly increases the risk of unneeded surgery or postpones intervention. In the current work, the notion of learning to transfer trained ResNet 50 of deep neural network model and frequency time representation of FHR signal that is used to generalize Morse wavelet which constructs a unique computer-aided fetal distress diagnostic model. Just the FHR signal is isolated and is pre-processed to eliminate noise from the data which is acquired from the exclusive open access CTU-UHB data repository.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

CTG	Cardiotocography
AI	Artificial Intelligence
SVM	Support Vector Machine
CNN	Convolution Neural Network
KNN	K-Nearest Neighbour
FHR	Fetal Heart Rate

CHAPTER 1
INTRODUCTION

1.1 GENERAL

A prenatal technique called cardiotocography (CTG) tracks the heart rate of the foetus as well as uterine contractions. It offers important details regarding the health of the foetus throughout pregnancy and childbirth. Medical professionals have historically examined CTG tracings visually, but this method can be laborious and subjective. A viable approach to raising the precision and effectiveness of CTG analysis is machine learning.

1.2 OBJECTIVE

The goal of this work is to create a trustworthy AI system for CTG picture analysis. This technology will help physicians evaluate the health of the foetus by automatically classifying CTG tracings as normal or abnormal.

1.3 EXISTING SYSTEM

Currently, due to subjectivity and time restrictions, obstetricians interpret CTG tracings visually, which might lead to errors. Furthermore, it's possible that current automated CTG analysis technologies are ineffective at precisely anticipating possible fetal distress.

1.4 PROPOSED SYSTEM

This research suggests a brand-new method for CTG image interpretation that makes use of machine learning and image processing tools. The fetal heart rate signal that was taken from the CTG picture is the main focus of the system. The system readies the data for classification using a Support Vector Machine (SVM) algorithm by executing a sequence of preprocessing operations, feature extraction, and selection. The goal of this strategy is to create a CTG analysis system that is more dependable and accurate.

CHAPTER 2
LITERATURE SURVEY

In [1] The paucity of clustering approaches in medical imaging literature as compared to natural imaging illustrates how little consideration this strategy receives in the field. By altering the Deep-Cluster architecture, Kartetal utilized clustering to cardiac magnetic resonance imaging and produced high-performance outcomes. When it comes to magnetic resonance imaging (MRI) image clustering, this method has shown good results. Nonetheless, the issue is well defined, and compared to other medical applications, particularly imaging ultrasound, the image quality is noticeably better. Dadounetal used Huangetal's concept of grouping abdominal organ ultrasound pictures for multilabel classification as task pretext. Yuetal refined classification on CNN that was trained previously on Image Net in order to identify the fetal standard plane for the image classification task. The technique was evaluated on 2418 images, and it achieved under an area of receiver operating characteristic curve (AUC), accuracy, precision, recall, and F1 score. In a different study, Quetal employed a classification for CNN that automatically recognize standard planes of fetal in 19,140 photos, achieving 93%, 93%, 92%, and 93% of accuracy, precision, and recall, respectively.

In [2] The goal of this research is to create a reliable and accurate artificial intelligence system that can analyze, interpret, and categorize CTG print images as normal or abnormal. As a result, a novel method is created for the digitization of CTG material as well as the division of the digitized signal into classes for normal and abnormal CTG signals. Machine learning is used to classify the CTG signals, while image processing is used for the CTG paper digitization stage. The scanned CTG paper is the system's input, and the class label is its output. It is important to note that our created technique only uses the FHR signal, hence in order to obtain the FHR signal portion of the scanned CTG paper, human cropping is required. For the purpose of detecting abnormalities in CTG printing papers, a two-stage method was suggested. These phases involved separating the signal from the printed CTG sheets and categorizing it into classes that corresponded to normal and pathological behaviour. The printed CTG papers, notably the FHR section, served as the input for the signal extraction stage. Furthermore, the recovered FHR signal served as the input for the signal categorization section. While the initial section comprises diverse image processing algorithms, the subsequent section relied on machine learning techniques, including feature extraction and feature classification.

In [3] Monitoring and decision-making for the well-being of the foetus are the goals of fetal medicine. Cardiotocography (CTG) is a diagnostic procedure used before to or during childbirth that uses Doppler ultrasonography and toco sensors to simultaneously monitor the uterus and the foetus. This allows for the identification of fetal neurological or cardiovascular risk factors or conditions. Heart rate is an important indicator for studying the cardiovascular system as well as the autonomic nervous system's impact on the circadian rhythms of the body. As a result, the literature is continuously presenting the development of various methodologies for computerized diagnostic systems. There are numerous methods for keeping an eye on the FHR. Everyone has benefits and cons. While accurate and reliable, the fetal scalp ECG is an intrusive procedure approach (and it's only accessible upon 'crowning'). Further Phonocardiography (PCG) has been utilized recently as a straightforward and trustworthy FHR detector based on the capture of The Hilbert Transform (HT) can be used to hear the heartbeat be applied to efficient noise reduction and real-time frequency detection. Using HT, ECG instantaneous energy has also taken into account for segmenting cardiac sounds.

In [4] Cardiotocograms simultaneously collect data from many monitoring techniques, such as fetal heart signals, mother uterine contraction pressure, and fetal movements within the womb. This information is crucial for evaluating the health of the foetus. By examining CTG data, potential future risks to the foetus can be avoided. The clinical CTG test is easy to use and reasonably priced, and it offers information about the developing baby's health. An antepartum CTG test is frequently used to track fetal well-being, starting from the pregnancy period of 28th, also known as the seventh month. In the case that fetal growth anomalies are detected, the results of this test can assist obstetricians in creating treatment plans. Actually, the CTG test evaluates the health of the foetus by determining whether or not its tissues are getting adequate oxygen, as well as by looking for indications of hypoxia or acidosis. These days, fetal heart rate patterns and uterine activity are among the features that obstetricians examine in order to interpret CTG. The interpretation is still arbitrary and vulnerable to inter-observer variation even when employing standardized methods like NIP and STV. Due to this intricacy and time restrictions, it may be possible to overlook minute indications of fetal discomfort. To overcome these constraints, the incorporation of machine learning models is suggested in this study. ML models greatly increases accuracy and efficiency of the foetus health, resulting in early detection of fetal health and balance the outcomes of pregnancy. This can be achieved examining data and uncovering the patterns that are hidden.

In [5] It may be possible to reduce the number of needless Caesarean sections brought on by suspected hypoxia and enhance the diagnosis of fetal hypoxia by creating new or better techniques for fECG monitoring. The primary goal of current research is to create an NI-fECG-based system that can perform analysis in terms of morphological akin to NI-STAN. The research suggested technique which could accomplish this goal with optimization. Finding appropriate methods for quality extraction and clinical feasibility—which is related to performance with computing fair—is required to accomplish this. The early trials and in-depth research were used to pick ICA algorithm for first component of hybrid approaches. The discovery where the algorithm can extract two types of ECG signals: an aECG component that contains the fECG signal amplitude level as the mECG signal and a mECG component that contains only the mECG signal. Thus, an ICA algorithm is formed by preprocessing input of aECG signals used for adaptive algorithms. Two distinct adaptive algorithms receive the pre-processed mECG and aECG data as inputs. These adaptive algorithms are ANFIS and RLS.

In [6] The most serious causes of morbidity and mortality is intrauterine growth restriction, which is characterized by pathological suppression of the growth of fetal and the resulting fetus failure to reach full potential growth, which is only related to prenatal hypoxia and asphyxia. Approximately 5% of pregnancies result in IUGR. Fetal monitoring is therefore crucial for identifying dangerous problems in fetus and aiding in clinicians to make the decision. According to official data about pregnancies in US, the use of FHR monitoring has significantly increased in past decades: 48% laboring women in 2000, 65% in 2010, 80% in 2020, and 94 in 2022 were subjected to screening process. There are multiple technological methods available to measure FHR. Cardiotocography combines measurement of FHR using Doppler ultrasonography probe with pressure sensor-based detection of contractions in uterine, is the most widely utilized approach. Doppler ultrasonography senses the motions of the fetal heart, enabling the detection of heartbeat events. Throughout the screening procedure, the device records heart rate variations via a trace that it generates. Fetal electrocardiography (FECG), which is recorded using either internal or external electrodes depending on the gestational age, is an alternate method for recording FHR. In [7] In the field of adult cardiology, arrhythmia identification for classification using the ML and DL algorithms. Pediatric cardiology has high standards for the identification arrhythmia in fetal and cardiac activity of fetal. To comprehend the cardiac health of the fetus, accuracy of heart rate is detected essentially (Hon and Petrie, 1975). Numerous techniques have been put out in the literature to detect estimate the heart rate of fetal and retrieve fetal ECG in an effective manner. To extract fetal ECG from abdominal signal and estimate heart rate using R-R interval, the majority of conventional methods try to remove maternal ECG and the disturbances that are from the signal explicitly. Ferrara and withdraw, 1982 initial demonstration of the fetal ECG extraction problem made use of a traditional adaptive noise canceller. Adaptive filters work by minimizes MSE in relation to mother's ECG in order to determine the component present in abdominal signal of the mother. In our earlier work, we compared the use of different Least Mean Square algorithms to lower error in filters adaptively. Availability of at least one reference of mother's ECG is the main drawback of ANC.

In [8] Prenatal care has faced difficulties recently, with obstetric services becoming less available mostly because of a growing scarcity of obstetricians and gynecologists and higher-risk people who want to get pregnant.1,2 Expectant mothers may encounter challenges in accessing high-quality perinatal care due to the requirement for multiple clinic visits to collect fetal measurements and the growing challenge of obtaining professional perinatal care, particularly in remote areas. The current gold standard of care for external monitoring of a fetus during labor for non-stress tests and the contraction stress tests is cardiotocography (CTG).3. CTG can currently only be used by a medical expert since CTG Doppler sensors may need to be adjusted in response to fetal or maternal movement and must be positioned precisely for a strong signal.4 Furthermore, Doppler ultrasound—which actively injects energy into the tissue—is used by CTG to record signals from both the mother and the fetus.4 Additional limitations of CTG include its lesser value in high-BMI pregnant women, absence of automated analysis, and episodic measurement in the clinic or hospital.

In [9] Congenital LQTS is an uncommon hereditary cardiac channelopathy caused by an ion channel gene mutation that causes delayed ventricular repolarization of cardiac cells. LQTS was initially identified by Jervell and Lange-Nielsen in 1957. It is characterized by a T-wave irregularity, a longer QT interval, and increased QT dispersion in the ECG. There is a rare correlation between the prevalence, which is believed to be 1:2000, and congenital heart disease (CHD), albeit this link has only been reported in patients with structurally normal hearts. There is little agreement on the diagnostic criteria for LQTS in individuals with repaired CHD, and confounding electrocardiographic signs typical in CHD may mask the diagnosis and true incidence. There aren't many examples of LQTS linked to congenital heart disease (CHD), including those involving tricuspid atresia, Tetralogy of Fallot, VSD, patent ductus arteriosus, and ASD. The disease's initial manifestations, syncope, ventricular tachyarrhythmias (torsade de pointes), and sickle cell disease (SCD), can all occur in a wide range of clinical presentations. Since the symptoms in young children might be ill-defined, LQTS is commonly diagnosed in conjunction with specific bradycardias. At least 16 genes have at least hundreds of pathogenic mutations for LQTS discovered to date. As advised by current recommendations, a thorough genetic investigation is necessary to identify the aetiology in 80–85% of all diagnosed cases.

In [10] The technique of extracting knowledge (interesting patterns) from large datasets is known as data mining (DM), and it is currently receiving a lot of attention and attention as a leading analytical tool.1. Recently, information Numerous industries, including stock market analysis, banking, telecommunications, education, human resource management, supermarkets, health care management (HCM), and traffic management, use mining techniques. Classification and prediction are mostly used in data mining for study of current trends and future planning. A broader idea with several steps is data mining: The pre-processing stage of the data involves normalizing missing values, fixing missing labels, and reducing noise before applying various mining techniques such as clustering, association rule mining, and classification. The outcomes of implemented mining methods are assessed and interpreted.

In [11] The most frequent causes of neonatal morbidity and mortality is fetal hypoxia. A condition known as fetal hypoxia arises throughout pregnancy. The initial phase, known as hypoxemia, is characterized by a drop in the arterial circulation, but there is little impact on organ or cellular activities. The fetal's adaptive and compensation mechanisms kick in as the hypoxemia gets worse, enabling them to survive in this state for a few days or weeks without suffering any serious consequences [3]. If fetal blood's oxygen saturation is further lowered, peripheral tissues will start to show signs of its shortage, which will set off the anaerobic mechanism and cause hypoxia. The fetus won't suffer any long-term harm from this state for several hours. only employing aECG signals, extracting high-quality fECG data through adaptive filtering, and smoothing the resultant fECG signal while preserving its morphology to enable ST segment The primary advantage of this algorithm is analysis. Furthermore, the study's findings demonstrated that it is feasible to get the same precise fHR and ST analysis results as in the case of the invasive variant by using well-scanned non-invasive signals. Its fast-computing speed is an additional advantage that would enable real-time operating systems to use it.

In [12] One of the most crucial tools for identifying fetal pathologies early on is prenatal cardiac monitoring. The majority of the developed world currently uses electronic fetal cardiac monitoring to identify the mother's and the fetus's risk factors. Eliminating potential causes of fetal morbidity or even mortality is the primary objective. Obstetricians and pediatric cardiologists can give appropriate medications or take essential measures during delivery or after birth with the aid of early and more effective diagnosis of fetal anomalies. Fetal monitoring is primarily used to detect intrauterine hypoxic infection early on, allowing the doctor to intervene promptly and prevent processing of signal methods that separates fetal ECG signals from the combination noisy recordings. Quality fetal ECG signal can be greatly impacted by movement artifacts, uterine contractions, and noise from the mother's ECG. To improve fetal ECG extraction, more research on this detecting process is required to increase accuracy to process signal methods. While the majority of fetal ECG monitoring technologies now in use have been designed for brief, transient surveillance, if we are to design inconspicuous technologies that are advanced enough to continuously monitor cardiac rhythms, we will need to rethink the current methods for studying fetal heart function. This will enable the continuous assessment of the heart's developing pulsations over extended periods of time, when congenital anomalies are suspected.

In [13] Standard clinical protocol is done by a sonographer in both standard 2D and 3D with the help of fetal sonography screening, which establishes criteria for the plane definition.2D planes of acquisition that are standard go through rigorous control the quality to make sure fulfill predetermined standards. In addition, sonographers require specialized training in order to fulfill these standards, since training initiatives have been demonstrated to enhance picture quality (Wanyonyi et al., 2014) and measurement variability (Sarris et al., 2011). ECG, the Electro Cardio Gram is a highly significant instrument for the practitioner to decide the cardiac health of a patient1. Similar to other parameters, fetal electrocardiogram (ECG) is used to determine the health of the fetus both during pregnancy and during childbirth. Both the mother's ECG and noise have an impact on the fetal ECG. This study's primary goal is to separate and extract just the fetal ECG from the conflicting cues. The current work suggests a technique for successfully and quickly isolating the fetal ECG alone. The benchmark ECG signals that were obtained from the mother's abdomen are available in the database that was used, which comes from PhysioNet. This study's algorithm is built on the Fast ICA framework. Software for graphical representation, like NI LabVIEW, is favored over Matlab because of its accuracy, affordability, and simplicity in understanding, building, and applying algorithms. In order to determine the accuracy of the current study, the beats per minute, amplitude, and correlation coefficient parameters the formula.

In [14] FMH has a significant part in fetal anemia, which is caused by a confluence of acute hypovolemia and a decreased blood oxygen carrying capacity, or hypoxemia. Anemia causes the circulation to become hyperdynamic, which is characterized by higher blood flow rates in different arterial beds. The middle cerebral artery (MCA) measurement was not considered by the authors. An elevated peak systolic velocity in fetal MCA has been reported by numerous writers in the literature to be useful in identifying anemic fetuses [2,4-6]. Doppler measurements, in my opinion, are simple to use and have a significant predictive potential for severe fetal anemia brought on by enormous FMH. Less than 10% of patients had nonreactive cardiotocography, which includes both tracings that have less fluctuation as opposed to a sinusoidal pattern. The patient did not exhibit contractile activity and reported less fetal movements. While computerized cardiotocography is not a diagnostic tool in and of itself, its predictive power for fetal acidemia risk is undeniable when it comes to the short-term variability (STV) value. Fetal acidemia, which is present when a major FMH occurs, is closely linked to a considerably reduced STV.

In [15] Temporary hypoxia is caused by the contractions of the uterus during labor, which restrict the mother's blood flow and the growing baby's oxygen delivery. Although most newborns are physiologically built to tolerate this kind of intrapartum hypoxia, individuals who are subjected to extreme hypoxia or have little physiological reserves may brain damage or passing away during childbirth. Cardiotocography (CTG) monitoring uses alterations in fetal heart rate (FHR) rhythms to identify infants at risk of hypoxia. In order to detect fetal hypoxia, CTG monitoring is commonly used in intrapartum care. However, the therapeutic efficacy of this technique is restricted due to the relatively low positive predictive value (PPV) of an abnormal CTG and the high inter- and nonobservant variability in CTG interpretation. The quality of CTG interpretation may be impacted by clinical risk and human factors. Misclassification of CTG traces can result in over-treatment (which could include needless surgical procedures that increase the risk of difficulties for both mother and child) or under-treatment (which carries a risk of fetal harm or death).

In [16] The Institutional Ethics Committee gave its approval to the study (IEC 490/ 2017). We got informed consent in writing from every participant. A tertiary-care hospital in South India carried up a prospective observational study involving 304 singleton term pregnancies with vertex presentation during labor. Women who got epidural analgesia and pregnancies with significant fetal growth limitation, fetal abnormalities, and preeclampsia were not included. We determined the sample size using a 5% margin of error and the predicted number of occipitoposterior (OP) positions in work (26%). 95% degree of confidence. There were 295 samples in all. Women in early labor with a cervical dilation of less than 4 cm were recruited. The body mass index (BMI) of the mother was determined. Using the formula BMI= (weight in kg)/(height in m) after determining weight (kg) and height (m).2. Utilizing a 2.5-MHz curved-array transducer, transabdominal ultrasonography was carried out to determine the location of the fetus. The relative position of the fetal occiput with respect to the mother pelvis was noted, along with the fetal vertebral column to support the findings. The arrowhead formed by the thalamus and falx cerebri in the fetal transthalamic plane pointed toward the fetal occiput, indicating the location of the fetal head. Fetal postures were divided into two groups: OP and non-OP.

In [17] One method for continuously monitoring fetal health is cardiotocography (CTG). From the CTG pictures, dynamic changes in two physiological signals, such as the uterine contraction and the fetal heart rate, can be retrieved. It is easy to use, non-intrusive, real-time, and straightforward to read. In clinical practice, doctors can use the data to observe the health status of the fetus of FHR monitoring in real-time (for at least 30 minutes) [1]. With this knowledge, prompt action can be performed in the event of an emergency to prevent fetal asphyxia (hypoxia) and other issues. The study of signal extraction on the CTG digital pictures will be beneficial to the creation of large-scale databases. A central monitoring system obtains the CTG digital images system or scanning apparatus. The primary obstacle in signal extraction is getting rid of background patterns, such grids. The background patterns affect the outcomes of data extraction negatively, even though they help with the physician's visual assessment. Based on the color of the grid lines, the CTG images can be classified as either a binary (black) or color (non-black) image. The majority of researchers analyze color CTG pictures using the color difference between the signal curve and background grids.

In [18] The incidence of older pregnancies increased as a result of rapid economic development, which also increased the need for ongoing prenatal and fetal monitoring. FHR and UC signals that can non invasivly recorded with low cost using cardiotocography (CTG), which is frequently used to detect early ischemia and hypoxia in fetuses. Regrettably, variations in obstetrician competence and experience have hampered the visual interpretation by obstetricians for CTG, leading to inconsistent outcomes that may be challenging to replicate. Establishing a trustworthy model for the automatic classification of CTG information is therefore essential. Deep Learning (DL) has mostly been used for extraction and classification. The former could be conventional or rule-based. Systematic visual assessment is carried out using a rule-based methodology to determine morphological CTG features and estimate fetal state in accordance with clinical recommendations for fetal monitoring. The number of decelerations/accelerations, morphological variability, and CTG morphological traits at baseline are combined. These parameters, however, are very dependent on expert knowledge; additionally, they concentrate on CTG shape, which results in high sensitivity, low specificity, and potentially even needless cesarean procedures. The advancement of classical machine learning techniques has been significant with the emergence of computational CTG technology.

In [19] In Netherlands, there has been an increase in the number of referrals from MLC to OLC in recent decades. By offering more services in MLC, continuity of care during pregnancy and delivery may be enhanced, hence lowering the number of referrals. Antenatal cardiotocography (aCTG) is a potential procedure for this shift when pregnant women are in circumstances where there is a higher risk to the health of the fetus, such as when there are fewer fetal movements, following external cephalic version in general care and postdate pregnancy. While recommendations generally recommend utilizing aCTG to assess fetal well-being during pregnancy in women at increased risk of problems, there is no conclusive evidence that it improves postnatal outcomes. In the past, only hospital-based OLC professionals had performed ACTG. Advances in e-health make MLC-aCTG possible since a second professional can evaluate the aCTG recording in real time. who is absent from the area where the aCTG is being done. MLC-aCTG has been implemented for women with the aforementioned indications in three locations of the Netherlands. It is crucial to assess the quality of care in accordance with VBHC principles when reorganizing duties and responsibilities. This means that outcomes should be monitored using crucial parameters, such as procedural and clinical parameters in addition to patient-reported outcome and experience measurements. Studies have indicated that women express great satisfaction with MLC-aCTG.

In [20] Artificial intelligence has evolved a long way from theoretical artifact to a well-defined domain in engineering which is introducing numerous applications in each and every upcoming year. The term “AI” is termed as an agglutinating a group of technologies that endow machines which includes cognitive functions which can be associated by humans with their mind, such as learning and problem solving. These systems are continuously available while decisions are taken and scaled up to an unlimited number of patients in a hospital, and are not affected by human factors which also reduces inter- and non-observant variability. Recent methods are attempted to imitate human analysis by encoding the rules which were extracted from domain expertise. ML replaced this strategy and learns big data sets for inference models. The discipline of machine learning has created a significant number of algorithms where their input can be anything from manually created features to the traced or raw data.

In [21] In order to gauge the comfort of the unborn child and identify an increased risk of pregnancy issues, cardiotocography defines monitoring and documenting the infant's heart rate and spams uterine during pregnancy. This makes it possible to identify and treat embryonic hypoxia early on, before it results in severe asphyxia or even death. Vital signs of the fetus's health include heart rate variability responsiveness, and possible slowdowns during uterine spasms. The author presented a brand-new clinical verdict assistance system that was constructed using an extreme machine learning algorithm and an improved adaptive genetic algorithm. The model's final classification accuracy was 94 percent. Predicting fetal health in utero is crucial for the physical well-being of a newborn. Therefore, the suggested model in this study predicts fetal health using federated machine learning in the womb of the mother.

CHAPTER 3
SYSTEM DESIGN

3.1 GENERAL

System design involves the formulation and creation of systems that meet the specific needs of users. Fundamentally, the essence of studying system design lies in comprehending the individual elements and how they interact with each other.

3.2 DEVELOPMENT ENVIRONMENT

Developing the fetal health assessment system using CTG data requires a Python environment with specific libraries. Start with NumPy for numerical computations, Pandas for data manipulation, scikit-learn for machine learning algorithms, and Matplotlib/Seaborn for data visualization. Install Python and the libraries using a package manager like pip. Choose a code editor or IDE that suits your preference. Organize your project with folders for data storage, Python scripts, and optional Jupyter notebooks for exploration. Consider using Git for version control. Public CTG datasets might be available online, but ensure proper permissions and data anonymization. For computationally heavy tasks, a powerful computer or cloud platforms like Google Colab can be helpful. Remember to consult relevant resources for each library or framework you use to get the most out of your development environment.

3.2.1 HARDWARE SPECIFICATIONS

This document offers a comprehensive overview of the hardware and its implementation, detailing the key components, their interactions, and the necessary requirements for seamless connectivity to utilities and installation.

PROCESSOR	Intel Core i7
RAM	4GB or above (DDR4 RAM)
GPU	Intel Integrated Graphics
HARD DISK	6GB
PROCESSOR FREQUENCY	1.5 GHz or above

Table 3.2.1 Hardware Specifications

3.2.2 SOFTWARE SPECIFICATIONS

The below table constitutes a thorough evaluation of requirements that precedes the more detailed phases of system design, aiming to minimize the need for subsequent revisions. Furthermore, it should offer a practical foundation for estimating product expenses, potential risks, and project timelines.

FRONT END	HTML, CSS, Bootstrap, JavaScript
BACK END	Python, Django
CODE EDITOR	Visual Studio Code

Table 3.2.2 Software Specifications

3.3 SYSTEM DESIGN

The fetal health assessment system analyzes CTG data to classify fetal health. The system first preprocesses the data by extracting the fetal heart rate (FHR), addressing missing values and outliers, and potentially segmenting specific CTG portions. Time-frequency analysis techniques like Short-Time Fourier Transform (STFT) help visualize FHR changes over time. Feature selection chooses the most relevant data points from the pre-processed CTG data. Then, machine learning algorithms like Random Forest are trained on labelled data to classify fetal health based on the extracted features. The system's performance is evaluated using cross-validation to ensure generalizability on unseen data. This design leverages machine learning to analyze CTG data and provide insights into fetal health.

3.3.1 PROPOSED MODEL

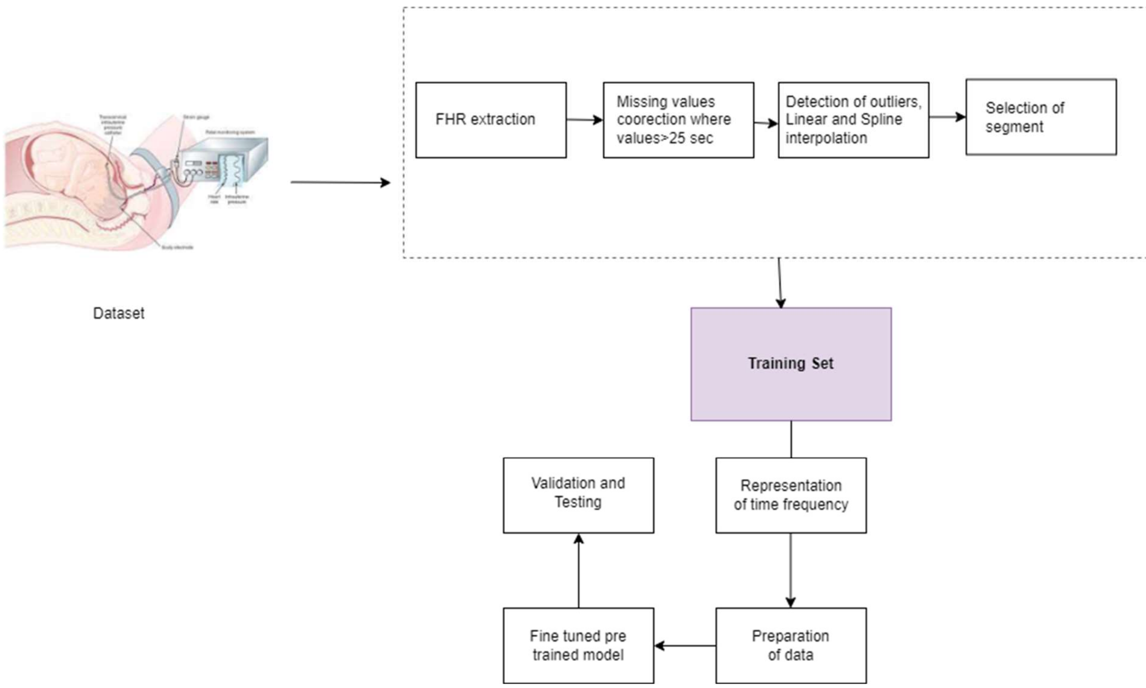

Fig 3.3.1 Fetal health prediction using cardiotocography

Datasets:

The system analyzes fetal health using cardiotocography (CTG) data. The CTG dataset has 28 features related to fetal heart rate, uterine contractions, and other measurements. There are two target variables: "Normal" and "Suspect" for fetal health, and a separate classification ranging from 1 to 17. The data is imbalanced, with most samples belonging to the "Normal" class. To improve model performance, only the most relevant features are chosen using chi-square selection. This reduces complexity by focusing on the top K=10 impactful features from the initial 28. Real-world data can have features with varying scales, so Min-Max scaling is applied to normalize all features between 1 and 3. This ensures each feature contributes equally to the model's prediction. K-fold cross-validation is used to evaluate different machine learning algorithms on the training data. The data is split into 10 folds. In each iteration, 9 folds are used for training, and the remaining fold is used for validation. This process is repeated for all 10 folds. During validation, a Random Forest classifier achieved the highest accuracy (98.94%), outperforming other classifiers like Decision Tree, Deep Forest, and Extra Trees. To further improve accuracy and reduce errors, ensemble learning with stacking is employed. Here, predictions from multiple base learners (like Random Forest) are combined to create a more robust final prediction. The base learners' outputs are fed into a meta-learner that learns from these predictions and aims to make better overall classifications on unseen data.

Preprocessing:

The preprocessing stage is crucial for preparing the fetal heart rate (FHR) data from CTG readings for analysis. First, the FHR needs to be extracted from the CTG data. Missing values, which can arise from various reasons during data collection, are addressed using imputation techniques like filling them with mean, median or values from nearest neighbors. Alternatively, outliers that significantly deviate from the rest of the data can be removed or adjusted using methods like interquartile range (IQR) or Z-score analysis. Segment selection involves choosing specific portions of the CTG data for analysis, based on time intervals or specific events. To understand how the FHR changes over time, time-frequency representation techniques like Short-Time Fourier Transform (STFT) are employed. This essentially creates a spectrogram that visualizes the frequency changes. Overall, data preprocessing ensures the CTG data is clean, consistent, and ready for further analysis in the fetal health assessment system.

Training and Testing:

This training content outlines the fetal health assessment system using CTG data. It covers data preprocessing, feature engineering, model training, and evaluation.

The training covers:

- **FHR Extraction and Missing Value Correction:** Importance of FHR, missing value imputation techniques (mean, median, nearest neighbors).

- **Outlier Detection and Treatment:** Identifying outliers, their impact, detection methods (IQR, Z-score), treatment methods (removal, winsorization).
- **Segment Selection:** Choosing specific CTG segments for analysis based on time or events.
- **Time-Frequency Representation:** Understanding time-frequency analysis, role of Short-Time Fourier Transform (STFT) in visualizing FHR changes (spectrograms).

Then it dives into feature engineering and model training:

- **Feature Selection:** Choosing relevant features for classification, benefits of improving model performance and reducing complexity.
- **Feature Scaling:** Importance of scaling features for machine learning algorithms, Min-Max scaling for normalization.
- **Model Selection and Training:** Exploring machine learning algorithms for classification (Random Forest, KNN), concept of model training using labelled CTG data.

The training concludes with evaluation and testing:

- **Cross-Validation:** K-fold cross-validation for evaluating model performance on unseen data, avoiding overfitting and providing reliable accuracy estimates.
- **Testing on New Data:** Importance of testing on separate data not used for training, evaluating model's ability to generalize and classify fetal health on unseen CTG data.

CHAPTER 4
PROJECT DESCRIPTION

4.1 MODULE DESCRIPTION

The provided code snippet showcases a crucial module within a system designed to assess fetal health using cardiotocography (CTG) readings. This module leverages the K-Nearest Neighbors (KNN) classification algorithm to analyze CTG data and categorize it into one of three classes: normal, suspect, or pathological. The functionality revolves around analyzing CTG readings to determine fetal health. The core function, named KNN_CTG_Classification, takes CTG data from test instances and performs the KNN classification. This function calculates how similar each test reading is to the training samples it has been provided. By identifying the k-nearest neighbors (training samples with the highest similarity scores), the algorithm essentially finds the closest data points in the training set to the test reading being analyzed. Finally, it employs a majority vote amongst these k-nearest neighbors to assign a final classification to the test reading. Helper functions like calculate_similarity_scores and find_k_nearest_neighbors support the core function by calculating these similarity scores and identifying the closest neighbors respectively. Another helper function, classify_kNN, analyzes the votes from the neighbors and assigns the most frequent class label (normal, suspect, or pathological) as the final classification for the test reading.

It's important to note that this module relies on a few key assumptions. The CTG data needs to be pre-processed and formatted specifically for KNN analysis to ensure accurate results. Additionally, the system requires a training dataset containing labelled CTG readings, where each data point is already classified as normal, suspect, or pathological. This training data allows the algorithm to learn and identify patterns that will be used for future classifications. Finally, a value for k, which represents the number of nearest neighbors to consider during voting, needs to be predetermined.

In essence, this module provides a classification tool within a larger system designed to assess fetal health. By leveraging the KNN algorithm and analyzing CTG readings, the system can categorize fetal health into different states, potentially aiding medical professionals in their decision-making processes.

CHAPTER 5

IMPLEMENTATION AND RESULTS

5.1 RESULT ANALYSIS

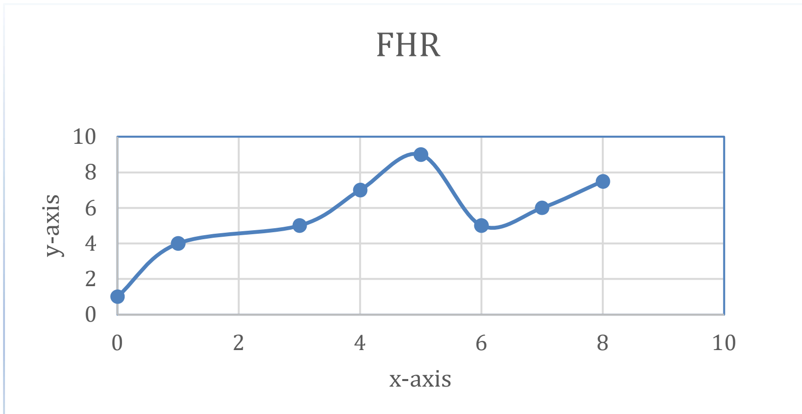

Fig 5.1.1 FHR Values

This interpolation creates a new data point between two points by applying the curve fitting approach and a linear polynomial. The new value of y is produced by linear interpolation for two known data points with coordinates of (x0, y0) and (x1, y1). Unstable sample points of the FHR signal that differ by more than 25 beats from the previous adjacent beat are not physiologic and are therefore removed using cubic spline interpolation. These unstable points manifest as spikes on the FHR signal. Piecewise smooth polynomials are a very effective and popular way for interpolating a function between a specified set of points. A piecewise polynomial function f(xk) = yk, given a cubic spline f(x) interpolating on the partition x0 < x1 < ⋯ < xn-1, The final dataset, after augmentation, had 1556-time frequency pictures, of which 878 belonged to the normal class and 678 to the pathologic or distressed class.

Table 5.1.1 Results from various classification models

Classifier Model	MSE	R2	Kappa	Precision	Recall	F1-Score	Accuracy	Error Rate	AUC
Decision Tree	0.089	0.952	0.7896	0.8743	0.7878	0.804	90.40%	0.0725	0.9427
Random Forest	0.079	0.915	0.5638	0.9123	0.599	0.9108	93.18%	0.0498	0.9347
Extra Trees	0.059	0.849	0.7658	0.9533	0.91	0.9152	95.72%	0.058	0.9045
Deep Forest	0.081	0.744	0.348	0.5097	0.8286	0.8054	97.56%	0.0546	0.9228

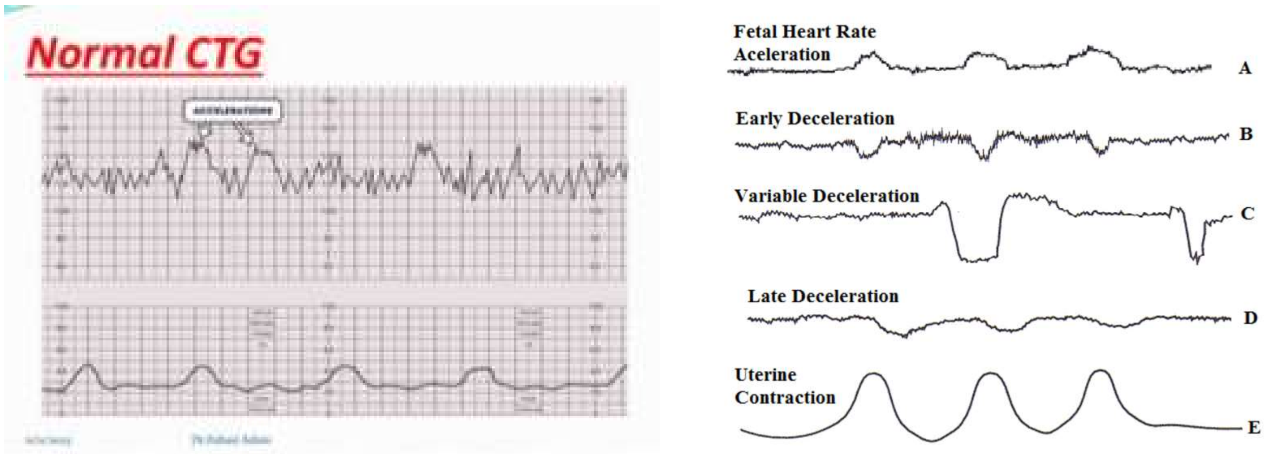

Fig 5.1.2 Different sinusoidal waveforms in cardiotocography

The number of data utilized to train the system is 790 for normal and 610 for distressed, depending on the data split ratio that was employed. The testing set consisted of the remaining 10%, or 156, of which 68 were abnormal and 88 were normal. 10% of the training data from each class was chosen at random during training using a validation frequency set of 15 iterations. The ResNet50 model is trained independently for the first and second experiments, which are the first 20 minutes and the last 15 minutes of the CTG recording, after the data was separated and prepared. The performance of the ResNet-50 model is assessed in order to determine the optimal fine-tuning parameters for the classification task. As a result, the validation dataset was used to validate the model after it had been trained using the training dataset. The training dataset is used to create the learning curve, which shows how well the model can learn. On the other hand, a validation dataset is used to create the validation learning curve, which shows how well the model generalizes. The training accuracy (blue curve), validation accuracy (black dot with blue curve), training loss (brown curve), and validation loss (black dot with brown curve) curve plots for the models are shown.

CHAPTER 6
CONCLUSION AND FUTURE ENHANCEMENTS

6.1 CONCLUSION

The discussed research represents FML model which suggests a classification for the fetal heart rate in the womb in order to assess physical heart rate health of the foetus, using Machine Learning Algorithm. This approach has obtained 99.08% testing rate of success using FML for both the testing and training data of the fetal heart rate simulation over the entire pregnancy period with precision at 0.95% CMR. The model here uses KNN which simulates the entire data, hence produces testing accuracy of 84.94% and CMR of 18.07. Results showed that FML performed better than KNN. clinical fields and Biotechnology will immensely benefit from enhanced results on the basis of improving physical health of foetuses, where suggested model outperforms research of previously performed ones in terms of accuracy, it is to be refined furtherly using a larger dataset to produce more accurate results. This suggested model will grow more in the future inventions when fuzzed data model and fuzzed technology are combined together, enabling the Internet of Things Medically. By the approach of a weighted federated machine learning methodology more accuracy can be achieved.

6.2 FUTURE ENHANCEMENTS

There are numerous methods to improve the KNN-based fetal health assessment system. To extract more useful information from CTG readings, we can investigate more sophisticated feature selection and extraction methods. Algorithms such as SVMs, Random Forest, or even deep learning models have the potential to enhance classification accuracy beyond KNN. A more comprehensive picture might be obtained by including data from other sources, such as fetal biophysical profiles or maternal health information. Subsequent versions might make real-time monitoring possible, clarify model predictions for improved comprehension, and make use of cloud platforms for scalability. For responsible creation and practical implementation, rigorous testing, clinical input, and ethical issues like data protection and bias reduction are essential. The system may become a useful instrument for enhancing fetal health outcomes as a result of these improvements.

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A NOVEL APPROACH FOR DETECTION OF FETAL HEALTH USING CARDIOTOCOGRAPHY AND DEEP LEARNING MODELS

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Abstract— Cardiotocography provides information on uterine shrinkages with fetal heart rate, that is highly helpful in determining if fetus is normal, questionable, or pathologic, it is used to measure FHR in fetus throughout pregnancy to assure physical health. Due to human error, several cardiotocography measures make incorrect inferences and predictions. The time required to read the cardiotocography measurements in the conventional manner is prone to many human errors. It is crucial to monitor the fetus's status at various stages and to provide it with the right medication for its wellbeing. It records FHR together with the contraction of the uterus continuously, where obstetricians evaluate health of fetus. Excellent results have been obtained by training deep learning models for intelligent fetal monitoring using CTG records that are identically distributed and extensively annotated. However, the collecting and annotation of CTG signals necessitates specialized personnel and a significant amount of time for the construction of these training sets. Multicenter studies have been shown in the past to enhance model performance. However, because datasets differ in their distribution, trained models for cross-domain data could not transfer effectively to target domains. In order to intelligently analyze antenatal CTG signals, where the paper performed a multicenter using DSSDA. Cardiotocography **is** a procedure clinically done to assess and track the degree of fetal discomfort.Despite the fact that CTG is the most often used tool for monitoring fetal health, the presence of positive false result towards interpretations visually significantly increases the risk of unneeded surgery or postpones intervention. In the current work, the notion of learning to transfer trained ResNet 50 of deep neural network model and frequency time representation of FHR signal that is used to generalize Morse wavelet which constructs a unique computer-aided fetal distress diagnostic model. Just the signal which is isolated and processed for elimination. Noises of the data that is acquired to exclusively open access for CTU-UHB data repository.Following preprocessing, the FHR signal's time frequency information is extracted by Morse wavelet and put forth to a ResNet 50 model that has already been trained and fine-tuned in accordance with the dataset. Principal outcome The model taken from the binary confusion matrix is measured for sensitivity , specificity , and accuracy . Following the model's successful training, a thorough testing and experimentation process is carried out using FHR data, for which recordings are made during the early and late stages of labor. A clinical method called cardiotocography (CTG) is used to monitor and assess the level of fetal distress. Despite being the most popular tool for tracking and evaluating fetal health, CTG frequently yields false-positive results because of visual interpretation, which can lead to unnecessary surgery or postponed intervention. This study introduces a revolutionary methodology in which printing digitized paper CTG is done, and the anomaly in the digitized CTG signal is found using a machine learning technique. To facilitate the extraction of the CTG signal during the printing of CTG paper, preparatory methods based on image processing are used. A range of signal processing methods are employed to adjust the retrieved CTG signal. The CTG signal is then broken down into its frequency components using empirical mode decomposition (EMD), and features related to instantaneous frequency and spectral entropy are then retrieved. Following Support vector machines (SVM) are utilized for feature selection and normalization using the ReliefF method to classify data into normal and pathological categories. The experimental investigations use a unique dataset, and a variety of performance assessment criteria are used to gauge how well the recommended strategy works. Ten-fold cross-validation experiments show the effectiveness of the recommended technique in anomaly detection in CTG paper printing, which results in an accuracy score of roughly 90.0% on average. Pregnancy complications affect women greatly and may be detrimental to the health of the fetus. Interventions that can save lives must be implemented as soon as these issues are identified. An obstetrician's traditional method of manually analyzing cardiotocography (CTG) test results is unreliable and labor intensive. Thus, advancement towards effective models of fetal health Classification become essential for time and resource optimization in medicine.This work applies machine learning (ML) approaches to address the need for enhanced fetal health classification**.** The main goal is investigating, and evaluate ML models which can reliably categorize fetal health using CTG data. Improving diagnosis accuracy and enabling prompt interventions are the main objectives.Despite its modest size, the cardiotocography data set that was used was made available to the public. Its rich properties are acknowledged by study. To evaluate the models' performance in categorizing fetal health, extensive training and testing are required.The study produces encouraging results; the applied machine learning models outperform earlier approaches, with a noteworthy of 96% accuracy level and emphasizes the efficacy of the suggested models in improving the accuracy of the CTG-based fetal health classification.The results support the expediting of fetal health assessments by incorporating machine learning models into standard clinical procedures. The study shows how machine learning (ML) can be used to optimize resources on the basis of medical allocation and efficiency of time, while also highlighting the importance of early complication diagnosis.

I. INTRODUCTION (*HEADING 1*)

During pregnancy and labor, uterine contractions and the fetal heartbeat are monitored using the cardiotocography (CTG) technique. A cardiotocograph is the name of the device that is used to do the monitoring. An approach that is frequently used to ascertain newborn status is cardiotocography. During birthing, cardiotocograms continuously and noninvasively monitor the infant's heart rate and vaginal hemorrhage. Over years, obstetricians have used visual inspections in infants using cardiotocography signals with ranges in heart rate, which can be defined as acceleration, retardation and electrocardiogram, to diagnose state of babies starting heart rate. The relationship between uterine spasm and newborn heart rate has been categorized as occurring sooner than normal retardation and is well recognized as a crucial component in the interpretation of cardiotocographs. Artificial intelligence has been used recently in bio-signal processing technologies to convert data from human body into estimating the future health of the baby. Most oncologists focus to build an interpretation automated cardiotocography , however the results so far could not predict potentially dangerous anomalies in the fetus , which led a large number of researchers to use ML algorithms to identify the condition of baby inside mother's womb. Therefore, the main goal of this study piece is to assess the fetus status in mother's womb using a variety of machine learning approaches and Federated machine learning , and then to help oncologists make the right decisions based on the fetal health status.

A tool that is used in prenatal health diagnosis of fetus that monitors fetal activity, heart rate, and uterine contractions in the womb is known as CTG. This allows doctors to determine the health condition of the fetus before and during birth. CTG results provide crucial pathological and physiological information to obstetricians, reducing risk of perinatal death. The (FIGO) International Federation of Gynecology and Obstetrics classifies the test of CTG findings into three forms such as normal, suspicious, and abnormal. These classifications are based on FHR (Fetal Heart beats per minute) variability, accelerations, and decelerations. Obstetricians may conduct manually or with the help of software. However, this study's data contains moderate quality, with more research into the effect of CTG on perinatal outcomes is needed. signal processing technology has made use of artificial intelligence to transform data from human body to a diagnostic. However medical practitioners attempts to automate CTG interpretations, and find way to accurately predict fetal heart rate. Numerous academics started to research using various ML algorithms to forecast status of the fetus inside mother's womb. Thereby, the goal is to create a machine learning model that can properly detect the condition of the fetuses heart beats per minute.

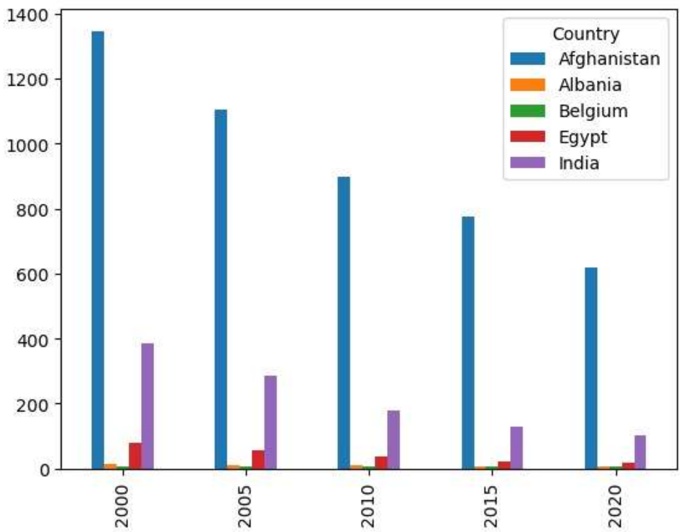
In 2023, there were over 140 million pregnancies worldwide. There were registered pregnancies in 20 million wealthy countries (20%) and 180 million impoverished countries (11%). Percent of all deliveries by Cesarean is 32%, The number of vaginal deliveries are 2,486,856 and the number of Cesarean deliveries: 1,174,545. Obstructed labor, elevated blood pressure, problems with abortion, and infection in the mother. The World Health Organization (WHO) reports that in 2023, problems during pregnancy or childbirth claimed the lives of over 4 lakhs women, both during and after pregnancy and delivery. An estimated 980 women die from these causes per day. Fetal health predictions that are made too late can lead to birth defects, genetic problems, and problems with the mother's antibodies. Therefore, it is essential to diagnose prenatal health issues early in order to prevent any inherited problems. The term "infant heart rate" refers to the number of baby heartbeats per minute. Cardiotocograms are used for assessing the baby's activity level, pelvic spasms and heart rate while it is still in the womb for prenatal clinical diagnosis of infant health. Physicians might utilize this test to ascertain whether the Both before and after birth, the fetus is healthy. Cardiotocogram results provide vital pathological and physiological information to the respected gynecologists, for reducing the cause of neonatal death and avoid premature delivery.

A situation of baby, when it doesn't get enough oxygen during labor, it's called fetal hypoxia. Numerous terrible consequences, including hypoxia, neonatal encephalopathy, intrapartum stillbirth, neonatal death, and neurodevelopmental disability, can result from fetal hypoxic injury. Fetal hypoxia overall occurs in European hospitals at a rate between 0.7% and 5.8%. An estimated 2.6 million stillbirths are occurring during childbirth, over 1 million neonatal fatalities, and 0.6 to 1 million cases of impairment that are long term due to neonatal hypoxic-ischemic encephalopathy are caused by intrapartum fetal hypoxia annually worldwide. Thus, in order to stop more hypoxic incidents, this problem needs to be resolved. When uterine contractions compromise perfusion of placenta in mother, reduces oxygen delivery to fetus, that induces a degree of hypoxic stress which might be expected during labor. Finding the small percentage of infants in whom the body's natural defenses against the hypoxic stress of labor are ineffective and cause serious brain damage is the main problem faced by clinicians. In order to shield newborns and families from the catastrophic consequences of prenatal hypoxia, fetal monitoring is essential during labor. In order to reduce needless iatrogenic operations, such as surgical births (caesarean sections), which have hazards for both the mother and the child, it must also be adequately discriminate.

This research aims to create an accurate and reliable artificial intelligence system that analyze and categorize CTG print pictures as either normal or abnormal. As a result, a unique method is created for the digitization of CTG material as well as the division of the digitized signal into classes for normal and pathological CTG signals. As the CTG document. While machine learning is used to classify the CTG signals, image processing is the foundation of the digitization step. The scanned CTG paper is the system's input, and the class label is its output. It should be noted that our created system only uses the FHR signal, hence in order to obtain the FHR signal portion of the the CTG paper scan. This facilitates more natural modifications to an image's brightness and hue. Subsequently, median filtering is implemented independently for every Lab color channel. Additionally, the input image's lightness is increased by weighting the L channel (multiplying it by a constant amount). After that, the RGB color system is once more transformed to the Lab color space.

Following these preprocessing steps, the signal from the red grid background is solely extracted using the red channel.

To eliminate undesirable binary noise, certain morphological processes are used, and the signal's amplitude in beats per minute (BPM) scale is measured using signal amplitude calibration. An interpolation process is used to fill in the signal's missing points following signal extraction in light of that. Additionally, all signals undergo resampling in order to maintain a constant length. The extracted FHR signals are subjected to a multiresolution signal analysis technique which is referred to as Empirical Mode Decomposition (EMD), breaks signals into their frequency components. Two feature extraction techniques, instantaneous frequency and spectral entropy, are then used for each decomposed signal to extract features from the normal and abnormal FHR signals. To find the most effective feature set, a feature selection process is used. The feature selection process employs the well-known Relief technique. Lastly, anomaly identification is accomplished through the application of the SVM classification technique which comprises of metrics such as F1-score, accuracy, specificity and sensitivity are employed to assess the suggested method's performance.



II. LITERATURE SURVEY

In [1] The paucity of clustering approaches in medical imaging literature as compared to natural imaging illustrates how little consideration this strategy receives in the field. By altering the Deep-Cluster architecture, Kartetal utilized clustering to cardiac magnetic resonance imaging and produced high-performance outcomes. When it comes to magnetic resonance imaging (MRI) image clustering, this method has shown good results. Nonetheless, the issue is well defined, and compared to other medical applications, particularly imaging ultrasound, the image quality is noticeably better. Dadounetal used Huangetal's concept of grouping abdominal organ ultrasound picturesfor multilabel classification as task pretext. Yuetal refined classification on CNN that was trained previously on Image Net in order to identify the fetal standard plane for the image classification task. The technique was evaluated on 2418 images, and it achieved under an area of receiver operating characteristic curve (AUC), accuracy, precision, recall, and F1 score. In a different study, Quetal employed a classification for CNN that automatically recognize standard planes of fetal in 19,140 photos, achieving 93%, 93%, 92%, and 93% of accuracy, precision, and recall, respectively.

In [2] The goal of this research is to create a reliable and accurate artificial intelligence system that can analyze, interpret, and categorize CTG print images as normal or abnormal. As a result, a novel method is created for the digitization of CTG material as well as the division of the digitized signal into classes for normal and abnormal CTG signals. Machine learning is used to classify the CTG signals, while image processing is used for the CTG paper digitization stage. The scanned CTG paper is the system's input, and the class label is its output. It is important to note that our created technique only uses the FHR signal, hence in order to obtain the FHR signal portion of the scanned CTG paper, human cropping is required. For the purpose of detecting abnormalities in CTG printing papers, a two-stage method was suggested. These phases involved separating the signal from the printed CTG sheets and categorizing it into classes that corresponded to normal and pathological behavior. The printed CTG papers, notably the FHR section, served as the input for the signal extraction stage. Furthermore, the recovered FHR signal served as the input for the signal categorization section. While the initial section comprises diverse image processing algorithms, the subsequent section relied on machine learning techniques, including feature extraction and feature classification.

In [3] Monitoring and decision-making for the well-being of the fetus are the goals of fetal medicine. Cardiotocography (CTG) is a diagnostic procedure used before to or during childbirth that uses Doppler ultrasonography and toco sensors to simultaneously monitor the uterus and the fetus. This allows for the identification of fetal neurological or cardiovascular risk factors or conditions. Heart rate is an important indicator for studying the cardiovascular system as well as the autonomic nervous system's impact on the circadian rhythms of the body. As a result, the literature is continuously presenting the development of various methodologies for computerized diagnostic systems. There are numerous methods for keeping an eye on the FHR. Everyone has benefits and cons. While accurate and reliable, the fetal scalp ECG is an intrusive procedure approach (and it's only accessible upon 'crowning'). Further Phonocardiography (PCG) has been utilized recently as a straightforward and trustworthy FHR detector based on the capture of The Hilbert Transform (HT) can be used to hear the heartbeat be applied to efficient noise reduction and real-time frequency detection. Using HT, ECG instantaneous energy has also taken into account for segmenting cardiac sounds.

In [4] Cardiotocograms simultaneously collect data from many monitoring techniques, such as fetal heart signals, mother uterine contraction pressure, and fetal movements within the womb. This information is crucial for evaluating the health of the fetus. By examining CTG data, potential future risks to the fetus can be avoided. The clinical CTG test is easy to use and reasonably priced, and it offers information about the developing baby's health. An antepartum CTG test is frequently used to track fetal well-being, starting from the pregnacy period of 28^{th} also known as the seventh month . In the case that fetal growth anomalies are detected, the results of this test can assist obstetricians in creating treatment plans. Actually, the CTG test evaluates the health of the fetus by determining whether or not its tissues are getting adequate oxygen, as well as by looking for indications of hypoxia or acidosis. These days, fetal heart rate patterns and uterine activity are among the features that obstetricians examine in order to interpret CTG. The interpretation is still arbitrary and vulnerable to inter-observer variation even when employing standardized methods like NIP and STV. Due to this intricacy and time restrictions, it may be possible to overlook minute indications of fetal discomfort. To overcome these constraints, the incorporation of machine learning models is suggested in this study. ML models greatly increases accuracy and efficiency of the fetus health, resulting in early detection of fetal health and balance the outcomes of pregnancy. This can be achieved examining data and uncovering the patterns that are hidden.

In [5] It may be possible to reduce the number of needless Caesarean sections brought on by suspected hypoxia and enhance the diagnosis of fetal hypoxia by creating new or better techniques for fECG monitoring. The primary goal of current research is to create an NI-fECG-based system that can perform analysis in terms of morphological akin to NI-STAN.The research suggested technique which could accomplish this goal with optimization. Finding appropriate methods for quality extraction and clinical feasibility—which is related to performance with computing fair—is required to accomplish this. The early trials and in-depth research were used to pick ICA algorithm for first component of hybrid approaches. The discovery where the algorithm can extract two types of ECG signals: an aECG component that contains the fECG signal amplitude level as the mECG signal and a mECG component that contains only the mECG signal. Thus, an ICA algorithm is formed by preprocessing input of aECG signals used for adaptive algorithms. Two distinct adaptive algorithms receive the pre-processed mECG and aECG data as inputs. These adaptive algorithms are ANFIS and RLS.

In [6] The most serious causes of morbidity and mortality is intrauterine growth restriction , which is characterized by pathological suppression of the growth of fetal and the resulting fetus failure to reach full potential growth, which is only related to prenatal hypoxia and asphyxia. Approximately 5% of pregnancies result in IUGR.Fetal monitoring is therefore crucial for identifying dangerous problems in fetus and aiding in clinicians to make the decision. According to official data about pregnancies in US, the use of FHR monitoring has significantly increased in past decades: 48% laboring women in 2000, 65% in 2010, 80% in 2020, and 94 in 2022 were subjected to screening process. There are multiple technological methods available to measure FHR. Cardiotocography combines measurement of FHR using Doppler ultrasonography probe with pressure sensor-based detection of contractions in uterine, is the most widely utilized approach. Doppler ultrasonography senses the motions of the fetal heart, enabling the detection of heartbeat events. Throughout the screening procedure, the device records heart rate variations via a trace that it generates. Fetal electrocardiography (FECG), which is recorded using either internal or external electrodes depending on the gestational age, is an alternate method for recording FHR.

In [7] In the field of adult cardiology, arrhythmia identification for classification using the ML and DL algorithms. Pediatric cardiology has high standards for the identification arrhythmia in fetal and cardiac activity of fetal. To comprehend the cardiac health of the fetus, accuracy of heart rate is detected essentially (Hon and Petrie, 1975). Numerous techniques have been put out in the literature to detect estimate the heart rate of fetal and retrieve fetal ECG in an effective manner. To extract fetal ECG from abdominal signal and estimate heart rate using R-R interval, the majority of conventional methods try to remove maternal ECG and the disturbances that are from the signal explicitly. Ferrara and Widraw, 1982 initial demonstration of the fetal ECG extraction problem made use of a traditional adaptive noise canceller. Adaptive filters work by minimizes MSE in relation to mother's ECG in order to determine the component present in abdominal signal of the mother. In our earlier work, we compared the use of different Least Mean Square algorithms to lower error in filters adaptively. Availability of at least one reference of mother's ECG is the main drawback of ANC.

In [8] Prenatal care has faced difficulties recently, with obstetric services becoming less available mostly because of a growing scarcity of obstetricians and gynecologists and higher-risk people who want to get pregnant.1,2 Expectant mothers may encounter challenges in accessing high-quality perinatal care due to the requirement for multiple clinic visits to collect fetal measurements and the growing challenge of obtaining professional perinatal care, particularly in remote areas. The current gold standard of care for external monitoring of a fetus during labor for non-stress tests and the contraction stress tests is cardiotocography (CTG).3. CTG can currently only be used by a medical expert since CTG Doppler sensors may need to be adjusted in response to fetal or maternal movement and must be positioned precisely for a strong signal.4 Furthermore, Doppler ultrasound—which actively injects energy into the tissue—is used by CTG to record signals from both the mother and the fetus.4 Additional limitations of CTG include its lesser value in high-BMI pregnant women, absence of automated analysis, and episodic measurement in the clinic or hospital.

In [9] Congenital LQTS is an uncommon hereditary cardiac channelopathy caused by an ion channel gene mutation that causes delayed ventricular repolarization of cardiac cells. LQTS was initially identified by Jervell and Lange-Nielsen in 1957. It is characterized by a T-wave irregularity, a longer QT interval, and increased QT dispersion in the ECG. There is a rare correlation between the prevalence, which is believed to be 1:2000, and congenital heart disease (CHD), albeit this link has only been reported in patients with structurally normal hearts. There is little agreement on the diagnostic criteria for LQTS in individuals with repaired CHD, and confounding electrocardiographic signs typical in CHD may mask the diagnosis and true incidence. There aren't many examples of LQTS linked to congenital heart disease (CHD), including those involving tricuspid atresia, Tetralogy of Fallot, VSD, patent ductus arteriosus, and ASD. The disease's initial manifestations, syncope, ventricular tachyarrhythmias (torsade de pointes), and sickle cell disease (SCD), can all occur in a wide range of clinical presentations. Since the symptoms in young children might be ill-defined, LQTS is commonly diagnosed in conjunction with specific bradycardias. At least 16 genes have at least hundreds of pathogenic mutations for LQTS discovered to date. As advised by current recommendations, a thorough genetic investigation is necessary to identify the aetiology in 80–85% of all diagnosed cases.

In [10] The technique of extracting knowledge (interesting patterns) from large datasets is known as data mining (DM), and it is currently receiving a lot of attention and attention as a leading analytical tool.1. Recently, information Numerous industries, including stock market analysis, banking, telecommunications, education, human resource management, supermarkets, health care management (HCM), and traffic management, use mining techniques. Classification and prediction are mostly used in data mining for study of current trends and future planning. A broader idea with several steps is data mining: The pre-processing stage of the data involves normalizing missing values, fixing missing labels, and reducing noise before applying various mining techniques such as clustering, association rule mining, and classification. The outcomes of implemented mining methods are assessed and interpreted.

In [11] The most frequent causes of neonatal morbidity and mortality is fetal hypoxia. A condition known as fetal hypoxia arises throughout pregnancy. The initial phase, known as hypoxemia, is characterized by a drop in the arterial circulation, but there is little impact on organ or cellular activities. The fetal's adaptive and compensation mechanisms kick in as the hypoxemia gets worse, enabling them to survive in this state for a few days or weeks without suffering any serious consequences [3]. If fetal blood's oxygen saturation is further lowered, peripheral tissues will start to show signs of its shortage, which will set off the anaerobic mechanism and cause hypoxia. The fetus won't suffer any long-term harm from this state for several hours. only employing aECG signals, extracting high-quality fECG data through adaptive filtering, and smoothing the resultant fECG signal while preserving its morphology to enable ST segment The primary advantage of this algorithm is analysis. Furthermore, the study's findings demonstrated that it is feasible to get the same precise fHR and ST analysis results as in the case of the invasive variant by using well-scanned non-invasive signals. Its fast computing speed is an additional advantage that would enable real-time operating systems to use it.

In [12] One of the most crucial tools for identifying fetal pathologies early on is prenatal cardiac monitoring. The majority of the developed world currently uses electronic fetal cardiac monitoring to identify the mother's and the fetus's risk factors. Eliminating potential causes of fetal morbidity or even mortality is the primary objective. Obstetricians and pediatric cardiologists can give appropriate medications or take essential measures during delivery or after birth with the aid of early and more effective diagnosis of fetal anomalies. Fetal monitoring is primarily used to detect intrauterine hypoxic infection early on, allowing the doctor to intervene promptly and prevent processing of signal methods that separates fetal ECG signals from the combination noisy recordings. Quality fetal ECG signal can be greatly impacted by movement artifacts, uterine contractions, and noise from the mother's ECG. To improve fetal ECG extraction, more research on this detecting process is required to increase accuracy to process signal methods. While the majority of fetal ECG monitoring technologies now in use have been designed for brief, transient surveillance, If we are to design inconspicuous technologies that are advanced enough to continuously monitor cardiac rhythms, we will need to rethink the current methods for studying fetal heart function. This will enable the continuous assessment of the heart's developing pulsations over extended periods of time, when congenital anomalies are suspected.

In [13] Standard clinical protocol is done by a sonographer in both standard 2D and 3D with the help of fetal sonography screening, which establishes criteria for the plane definition.2D planes of acquisition that are standard go through rigorous control the quality to make sure fulfill predetermined standards. In addition, sonographers require specialized training in order to fulfill these standards, since training initiatives have been demonstrated to enhance picture quality (Wanyonyi et al., 2014) and measurement variability (Sarris et al., 2011). ECG, the Electro Cardio Gram is a highly significant instrument for the practitioner to decide the cardiac health of a patient1. Similar to other parameters, fetal electrocardiogram (ECG) is used to determine the health of the fetus both during pregnancy and during childbirth. Both the mother's ECG and noise have an impact on the fetal ECG. This study's primary goal is to separate and extract just the fetal ECG from the conflicting cues. The current work suggests a technique for successfully and quickly isolating the fetal ECG alone. The benchmark ECG signals that were obtained from the mother's abdomen are available in the database that was used, which comes from PhysioNet. This study's algorithm is built on the Fast ICA framework. Software for graphical representation, like NI LabVIEW, is favored over Matlab because of its accuracy, affordability, and simplicity in understanding, building, and applying algorithms. In order to determine the accuracy of the current study, the beats per minute, amplitude, and correlation coefficient parameters the formula.

In [14] FMH has a significant part in fetal anemia, which is caused by a confluence of acute hypovolemia and a decreased blood oxygen carrying capacity, or hypoxemia. Anemia causes the circulation to become hyperdynamic, which is characterized by higher blood flow rates in different arterial beds.The middle cerebral artery (MCA) measurement was not considered by the authors. An elevated peak systolic velocity in fetal MCA has been reported by numerous writers in the literature to be useful in identifying anemic fetuses [2,4-6]. Doppler measurements, in my opinion, are simple to use and have a significant predictive potential for severe fetal anemia brought on by enormous FMH. Less than 10% of patients had nonreactive cardiotocography, which includes both tracings that have less fluctuation as opposed to a sinusoidal pattern. The patient did not exhibit contractile activity and reported less fetal movements. While computerized cardiotocography is not a diagnostic tool in and of itself, its predictive power for fetal acidemia risk is undeniable when it comes to the short-term variability (STV) value. Fetal acidemia, which is present when a major FMH occurs, is closely linked to a considerably reduced STV.

In [15] Temporary hypoxia is caused by the contractions of the uterus during labor, which restrict the mother's blood flow and the growing baby's oxygen delivery. Although most newborns are physiologically built to tolerate this kind of intrapartum hypoxia, individuals who are subjected to extreme hypoxia or have little physiological reserves may brain damage or passing away during childbirth. Cardiotocography (CTG) monitoring uses alterations in fetal heart rate (FHR) rhythms to identify infants at risk of hypoxia. In order to detect fetal hypoxia, CTG monitoring is commonly used in intrapartum care. However, the therapeutic efficacy of this technique is restricted due to the relatively low positive predictive value (PPV) of an abnormal CTG and the high inter- and nonobservant variability in CTG interpretation. The quality of CTG interpretation may be impacted by clinical risk and human factors. Misclassification of CTG traces can result in over-treatment (which could include needless surgical procedures that increase the risk of difficulties for both mother and child) or under-treatment (which carries a risk of fetal harm or death).

In [16] The Institutional Ethics Committee gave its approval to the study (IEC 490/ 2017). We got informed consent in writing from every participant. A tertiary-care hospital in South India carried up a prospective observational study involving 304 singleton term pregnancies with vertex presentation during labor. Women who got epidural analgesia and pregnancies with significant fetal growth limitation, fetal abnormalities, and preeclampsia were not included. We determined the sample size using a 5% margin of error and the predicted number of occipitoposterior (OP) positions in work (26%). 95% degree of confidence. There were 295 samples in all.Women in early labor with a cervical dilation of less than 4 cm were recruited. The body mass index (BMI) of the mother was determined. Using the formula BMI= (weight in kg)/(height in m) after determining weight (kg) and height (m).2. Utilizing a 2.5-MHz curved-array transducer, transabdominal ultrasonography was carried out to determine the location of the fetus. The relative position of the fetal occiput with respect to the mother pelvis was noted, along with the fetal vertebral column to support the findings. The arrowhead formed by the thalamus and falx cerebri in the fetal transthalamic plane pointed toward the fetal occiput, indicating the location of the fetal head. Fetal postures were divided into two groups: OP and non-OP.

In [17] One method for continuously monitoring fetal health is cardiotocography (CTG). From the CTG pictures, dynamic changes in two physiological signals, such as the uterine contraction and the fetal heart rate, can be retrieved. It is easy to use, non-intrusive, real-time, and straightforward to read. In clinical practice, doctors can use the data to observe the health status of the fetus of FHR monitoring in real-time (for at least 30 minutes) [1]. With this knowledge, prompt action can be performed in the event of an emergency to prevent fetal asphyxia (hypoxia) and other issues. The study of signal extraction on the CTG digital pictures will be beneficial to the creation of large-scale databases. A central monitoring system obtains the CTG digital images system or scanning apparatus. The primary obstacle in signal extraction is getting rid of background patterns, such grids. The background patterns affect the outcomes of data extraction negatively, even though they help with the physician's visual assessment. Based on the color of the grid lines, the CTG images can be classified as either a binary (black) or color (non-black) image. The majority of researchers analyze color CTG pictures using the color difference between the signal curve and background grids.

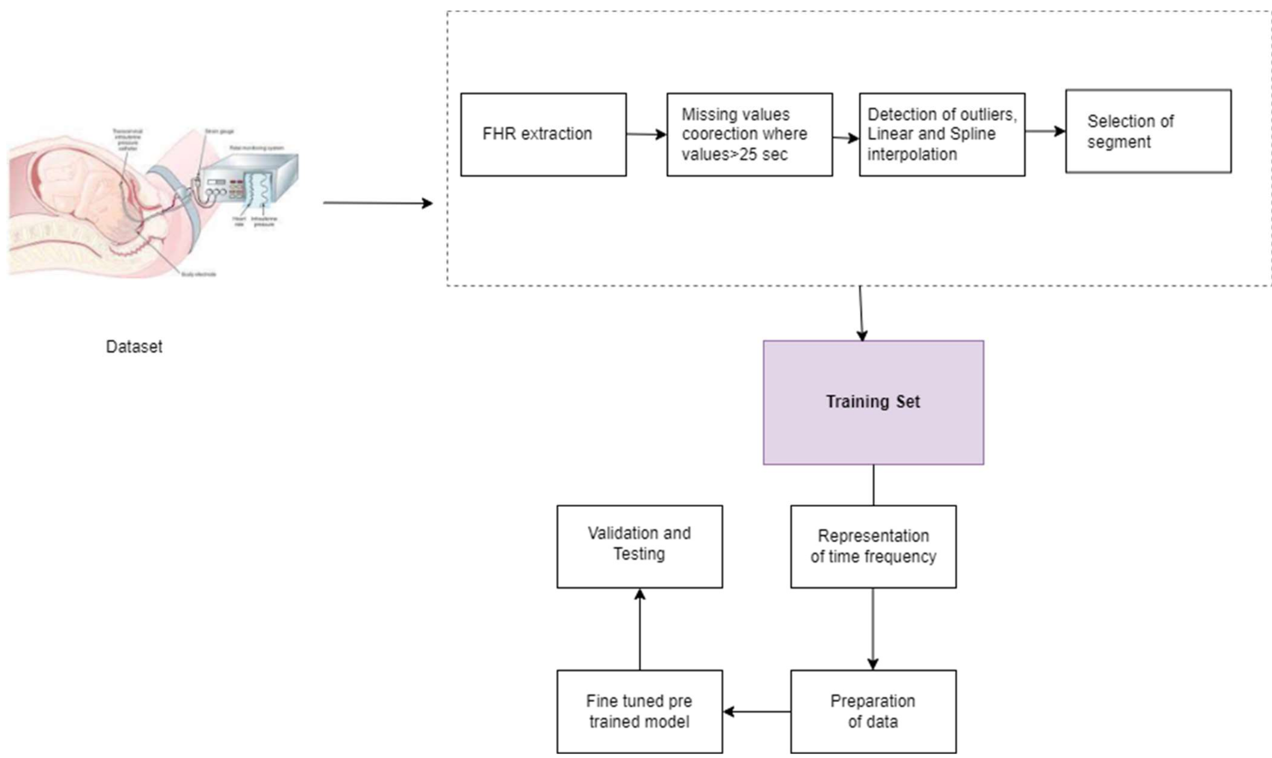
In [18] The incidence of older pregnancies increased as a result of rapid economic development, which also increased the need for ongoing prenatal and fetal monitoring. FHR and UC signals that can non invasivly recorded with low cost using cardiotocography (CTG), which is frequently used to detect early ischemia and hypoxia in fetuses. Regrettably, variations in obstetrician competence and experience have hampered the visual interpretation by obstetricians for CTG, leading to inconsistent outcomes that may be challenging to replicate. Establishing a trustworthy model for the automatic classification of CTG information is therefore essential. Deep Learning (DL) has mostly been used for extraction and classification. The former could be conventional or rule-based. Systematic visual assessment is carried out using a rule-based methodology to determine morphological CTG features and estimate fetal state in accordance with clinical recommendations for fetal monitoring. The number of decelerations/accelerations, morphological variability, and CTG morphological traits at baseline are combined. These parameters, however, are very dependent on expert knowledge; additionally, they concentrate on CTG shape, which results in high sensitivity, low specificity, and potentially even needless cesarean procedures. The advancement of classical machine learning techniques has been significant with the emergence of computational CTG technology.

In [19] In Netherlands, there has been an increase in the number of referrals from MLC to OLC in recent decades. By offering more services in MLC, continuity of care during pregnancy and delivery may be enhanced, hence lowering the number of referrals. Antenatal cardiotocography (aCTG) is a potential procedure for this shift when pregnant women are in circumstances where there is a higher risk to the health of the fetus, such as when there are fewer fetal movements, following external cephalicversion in general care and postdate pregnancy. While recommendations generally recommend utilizing aCTG to assess fetal well-being during pregnancy in women at increased risk of problems, there is no conclusive evidence that it improves postnatal outcomes. In the past, only hospital-based OLC professionals had performed ACTG. Advances in e-health make MLC-aCTG possible since a second professional can evaluate the aCTG recording in real time. who is absent from the area where the aCTG is being done. MLC-aCTG has been implemented for women with the aforementioned indications in three locations of the Netherlands. It is crucial to assess the quality of care in accordance with VBHC principles when reorganizing duties and responsibilities. This means that outcomes should be monitored using crucial parameters, such as procedural and clinical parameters in addition to patient-reported outcome and experience measurements. Studies have indicated that women express great satisfaction with MLC-aCTG.

In [20] Artificial intelligence has evolved a long way from theoretical artifact to a well-defined domain in engineering which is introducing numerous applications in each and every upcoming years. The term “AI” is termed as an agglutinating a group of technologies that endow machines which includes cognitive functions which can be associated by humans with their mind, such as learning and problem solving. These systems are continuously available while decisions are taken and scaled up to an unlimited number of patients in a hospital, and are not affected by human factors which also reduces inter- and non-observant variability. Recent methods are attempted to imitate human analysis by encoding the rules which were extracted from domain expertise. ML replaced this strategy and learns big data sets for inference models. The discipline of machine learning has created a significant number of algorithms where their input can be anything from manually created features to the traced or raw data.

In [21] In order to gauge the comfort of the unborn child and identify an increased risk of pregnancy issues, cardiotocography defines monitoring and documenting the infant's heart rate and spams uterine during pregnancy. This, makes it possible to identify and treat embryonic hypoxia early on, before it results in severe asphyxia or even death. Vital signs of the fetus's health include heart rate variability responsiveness, and possible slowdowns during uterine spasms. The author presented a brand-new clinical verdict assistance system that was constructed using an extreme machine learning algorithm and an improved adaptive genetic algorithm. The model's final classification accuracy was 94 percent. Predicting fetal health in utero is crucial for the physical well-being of a newborn.

III. PROPOSED METHODOOOGY



Dataset:

Feature selection and scaling:

CTG dataset consist of 28 recorded features which are the regarded as the combination of signals depicted from the heart rate, uterine contraction pressure and many more measurements of the fetus. Target variables are classified into 2 types, they are fetal health status (Normal and Suspect) and classifying pattern which is of range (1-17). The datasets consist of 2227 observations where 1765 comes under N-class, 301 for S and 198 for P-class and is regarded as an imbalance dataset which includes 78.96% of the overall samples. In recent studies, choosing the most pertinent features from a dataset which connects a strong link between chosen attributes and intended variable. The feature selection method trains models and avoids the curse of dimensionality. Dataset consists of 28 features, where not all of them are for prediction. To extract the best features from K=10 from CTG data, limits data form (2227, 20), which includes Chi-square feature selection approach. For smaller feature size, fewer calculations will be involved, which reduces final classifier model's complexity. Value of observable attributes varies in an unstable range in real-world data. Traits with high weight may influence objective function more and skew the experimental results. Scaling features is a crucial process for data technique in ml research where the variables are independent features of a fixed scale is used to standardize a dataset and permits all the feature to contribute equally to the goal function's optimization. The dataset split, contains both testing as well as training data and normalize within range of [1-3] using method of Min-Max feature scaling. Scaled features produces accurate and predictions that are biased free because data contains both continuous as well as discrete values. Assuming X as a randomly selected feature in the space. Xscaled and Xval, respectively, are the normalized values which are described as maximum and minimum values for the feature in list are denoted by Xmin and Xmax, respectively.

Validation for K-FOLDS:

Cross validation for k folds is done using training dataset at "Level 0" system for every algorithm. Training data is splitted in ten folds, and during cross validation, nine of ten folds are train data and the remaining folds are termed as validation data and is known as K-1 fold. Each iteration's validation fold varies with each iterations that are equal to number of foldings. Validation data on Base learners' prediction, where "Level 1" meta classifier performs in-depth during the cross-validation. In validation data, Model for Random Forest classifier outperforms three models and demonstrates an accuracy of 98.94%. The Decision Tree classifier, Deep forests and Extra Trees obtains respective accuracy of 93.01%, 85.05%, and 97.09%. Standard Deviation value was estimated by the study. Random Forest, is used as ensemble learning model for meta classifier as it produces the highest number of outcomes during validation.

El classifier with stacking:

The output vector by base learning algorithms that are passed and stacked into ensemble learning classifier model where individual base learners' predictions teaches the meta about patterns. EL method is used where the meta learner is trained well and lowers down error rate as the decisions are made by all the basic learners. On the other hand, EL stacked classifier model is created to make predictions on dataset testing which is being ensembled and trained.

Preprocessing:

FHR Extraction:

Fetal monitoring keeps tabs on the rhythm and pace of your unborn child's heartbeat. An unborn child's heart beats between 110 and 160 beats per minute on average. Your baby's heart rate can be monitored to see whether it is too high, too low, or fluctuates too much. Over the course of ten minutes, mild variations between six and 25 beats per minute are typical. Heart rate irregularities may indicate that your baby is experiencing oxygen deprivation or other issues. Your healthcare professional may employ fetal monitoring in the following circumstances:

Prenatal checkups: During typical prenatal care visits, your healthcare professional may take your baby's heart rate.

High-risk pregnancies: If your pregnancy is high risk, you will probably need to be monitored. Preeclampsia, diabetes, or bleeding during pregnancy are conditions that could increase your chance of complications during your pregnancy. Your infant will be monitored by your provider during labor and delivery. Fetal heart rate monitoring comes in several forms.

Fetoscope: This device is used to listen to your heart and lungs, much like a stethoscope. It has a cone-shaped tip. To hear your unborn child's heartbeat, your healthcare provider applies the cone to your abdomen.

Doppler ultrasound on a handheld device: Doppler ultrasound measures your baby's heart rate by using sound waves. During prenatal visits, providers frequently employ handheld Doppler machines. Your healthcare professional will apply gel to your stomach and insert the probe into the gel. The gadget detects the heartbeat of your child and shows the result on a screen. Versions of handheld Doppler instruments are available for use at home. The Food and Drug Administration (FDA), however, opposes using these gadgets at home. Continuous **Doppler ultrasound**: An apparatus that measures your contractions is attached to a second strap. The monitor that receives the wires from the devices shows your baby's heart rate continuously.Physicians check on your unborn child less frequently. To continuously monitor your baby's heart rate, your healthcare practitioner will affix a cable to their head. Internal monitoring is only used by providers during labor and delivery if and when your water breaks. The results of external electronic fetal monitoring are not trustworthy. You require more accurate observation.

Missing values correction:

One of the most important steps in preparing data that is necessary for precise analysis and modeling is correcting missing values. It starts by locating missing or incomplete entries in the dataset, which can be caused by a number of things, including incorrect data entry or a lack of response. Once found, there are a number of ways to make the repair. Imputation is the process of substituting estimates from the available data for missing values using methods such as mean, median, regression, or nearest neighbors. As an alternative, deletion eliminates entries that are incomplete; nevertheless, if this method is not used correctly, it may result in bias and information loss. By providing insights into the causes of missing values and guiding the most suitable repair techniques, domain knowledge can help direct the corrective process. But whatever strategy is used, validation is necessary. Various methods in data analysis support the processing of missing values. They are isnull(), dropna(), isna(), .notnull(), fillna(), replace(), drop_duplicates(), unique(), etc. The missing values that are greater than 25 seconds can be removed by specifying the condition within the function we use. This helps in removal or appropriate replacement of unwanted data.

Detection of outliers, Linear and Spline interpolation:

Data points known as outliers causes the statistical analyses that is been distorted and are drastically differed from the rest of dataset.The process of detecting and managing these abnormal data is known as outlier detection. Common ways include methods based on the interquartile range (IQR), where outliers lie outside a specified range of the quartiles, or statistical techniques like Z-score analysis, where data points over a given threshold of standard deviations from the mean are flagged as outliers. Outliers can be dealt with in a number of ways after they are identified, such as trimming (deleting extreme numbers), winsorization (changing extreme values with less extreme ones), or transformation (normalizing the data using mathematical procedures). By linear relationship between linear interpolation, neighboring data points and calculates the missing values. A line that is straight connects the known. Along a straight line connecting the known data points, it computes the values at missing points. For datasets with linear trends or connections, this strategy is easy to use and quite effective.

Spline interpolation, on the other hand, interpolates between data points using piecewise polynomial functions. By fitting distinct polynomial functions to neighboring subsets of the data, or "splines," it produces a smooth curve that intersects every data point. Spline interpolation can more precisely capture nonlinear relationships in the data and is more versatile than linear interpolation. To get accurate results, though, it might need more data points and require greater processing power.

Selection of segment:

The process of locating and selecting particular subsets or segments within a dataset for modeling or analysis is known as segment selection. The objectives of the study and the properties of the data frequently serve as a guidance for this choice. The segments selected should be in line with the goals of the modeling or analysis assignment. For example, segments may be created based on demographics, purchasing history, or geographic area if the objective is to comprehend client behavior. Segments should have unique, significant qualities that are pertinent to the analysis. Patterns, trends, or behaviors that set one section apart from another could be among them. Segments ought to be both outwardly and inwardly heterogeneous. This indicates that while data points in various segments should differ from each other, they should also be comparable to each other within a segment.Parts ought to be big enough to make useful inferences from, but not so big that they become indistinct. They should also be a good representation of the larger population or topic being studied. It is important to think about how practical and actionable the chosen parts are for intervention or decision-making. It's crucial to use analysis and testing to confirm the relevancy and efficacy of the segments you've chosen. Based on the outcomes, repeat the segment selection procedure as needed. In data analysis and modeling, segment selection is essential because it establishes scopes of study and obtains insights from data. Through meticulous segmentation that is pertinent to the goals, analysts can extract insightful information and arrive at well-informed conclusions.

Representation of time frequency:

In order to comprehend dynamic signals such as speech, music, and seismic data, time-frequency representation (TFR) techniques are essential. TFR approaches show how a signal's frequency content changes over time. By dividing the signal into brief time intervals, the Short-Time Fourier Transform (STFT) produces spectrograms that show how the frequency changes over time. Continuous Wavelet Transform, provides flexibility to signal features at several scales, employs wavelets of various scales for simultaneous frequency of time analysis. Discrete Wavelet Transform breaks (DWT) breaks down signals into wavelet coefficients at different scales and places to allow multiresolution analysis. For non-stationary signals, time-frequency distributions (TFDs) such as the Wigner-Ville Distribution provide direct time-frequency visualization without the need for predetermined basis functions. The Gabor Transform combines elements of windowed Fourier and Fourier transforms to achieve a balance between temporal and frequency resolution. The needed time and frequency resolutions, computational complexity, and result interpretability all play a role in selecting the best TFR approach. TFRs provide insights into the dynamic behavior of signals across both time and frequency domains makes them essential for many applications such as audio processing, biomedical signal analysis, and communication systems.

Preparation of data:

A crucial step in the data analysis process is data preparation, which involves converting raw data into an organized, clean format that can be analyzed. There are multiple crucial phases involved in this. First, data collection makes sure that pertinent information is gathered from several sources and fits the objectives of analysis. Next, data cleaning uses methods like imputation and outlier identification to address missing values, outliers, and inconsistencies. Integration resolves discrepancies in variables and formats by merging data from several sources. While feature engineering adds new variables or changes existing ones to increase prediction power, transformation adjusts variables to better analysis. The dataset is split into subgroups for testing, validation, and training. Normalization guarantees consistent feature scaling, avoiding the dominance of particular factors. Categorical variables are encoded to create numerical representations that can be used in modeling. In order to ensure fair representation of classes in classification tasks, it is imperative to address data imbalance. Lastly, validation uses statistical tests and exploratory analysis to confirm the integrity and quality of the data. Reliable analysis and well-informed decision-making are made possible by accurate, full, and correctly formatted datasets, which are guaranteed by effective data preparation.

Algorithms used:

Prediction of health of fetal in womb of mother is very crucial for health of new born baby. The proposed model consists of numerous layers like training data layer, testing data layer, training layer, testing layer, and the proposed model extracts bio-signal cardiotocography data using a device called cardiotocograph and uses various techniques of data preprocessing like fetching overall data insights from each class instance and then applying techniques for cleaning the data like removing the data redundancy. Once the processing of data is over, the training layer is initiated by the proposed model and the data is imported into KNN machine learning algorithm. This algorithm does the checking of learning criteria using performance meter, if not satisfied the model is retrained.

On the other hand, in Levenberg Marquardt, Bayesian Regression and Stochastic Gradient Descent machine learning algorithms the proposed model imports data and learning criteria is checked whether it meets the requirements and then moves trained weights into federated average process otherwise the weights are retuned and check the learning criteria again. The testing phase is initiated by proposed model, where the data is fetched from bio-signal cardiotocography using cardiotocograph equipment and given to testing process. If the fetal has normal heart rate then the infant is healthy, otherwise medications are required.

The suggested model predicts health of fetus inside mother's womb for the KNN and FML algorithms. using the KNN and FML algorithms. FML is used by Algorithm 1 in both the client and server stages. The suggested model computes backpropagation error and trains FML weights using feedforward and tuning weights (Rij and Gjp) in the server phase. Once training is complete, the session server forwards the tuned weights to the client phase for aggregation to improve performance. Phases 6 and 7 of the client do average aggregation in order to test the instances. The entire KNN training and testing procedure is demonstrated in Algorithm 2, where KNN first gathers cases and uses the K score for training. If K's score is below the predicted cutoff, the case is considered normal. Otherwise the instance is considered conjecture.

Algorithm 1

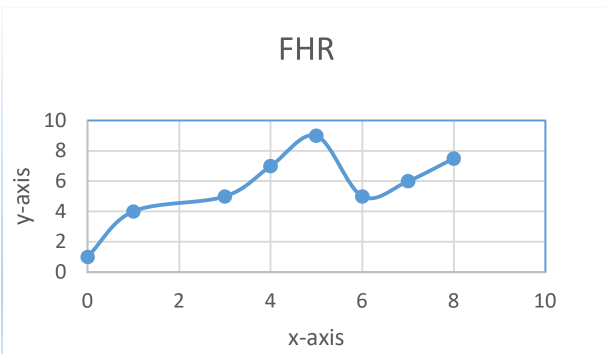
```
# Initialize counts for Normal, Suspect, and Pathologic readings
normal_count ← 0
suspect_count ← 0
pathologic_count ← 0
# For each CTG instance
for each_ctg_instance from h to p do:
  # Randomly select a cluster of readings for analysis
  selected_readings ← random_select_readings(each_ctg_instance)
  # Analyze each reading in parallel
  for each reading in selected_readings parallel do:
    # Analyze the reading
    status ← analyze_reading(reading)
    # Update counts based on the status
    if status = "Normal" then:
      normal_count ← normal_count + 1
    else if status = "Suspect" then:
      suspect_count ← suspect_count + 1
    else if status = "Pathologic" then:
      pathologic_count ← pathologic_count + 1
  end for
```

Algorithm 2

```
# Input: Training dataset Z (consisting of CTG readings and corresponding labels)
# Output: Classification of test CTG readings into Normal, Suspect, or Pathologic
# Define the KNN algorithm for CTG classification
function KNN_CTG_Classification(Z, test_data):
  # Initialize counts for Normal, Suspect, and Pathologic classifications
  normal_count ← 0
  suspect_count ← 0
  pathologic_count ← 0
  # Iterate over each test CTG reading
  for each test_reading in test_data:
    # Calculate similarity scores between the test reading and each training sample
    similarity_scores ← calculate_similarity_scores(test_reading, Z)
    # Find the k-nearest neighbors (kNN) based on similarity scores
    k_nearest_neighbors ← find_k_nearest_neighbors(similarity_scores)
    # Evaluate classification based on the majority label of kNN
    classification ← classify_kNN(k_nearest_neighbors)
    # Update counts based on the classification
    if classification == "Normal":
      normal_count ← normal_count + 1
    elif classification == "Suspect":
      suspect_count ← suspect_count + 1
    elif classification == "Pathologic":
      pathologic_count ← pathologic_count + 1
  # Determine the final classification based on counts
  if normal_count > suspect_count and normal_count > pathologic_count:
    return "Normal"
  elif suspect_count > pathologic_count:
    return "Suspect"
  else:
    return "Pathologic"
# Helper function calculates scores for a test and training samples reading
function calculate_similarity_scores(test_reading, training_data):
  similarity_scores ← empty list
  for each training_reading in training_data:
    similarity_score ← calculate_similarity(test_reading, training_reading)
    append similarity_score to similarity_scores
  return similarity_scores
# Helper function to find the k-nearest neighbors based on similarity scores
function find_k_nearest_neighbors(similarity_scores):
  # Sort similarity scores in descending order and select the k nearest neighbors
  sorted_indices ← sort_indices(similarity_scores, descending=True)
  k_nearest_neighbors ← sorted_indices[:k]
  return k_nearest_neighbors
# Helper function to classify based on the majority label of k-nearest neighbors
function classify_kNN(k_nearest_neighbors):
```

Count occurrences of K-nearest neighbors for individual labels
label_counts ← count_occurrences(k_nearest_neighbors)
Select the label with the highest count as the classification
majority_label ← label_counts.argmax()
return majority_label
Main code
Load training dataset Z
Z ← load_training_dataset()
Load test dataset
test_data ← load_test_dataset()
Set k value for KNN
k ← choose_k_value()
# Perform KNN classification for each test CTG reading
for each test_reading in test_data:
classification ← KNN_CTG_Classification(Z, test_reading)
print("Classification for test reading:", test_reading, "is", classification) is composed of n − 1 cubic polynomials fk defined on the ranges [xk, xk+ 1].

IV. RESULTS AND DISCUSSION



This kind of interpolation creates a new data point between two points by applying the curve fitting approach and a linear polynomial. The new value of y is produced by linear interpolation for two known data points with coordinates of (x0, y0) and (x1, y1). Unstable sample points of the FHR signal that differ by more than 25 beats from the previous adjacent beat are not physiologic and are therefore removed using cubic spline interpolation. These unstable points manifest as spikes on the FHR signal. Piecewise smooth polynomials are a very effective and popular way for interpolating a function between a specified set of points. A piecewise polynomial function f(xk) = yk, given a cubic spline f(x) interpolating on the partition x0 < x1 < ⋯ < xn-1,

The final dataset, after augmentation, had 1556 time frequency pictures, of which 878 belonged to the normal class and 678 to the pathologic or distressed class. The number of data utilized to train the system is 790 for normal and 610 for distressed, depending on the data split ratio that was employed. The testing set consisted of the remaining 10%, or 156, of which 68 were abnormal and 88 were normal. 10% of the training data from each class was chosen at random during training using a validation frequency set of 15 iterations.

The ResNet50 model is trained independently for the first and second experiments, which are the first 20 minutes and the last 15 minutes of the CTG recording, after the data was separated and prepared. The performance of the ResNet-50 model is assessed in order to determine the optimal fine-tuning parameters for the classification task. As a result, the validation dataset was used to validate the model after it had been trained using the training dataset.

The training dataset is used to create the learning curve, which shows how well the model can learn. On the other hand, a validation dataset is used to create the validation learning curve, which shows how well the model generalizes. The training accuracy (blue curve), validation accuracy (black dot with blue curve), training loss (brown curve), and validation loss (black dot with brown curve) curve plots for the models are shown

Classifier Model	MSE	R2	Kappa	Precision	Recall	F1-Score	Accuracy	Error Rate	AUC
Decision Tree	0.089	0.952	0.7896	0.8743	0.7878	0.804	90.40%	0.0725	0.9427
Random Forest	0.079	0.915	0.5638	0.9123	0.599	0.9108	93.18%	0.0498	0.9347
Extra Trees	0.059	0.849	0.7658	0.9533	0.91	0.9152	95.72%	0.058	0.9045
Deep Forest	0.081	0.744	0.348	0.5097	0.8286	0.8054	97.56%	0.0546	0.9228
Ensemble Learning	0.071	0.651	0.5877	0.6973	0.9306	0.912	96.05%	0.0359	0.9435

V. CONCLUSION

The discussed research represents FML model which suggests a classification for FHR in womb to assess heart rate health of the fetus womb in order to assess physical heart rate health of the fetus, using Machine Learning Algorithm. This approach has obtained 99.08% testing rate of success using FML for both the testing and training data of the fetal heart rate simulation over the entire pregnancy period with precision at 0.95% CMR. The model here uses KNN which simulates the entire data, hence produces testing accuracy of 84.94% and CMR of 18.07. Results showed that FML performed better than KNN. clinical fields and Biotechnology will immensely benefit from enhanced results on the basis of improving physical health of fetuses, where suggested model outperforms research of previously performed ones in terms of accuracy, it is to be refined furtherly using a larger dataset to produce more accurate results. This suggested model will grow more in the future inventions when fuzzed data model and fuzzed technology are combined together, enabling the Internet of Things Medically. By the approach of a weighted federated machine learning methodology more accuracy can be achieved.

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