Exploring the Insights of Bat Algorithm-Driven XGB-RNN (BARXG) for Optimal Fetal Health Classification in Pregnancy Monitoring

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***Abstract*—Pregnancy monitoring plays a pivotal role in ensuring the well-being of both the mother and the fetus. Accurate and timely classification of fetal health is essential for early intervention and appropriate medical care. This work presents a novel method for classifying fetal health optimally by combining the Bat Algorithm (BA) in an effective manner with a hybrid model that combines Recurrent Neural Networks (RNN) and Extreme Gradient Boosting (XGB). The Bat Algorithm, inspired by the echolocation behaviour of bats, is employed to optimize the hyperparameters of the XGB-RNN hybrid model. This enables the model to adapt dynamically to the complexities of fetal health data, enhancing its performance and predictive accuracy. The XGB-RNN hybrid model is designed to capitalize on the strengths of both algorithms. XGB provides superior feature selection and gradient boosting capabilities, while RNN excels in capturing temporal dependencies in the data. This approach effectively deals with the difficulties involved in classifying fetal health in the context of pregnancy monitoring by combining these approaches. Python is used to implement the proposed framework. To validate the performance of the proposed approach, extensive experiments were conducted on a comprehensive dataset comprising a wide range of physiological parameters related to fetal health. When it comes to fetal health, BAT Algorithm's XGB-RNN (BARXG) performs outstandingly, greater than other classifiers in terms of accuracy, sensitivity, and specificity. The proposed BARXG model has greater accuracy (98.2%) than existing techniques, which include SVM, Random Forest Classifier, LGBM, Voting Classifier, and EHG.**

Keywords*—BAT; fetal health; pregnancy monitoring; RNN; XGBoost

I. Introduction

Embryogenesis and maternity are essential components for human life and fertility. Whenever the fertilized egg, also called as a zygote, grows becomes a developing embryo, becomes a fetus, and finally culminates with the conception as a new human being, it is called pregnancy. Although becoming pregnant is an amazing experience, there are dangers and uncertainty involved. It is crucial to protect the mother's wellness and health in addition to the developing fetus. Regular fetal health monitoring is essential to prenatal treatment in order to identify and quickly fix any possible problems. This is a complicated and transformational process. Monitoring the development of the fetus throughout pregnancy is one of the hardest and most complex treatments. Although the average duration of this incredible journey is forty weeks, individual experiences may vary greatly [1]. The growing child of a person around the final stages of pregnancy is called a fetus. It is a crucial phase that comes after the embryonic stage and before childbirth during the entire human gestational process. In the fetus, the life form develops significantly. Usually, the fetus is just a few millimeters long at the start of the fetal stage, which occurs during the ninth week of development [2]. The fetus may grow to a size of 19 to 21 inches or greater by the conclusion of the trimester. The following are the phases of fetal growth. Weeks 9–12 of the first trimester, the fetus experiences tremendous expansion and growth. Important organs and tissues develop, and the fetus starts to take on characteristics of a little human. Weeks 13–27 of the second trimester, the fetus's body is growing as well as becomes more proportional. The embryo starts to move more deliberately and has the ability to grab items and sucks its thumb. Weeks 28 to Birth of the third trimester, a noticeable increase in size characterizes the last trimester.

This tissues and structures of the fetus develop more in order to get prepared for living beyond the mother's body [3]. The mother can clearly observe the fetus's movements, and it is capable of reacting to outside stimuli. A fetus is vulnerable to various issues throughout the course of pregnancy. Obstetrics carelessness can have devastating consequences, such as during childbirth fetal mortality, deaths from stillbirth, including over time infant neurological abnormalities. More than 1.3 million fetal fatalities happen throughout childbirth every year [4]. Birth asphyxia represents one causing the main causes of fetal death. Birth asphyxia, also known as hypoxia, is the result of a disruption in the blood supply via the placenta, which results in low oxygen levels in the fetus's brain. Hypoxia-induced fetal distress can result in a range of anomalies during birthing that can be classified as either life-threatening or non-life-threatening. A newborn's brain is very susceptible to the effects of oxygen; hence a shortage of oxygen can have fatal consequences for the developing brain. Therefore, in order to identify fetal acidic conditions early on, we require an effective method that can track the fetal condition in real time and notify obstetricians when something odd happens so they may act quickly to save the fetus from irreversible harm. Birth asphyxia caused hypoxia causes permanent mental and physical disabilities such as spinal cord injury, deafness and visual impairment, speech difficulties, and autism. One typical outcomes diagnosis linked to fetal/perinatal brain damage is cerebral palsy (CP).

Most people agree that cerebral palsy (CP) is a disorder for neurological growth that causes dyskinesias and spastic quadriplegia or diplegia, and hemiplegia. In full-term newborns, the rate of CP ranges from 2.5 to 4.0 in 1000 births. However, this number rises to 16–22 per 1000 live births for children delivered preterm or individuals that are tiny for their gestational age (growth limited). In industrialized nations, the Maternal Mortality Ratio (MMR) is significantly lower than in impoverished nations. High MMR frequently results in issues such as pre-eclampsia, insufficient tracking of both the maternal and unborn child's health, and pregnancy-related diabetes. With the right medical attention, MMR can be decreased and avoided. Monitoring of the baby is a routine practice carried out in the third trimester. Fetal tracking involves assessing the unborn child's health [2]. The well-being of the mother has a direct impact on fetal development. Cardiotocography is used to continuously measure the well-being and development progress of the fetus in order to prevent such issues. The goal of the cardiotocography is to assess the maternal uterine contractions while simultaneously monitoring the fetus' heartbeat. This procedure could be carried out in the last trimester, after the fetus's development has fully synchronized with its heart beat. Because this technique is simple and inexpensive, it should only be used by qualified medical professionals to diagnose fetal condition early and lower fetal mortality. The results of the CTG will show the mother's uterine contractions alongside the unborn child's heart rate, acceleration, deceleration, among other intricate measurements. Mother and fetal well-being are closely related. Managing the well-being of mother as well as baby depends on lowering the number of fetal deaths and keeping an eye on the circumstances of fetal health [5]. A prenatal test used to track the heartbeat of the fetus and uterine contractions throughout both gestation and delivery is called CTG, or Electronic Fetal Monitoring (EFM).

These variables are monitored by two sensors, and the initial value, allowable variations, decelerations, and accelerations are used to classify the fetal health state. Medical professionals regularly look at these amounts and classify the fetus's health. Any numbers that deviate from a healthy state should raise suspicions about one's health. Healthcare workers review the data and assign an identifier to each characteristic. The CTG technique, which uses an electromagnetic field (EMF) equipment to track heart rate and uterine reductions throughout pregnancy, is used to get these data. Healthcare professionals physically categorize collected information and match it within a category in which the criteria are fulfilled; whenever the values fall outside of this range, an anxious condition is indicated. Through health state prediction, machine learning techniques can help physicians determine the fetal medical condition [6]. Doctors often use cardiotocography (CTG) for their clinical duties to track and evaluate the fetal status throughout gestation and delivery. CTG entails constant recording of both uterine contraction (UC) and fetal heart rate (FHR) signals. However, as fetal physiological changes are intricate and controlled through neurological mechanisms, there is typically a great deal of intra-observer and inter-observer discrepancy when utilizing standard criteria over visual interpretation of FHR signals. Obstetricians reduce diagnostic errors during labour by doing several subjective judgments. The key issue with the previously described procedure, nevertheless, is that it cannot be empirically realised; instead, obstetricians rely their conclusions only their own observations. As a result, the frequency of needless cesarean sections (CSs) brought on by subjectively mistake is rising, and this has made the pursuit on an additional accurate examination of the FHR signal its primary motivation.

The principal technique used most commonly in hospital routine tests for fetal status identification is the cardiotocogram (CTG). Prenatal surveillance of CTG primarily uses two physiological signals: fetus heartbeat and uterine contractions. The distress of the fetus affects FHR, resulting in anomalous high or decreased FHR occurrences. Initial pathogenic condition identification is accomplished with the help using such data. CTG data may be used to categorize the fetus's pathogenic status in relation to regular, which indicates its healthy state. A hypoxic fetus is extremely susceptible and might be temporarily impaired or even die after birth. Over half of all the deaths that occur can be attributed to insufficient therapy and misinterpretation of FHR [7]. Fetal health diagnosis is a challenging procedure that depends on a number of input elements. The identification of fetal healthy state is made based on the levels or range of values associated with these symptoms. Determining the precise amounts for the periods among the provided signs that influence the diagnosis's outcome can be challenging with occasions. Physicians frequently divide the entire pain phase value into smaller segments, examine each segmented segment, and determine the person's overall health status based on their analysis. These periods frequently convey uncertainty and might vary from patient to patient. Additionally, distinct patients may respond to similar illnesses in varying ways. Women who are getting ready to become mothers have begun looking for prenatal guidance and knowledge about risks while illness symptoms through online resources. Despite approximately 3.7 billion application downloads in 2017, there were over 325,000 fitness, health, and medical applications accessible; pregnancy-related apps make up a significant portion of this category [8].

Apps for smartphones and tablet computers can help expectant mothers obtain information, track the growth of their fetus, comprehend alterations to their own bodies, and get comfort when they have worries. A gadget like a video camera, wellness tracker, Kegel "exerciser," fetal heart rate "listener," or another kind of device allowing participants to monitor and communicate their personal data might be linked to maternity applications. On the other hand, nothing exists regarding the way smartphone app-based health treatments affect mother's behaviours or perinatal well-being [9]. However, there is a lack of research on the effectiveness of apps, their content, how mothers use them, or the best methods to include them into normal prenatal education and care. Midwives along with other professionals often speak to pregnant women that download and utilize applications. Classification systems for fetal health aid in the early detection of anomalies, problems, or departures from the typical developing processes [10]. Healthcare personnel have the ability to swiftly implement suitable treatments since earlier diagnosis. Rapidly healthcare treatments might be critical towards avoiding or minimizing problems, and early diagnosis of fetal health abnormalities facilitates these therapies. Based on the severity of the problem, this may involve measures including suggesting surgery, giving medicine, or altering mom's lifestyle. Pregnant women might feel less stressed and anxious when they realize their unborn child is well and under constant observation. Improved outcomes and fewer needless healthcare procedures might arise from personalized care. More precise fetal health categorization enables improved delivery process preparation. This helps in deciding if early labour inducers or cesarean section is required, as well as ensuring the right doctors remain on hand for the birth. In healthcare applications, selecting features is a critical process that is handled using the Bat Algorithm. The research shows how this method may be used to improve model accuracy and comprehension by identifying the most pertinent characteristics in the Cardiotocography (CTG) dataset.

The following are the main contributions to the suggested work:

- In an initial processing measure, it employs class weighting to prevent overfitting when training the model.
- Sequencing and temporal connections in data are captured by RNNs. RNNs may simulate how fetal heart rate and uterine contraction patterns change over time within the framework of fetal health monitoring. This is necessary in order to identify any abnormalities or anomalies.
- A hybrid design fuses the RNN and XGBoost models together. This combination enables the model to take use of RNNs' capacity for capturing temporal dynamics and XGBoost's expertise in feature engineering.
- The output of RNN is fed into XGBoost for classification. RNN-XGBoost model had hyperparameters tuned using the BAT algorithm.
- In the end, the optimization process of the Bat Algorithm yields a collection of characteristics regarded most significant for the goal of classifying fetal health.

This article's remaining sections are organized as follows: In Section II, an overview of relevant studies is provided. Section III presents the problem description for the current system. The approach and architecture of the suggested BARXG model for Fetal health classification are explained in Section IV of the paper. Section V presents the findings from the investigation and the subsequent discussion. Conclusion and future application of the suggested paradigm are covered in Section VI.

II. Related Works

The research in [11] proposed a fetal health classification using T2-FNN method. The fetal medical diagnosis can be a challenging procedure which requires a variety of inputs elements. An assessment of fetal medical condition has been carried out via the numbers or varying numbers associated with those given signs. Their will likely be discussion among specialized physicians when determining the precise ranges that constitute gaps while identifying illnesses. Since a consequence, illness diagnosis frequently takes place in unreliable circumstances and occasionally results in unfavourable mistakes. Precisely a result, choices may be questionable due towards the ambiguous aspect of illnesses or insufficient patient information. The 21 intake criteria define the fetal medical condition. The estimation of these numbers included testing and observations. Three outcome diagnoses for good stages for fetal growth have been defined using potential amounts for these variables. Average, Suspected, as well as Abnormal include these. It had been possible to establish overall type-2 fuzzy neural networks (T2-FNN) method's architecture utilizing the quantity combined inputs and outcomes symptoms. Utilizing fetal records, the developed T2-FNN is evaluated. The structure of the system makes use of a variety of criteria. The design turns out that while the number of criteria increases, so does the efficiency of the system. Utilizing fetal records, the developed T2-FNN is evaluated. The structure of the system makes use of a variety of criteria. The design turns out that while the number of criteria increases, so does the efficiency of the system. Although T2FNNs become more sophisticated than regular neural networks, they may be costly to compute and more difficult to carry out, particularly for applications that operate in real time.

The research in [12] proposed a fetal health classification using machine learning techniques. Cardiotocography (CTG) depicts the fetus's condition while in labour within the uterus. Yet, based on the obstetrician's experience, evaluating the results might be a very biased procedure. Infant monitoring digitally collect data (such as baby heart rate, movements and accelerating). Many investigators have concentrated their efforts on CTG information in order to evaluate fetal health utilizing different AI algorithms. Utilizing fetal heart rate data, certain investigators utilized neural networks to forecast fetal health. The suggested approach used the Fetal Health Assessment information set, which consists of CTG files, along with five ensembles participants: Random Forest, AdaBoost, XGBoost, CatBoost, and LGBM. The voting classifier, sometimes referred to by the term Meta classifier, classifies the CTG information using the results obtained from RF, XGBoost, AdaBoost, CatBoost, and LGBM. To categorize

CTG data, a soft voting technique is implemented using the mean result from every ensemble classifier. Regarding situations when many ensembles learner work identically, a soft voting classifier may be useful. The deficiencies of each individual ensemble's learners might be compensated by combining their work. In order to improve the efficiency of the entire model, the soft voting classifier ultimately removes the flaw of one particular classifier. Ensembles approaches, including the majority of machine learning algorithms, were dependent on noisy data; particularly the existence of disturbance in fetal health surveillance information may have an influence overall the model's efficiency.

The study in [13] suggested a strategy for fetal health classification. It is usual practice to utilize uterine contractions (UC) activities to gauge when labour and delivery will begin. In order to monitor UC and discriminate between effective and unproductive contractions, electro hysterograms (EHGs) have lately been adopted. From this investigation, the researchers utilized a convolutional neural network also known as CNN to detect UC in EHG signals. In order to create a CNN model, an open-access database has been utilized. Utilizing by five times cross-validation, a model based on CNN was created then learned with DB1. The CNN framework created with DB1 was utilized with DB2, a separate clinical database, to assess its generalizability for identifying UCs. Employing the multiple channels of communication system as well, the EHG signals in DB2 have been collected via 20 pregnant women, as well as 308 parts have been retrieved. The number of trials might be increased by combining both databases that might be preferable to teach the CNN model. The research has shown how CNN would effectively distinguish UCs with EHG signals. This technique makes it possible to consistently and correctly identify UCs, offering a unique tool for keeping track of the status of the labour and the health of the mother and fetus. Uneven classes might exist in EHG datasets, including UCs occurring less frequently than non-UCs. Unbalanced data may generate unbalanced models while having an impact on effectiveness in reality. It might be challenging and exhausting to integrate the CNN approach within present clinical processes and medical records systems.

[14] suggested a fetal health monitoring approach. To limit development negotiation, lower mortality, and avert premature birth, considerable health care services have been devoted toward tracking risky pregnancies. Another crucial sign for prenatal health was recently identified as fetal movement. Surveys showed that undesirable delivery rates occurred in 25% of pregnancy with reduced fetal movement during the 3rd trimester. They provide a better iteration of the automatic FetMov identification they already recommended. FetMov means Processes identified as FetMov by an ultrasonographer. Activities not identified from the ultrasonographer as FetMovs but with FetMov-like characteristics are called artefacts (Artf). They consist of parental body motions and sensor shifts. Information from accelerometers have been pre-processed using separate component analysis while wavelet decomposition over the initial time. The categorization set of characteristics has been increased by one attribute to 31 factors. Various models have been assessed employing a ten-fold cross-validation approach with the aim evaluate the performance of the suggested parameters. Thirty-one characteristics were taken using acceleration information in order to recognize fetal movements. Various predictors had been used for distinguishing fetal from non-fetal moves according to these characteristics. The models' reliability has been investigated across various artefact levels within the categorizing information. Bagging classifier method produced the most effective results. Automatic identification systems could result in false positives or false negatives, which could cause worry in expectant parents and result in pointless treatments or undetected problems in professional settings. Datasets that are unbalanced may result from uterine contractions being comparatively uncommon occurrences as compared to non-contraction times. This disparity problem might not be sufficiently addressed by bagging, which could lead to skewed predictions.

The research in [15] proposed a Fetal health monitoring using IoT method. Digital health apps utilizing the Internet of Things provide helpful instruments enabling efficient and dispersed automated systems for diagnosis. In order to track mother's and baby messages over pregnancy at high risk, this research suggests developing a combined approach utilizing Internet of Things (IoT) sensors, extracted features from data analysis, along with a predictive evaluation assist method built around a single-dimensional CNN classifier. In addition to recording the heart rate of the fetus, a number of clinical indications connected with the mother are also tracked, including blood pressure, temperature, heartbeat rate, uterine tonus action, and oxygen consumption. A substantial volume of data is produced at various speeds along with diverse formats by various sources. Utilizing a fog computing layer, a critical diagnosis system is suggested, considering the acquisition of various features along with the computation of both linear and nonlinear measurements, intelligent analytics for health system is suggested. Lastly, taking into account six potential outcomes, a method of classification is suggested as a system of forecasting for the categorization of maternal, fetal, and simultaneous health status. The crisis system receives information produced by IoT devices and employs it to evaluate and figure out whether it detects either severe fetal or maternal discomfort. The healthcare team is notified right away if a critical situation emerges. Following this analysis stage, every feature is computed and transmitted to the suggested estimation system using a single-dimensional CNN in the cloud-based approach. Lastly, the healthcare professional is supplied with a categorization that validates the diagnosis of illness. Severe legal requirements have to be met by IoT devices utilized in the healthcare industry. It might take money and effort to fulfill these criteria.

When it comes to predicting specific fetal health problems, like with a late- difficulties, which might arise following regular monitoring happened, the current categorization approach may not be very reliable. Several variables, consisting as mother health, genetics, and surroundings, might affect the health of the fetus. Such factors may lead to fetal reaction inconsistency and make categorization more difficult. The categorization scheme is predicated on data gathered from typical prenatal visits, although might not necessarily offer an all-encompassing picture of fetal health. Reliable evaluation of several crucial factors is difficult, including fetal activity along with placenta functioning. T-2FNNs are more complex than their Type 1 counterparts due to the additional dimension of uncertainty they handle. This complexity can make the model challenging to understand and implement, especially for healthcare professionals who may not be familiar with fuzzy logic or neural networks. In contrast to simpler models, Random Forest models might be more difficult to read, which can make it difficult to comprehend the rationale behind certain categorization decisions—a critical skill in medical contexts. AdaBoost are very complicated, it may also overfit. Despite CatBoost's economical architecture, it could need an extended period to train than other algorithms, which could be a drawback for healthcare applications that need to respond quickly. LGBM may not perform as well with small datasets, as it is optimized for large-scale data.

III. Problem Statement

There are a number of issues with the current Optimum Fetal Health Classification during Pregnancy Monitoring which might affect how accurate and useful it is. Compared with other classification models, T2FNNs can be harder to comprehend, which makes it harder to justify certain categorization choices. Readability is essential in medical settings to win over healthcare professionals' confidence along with approval. Several machine learning models, particularly over fitting ones, exhibit weak results with unknown data yet good performance on training information. Overfit methods can't adjust effectively to novel patients or circumstances in healthcare settings, which might result in inaccurate diagnoses. The methods used today frequently depend on predictive models along with past information, and this may not be able to appropriately forecast difficulties in the future or account for each person pregnancy variances. Aspects such as fetal position, mother bodily habits, and electrode location might affect the quantity of EHGs. Errors in categorization might result from noisy or unreliable information [16]. The deployment of bagging classifiers along with other algorithms based on machine learning in healthcare facilities may be limited due to their computing demands, which necessitate substantial expenditures for both training and real-time usage.

IV. Proposed Bat Algorithm-Driven XGB-RNN for Optimal Fetal Health Classification in Pregnancy Monitoring

Compiling information on pregnancy monitoring is the initial stage. The information collected might contain the fetus's patterns of motion, heartbeat, and additional indicators of wellness throughout duration. Before being analysed, the gathered data must be cleansed. In order to handle values that are absent, normalize the data, and perhaps identify pertinent features for the classification task, all of this must be done. The framework and hyperparameters for a machine learning model are optimized using the Bat Algorithm. It can assist in choosing among the most important characteristics, determining the ideal model variables, and enhancing the efficiency of the framework as a whole. Along with the methods for categorization is XGBoost. Most commonly, it's employed to offer a preliminary data categorization. Sequential data, such as data on fetal health over time, are analyzed using the RNN. Utilizing a combined method like layering or mixing, merge the outcomes of the RNN and XGBoost model. Classification is done after hyperparameter tuning by BAT algorithm. Then fetal health is classified using BARXG model. Fig. 1 shows the overall diagram of proposed BARXG model for Fetal health classification.

A. Data Collection

Cardiotocograms (CTGs) are an easy-to-use, reasonably priced method of evaluating fetal health that enables medical practitioners to implement preventative measures against mother and infant death. The gadget essentially functions by delivering ultrasonic pulses and interpreting the reaction, thereby providing information on a variety of topics including uterine contractions, fetal movements, and fetal heart rate (FHR). The dataset is collected from fetal health classification from the website Kaggle [17]. 2126 sets with features taken from cardiotocogram tests are included in this collection of data. Three experienced obstetricians divided the characteristics among three categories: Normal, Suspect, and Pathology.

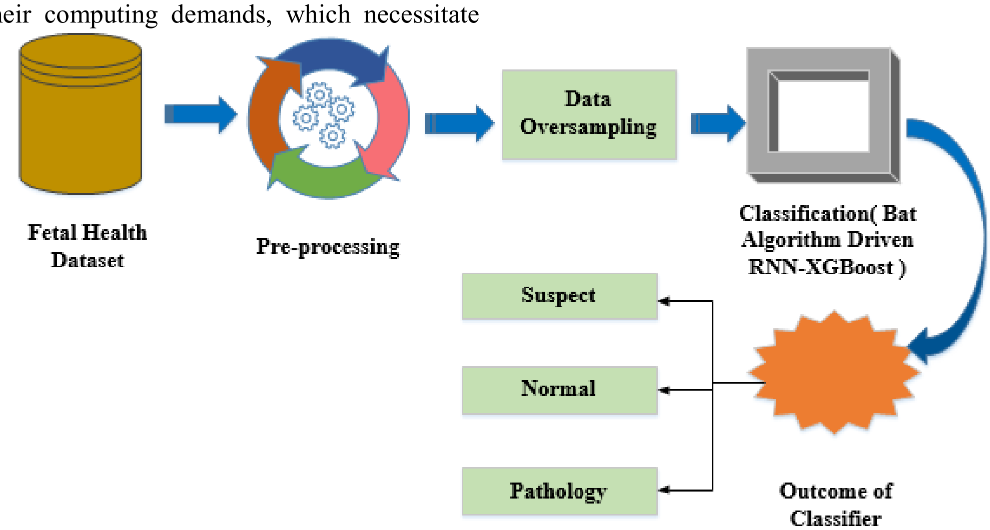

Fig. 1. Proposed BARXG model for fetal health classification.

B. Data Pre-processing

1) Data oversampling: To describe the relationship between variables during the model's development, the number of values provided in the dataset were standardized through a range from −1 to 1 during the preprocessing stage. The imbalanced dataset was handled using progressive class weighting following feature extraction. Adding some weight to every class to give the minority classes greater significance represents one among the easiest approaches to overcome this class imbalance and create a classifier which will learn similarly from all classes. It easily multiplies the entropy part of every class using the associated weight in a tree-based model, whereby the best split is defined using a certain metric, such lower entropy, to give the minority classes greater prominence.

In Eq. (1), a^1 represents a new value derived using the values, illustrates the normalizing and standardized procedure for feature extraction.

$$a^1 = \frac{a - min(a)}{max(a) - min(a)} \quad (1)$$

InEq. (2) provides the extended version that describes the polynomial expansion (PE) function utilized in feature extraction, where n denotes the degree of expansion and {b,c} are the independent variables within the dataset. Although the n degree in this study has been set at 2, the dataset in PE expands exponentially and horizontally with respect to n.

$$(b + c)^d = \sum \binom{d}{e} b^e c^{e-k} \quad (2)$$

However, computational expenses and horizontal expansion were kept to a minimal. Classes might be periodically evaluated by calculating their entropy function (f), as demonstrated by Eq. (3).

$$f = \sum_g q_g \log(q_g) \quad (3)$$

C. BAT Algorithm Driven RNN-XGBoost Model for Fetal Health Classification

This hybrid model combines the strength of XGBoost and Recurrent Neural Networks (RNN) with a feature selection method called Bat Algorithm (BA). The first step in the procedure is gathering data from fetal health monitoring. Numerous factors, such fetal heart rate and uterine contractions, are usually included in this data. The process of preparing data involves oversampling the dataset. The XGBoost and Recurrent Neural Network (RNN) models' hyperparameters are adjusted and refined by the BA. The goal of this optimization approach is to determine which hyperparameters will best fit the models and assist them capture intricate patterns in the fetal health data. Because RNNs are specifically designed to analyse sequential data, they are a good fit for time-series data sets such as fetal health monitoring. To increase prediction accuracy, XGBoost is used to the characteristics that were taken from the fetal health data. To arrive at a final forecast, the outputs of the RNN and XGBoost models are fused, or blended.

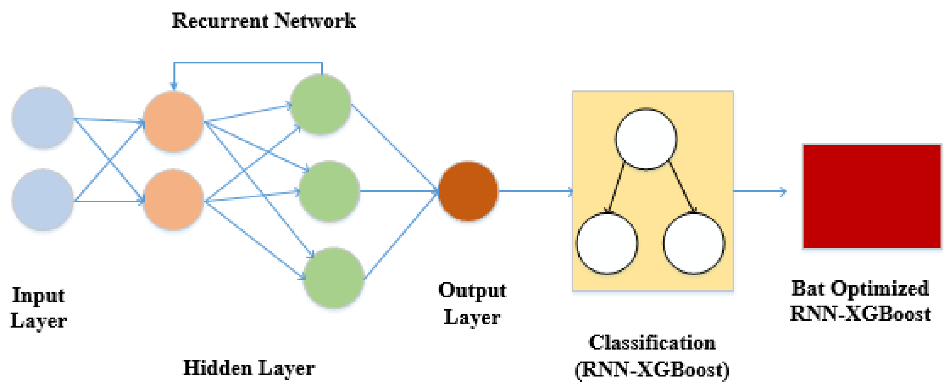

Fig. 2. Architecture diagram for proposed BARXG model.

The overall architecture diagram for Proposed BARXG Model is shown in Fig. 2. The Bat Algorithm-driven RNN-XGBoost model's overall design blends sequence modeling, combined learning, and bio-inspired optimization to produce a potent tool for classifying fetal health in prenatal monitoring. This novel strategy has the potential to greatly raise the standard of care provided to pregnant moms and their unborn kids.

1) RNN: An artificial neural network type called a recurrent neural network (RNN) is made to handle information in repetitions. These perform particularly well in tasks involving sequences, including speech, conversation, time series data, and numerous other tasks. For the purpose of to anticipate the layer's output, RNNs operate on the basis of reserving a certain layer's output then feeding it back into their input. One layer with recurrent neural networks is created by compressing the nodes within the various neural network layers. Both the present input data and previous inputs can be handled sequentially by an RNN. Because RNNs have memory within them, they are able to retain earlier inputs. Provide the RNN with a series of values as input at each time step. The Hidden state of an RNN, while retains certain details regarding a sequence, is its primary and crucial characteristic. Because the state retains recall of the prior input within the network, this state is known as well as Memory State. In order to create the output, it does a similar job on each of the inputs and hidden layers using identical settings for each input. In contrast to other neural networks, that lowers the complexity associated with the features. During every time step, that exists a fixed activation function unit in the recurrent neural network. Every unit possesses an internal state known as its hidden state. During a particular time, each hidden state represents the prior information which the network presently possesses. This hidden state gets revised at each time step to reflect any modifications to the network's previous information. The recurrence relation listed below is used to modify the hidden state. The following is the formula to find the present state Eq. (4).

$$s_u = f(s_{u-1,} w_u) \tag{4}$$

where, s_u represents the present state; s_{u-1} represents the previous state; w_u represents the input state.

By using the following Eq. (5) the hidden state can be calculated.

$$H\_t = V(G^* w_u + U^* H\_(t-1) \ + n) \tag{5}$$

where, H_t represents the hidden state at time step; G represents the weight matrix that multiplies the current input w_u; w_u represents the input at time step; U is a weight matrix that is multiplied by H_(t-1) previous hidden state; H_(t-1) this refers to the hidden state that was a part of the present hidden state at a prior time step. H_(t-1): This refers to the hidden state that was a part of the present hidden state at a prior time step; n this represents expression for bias.

2) XGBoost algorithm: Gradient Boosting methods operate by learning ensembles on shallow decision trees. The framework fits the subsequent decision tree by using its remaining error in each iteration. A weighted total is used to get the final forecast after several trees have been constructed. In contrast, the trees in an Extreme Gradient Boost model are constructed parallel to one another rather than sequentially. In addition to improving speed, this shortens the period needed to fit data into a model. Within the scientific community, this framework is highly regarded for its ability to solve a wide range of issues. XGBoost is used for classification for fetal health.

For data preparation Let the value X represent the feature matrices, whereby the features are contained in a N x M matrix. Y, an N-dimensional vector containing the three fetal health labels (0 for Normal, 1 for Suspect, and 2 for Pathological), should be the desired vector. The total of the normalization and loss terms can be used to describe the objectives function in XGBoost. The total of the normalization and loss terms can be used to describe the objective function(o) in XGBoost is mentioned in Eq. (6).

$$o = L(x, \hat{x}) + \Omega(y) \tag{6}$$

where, the loss function quantifying the difference between the real names (x) and predicted names ($\hat{x}$) is represented by the expression L$(x, \hat{x})$.The regularization term, Ω(y) regulates the ensemble of trees' complexities. The anticipated designation for every specimen is acquired by adding the forecasts of many decision trees, every one of which is influenced using a coefficient α is mentioned in Eq. (7).

$$\hat{z}(y) = \sum \alpha^* k(y) \tag{7}$$

Where, α provides the weight of every decision tree k(y), and $\hat{z}(y)$ represents the expected labelling for a sample x. From an input feature vector x, every decision tree within the ensemble appears by the sum of its leaf scores (w) is mentioned in Eq. (8).

$$I(j) = \sum u \tag{8}$$

where, each decision tree's leaf scores are represented using the letter u. To regulate the level of complexity of the individual trees, the regularization term Ω(y) incorporates both L1 and L2 regularization over the leaf scores. XGBoost employs a gradient boosting technique to maximize the objective function(o) in order to determine the optimum combination among decision trees and associated variables, including α, u, and Ω(y).

3) BAT optimization for hyperparameter tuning: The bat algorithm, often known as the BA, was an algorithm which mimics the echolocation as an activity of bats to enable to carry out worldwide optimization. Considering its superior performance, the BA is frequently utilized across a variety of optimizations situations. The RNN and XGBoost models' hyperparameters may be optimized using the Bat Algorithm. Typically, bats utilize echolocation to locate food. Bats typically emit small pulses while removing it, but once they come upon food, they start sending off pulses more often along with higher rates. A frequencies-tuning result from a rise within frequency, which decreases overall echolocation period and improves the precision of location is men.

$$f_j(r+1) = f_j(r) + m_j(r+1) \tag{9}$$

$$c_l(r+1) = c_l(r) + \left(f_j(r) - w(r)\right). x_k \tag{10}$$

$$x_k = x_m + (x_a - x_m). \beta \tag{11}$$

When the quantity of repetitions rises, every k within the typical bat algorithm has a determined location f_j is mentioned in Eq. (9) and c_l velocity in the search space is mentioned in Eq. (10). One may compute the new coordinates x_k along with velocities in the following way Eq. (11). where β is a uniformly distributed randomized vector with a range of [0, 1]. The entire optimum solution at the moment is $w(r)$, where $x_m = 0$, $x_a = 1$ is mentioned in Eq. (11).

$$f_j(r+1) = \vec{e}(r) + \varepsilon \bar{B}(r) \tag{12}$$

where, ε is a random value between -1 and 1 is represented in Eq. (12). d signifies a random integer between -1 and 1 and l(d) is the population's average loudness. Furthermore, it accomplishes worldwide search via managing pulse rate $f_j(r+1)$ and loudness (Loudness $(t$ +1) is mentioned in Eq. (13).

$$D_n(r+1) = \propto D_n(r) \tag{13}$$

$$w_i(r+1) = w_i(0)[1 - exp(-\gamma r)] \quad (14)$$

where, $\alpha > 0$, $\gamma > 0\}$ when α and γ are constants. The starting ranges for pulse rate and loudness are denoted by (0)} and D_n (0)}, correspondingly is mentioned in Eq. (14).

The bat algorithm's processing phases are described in the following.

Step 1: Using Eq. (3), randomly create the frequency along with the location, velocity, and parameters for each bat.

Step 2: Use Eq. (1) as well as Eq. (2) to update each bat's location and velocity.

Step 3: Choose a random number ($0 < rand1 < 1$) for every bat. If $rand1 < w_i(t)$ then update the temp location and compute the fitness level for the relevant bat using Eq. (4).

Step 4: Choose a random number ($0 < rand2 < 1$) for every bat. If $rand2 < (t)$ and

$x\left(f_j(r)\right) < x(w(r))$, then update (t) and $ri(t)$ using Eq. (5) along with Eq. (6), respectively.

Step 5: Sort each person according to fitness values, and then mark the top spot.

Step 6: When the condition is satisfied, the algorithm is complete; if not, proceed to Step 2.

The optimal configuration for both the RNN along with XGBoost models is represented by the optimum solution, or collection of hyperparameters, after the algorithm has finished running.

V. Results and Discussion

The results section provides a comprehensive overview of the outcomes and findings obtained from the experimental evaluation of the Bat Algorithm-Driven XGB-RNN For Optimal Fetal Health Classification in Pregnancy Monitoring. To ensure the quality of the dataset, preparation and data collection are the first steps in the procedure. XGBoost and RNN model modifying need independent optimization of hyperparameters, that's where the Bat Algorithm excels. The method of optimization includes the adjustment of hyperparameters such as RNN, tree depths, and learning rates. The Bat Algorithm runs repeatedly, assessing the accuracy of the models at each stage and modifying the hyperparameters according to ideas borrowed from echolocation. A measure of fitness that takes into account classification parameters such accuracy, F1-score, is used to gauge how well the framework performs. Whenever a termination criterion—such as a number of iterations or adequate model performance—is satisfied, the optimization loop keeps going. The hidden key to the model's performance is the resulting optimal selection of hyperparameters. The proposed framework is implemented in python. A device with an Intel(R) Core, 8GB of RAM, and windows 10 operating system is utilized.

A. *Outcome of Fetal Health Classification by Proposed BARXG Model*

Fig. 3 shows the categorization of fetal health dataset in percentage. As can be seen in the dataset, out of the 2126 samples, 1655 are normal, 295 are suspicious, and 176 are abnormal entries. Within the dataset, the fetal heart rate (FHR) patterns were classified as normal (0), suspicious (1), and abnormal (2).

The statistical summaries of the CTG data properties are displayed in Table I. This shows the outcome after the classification. The default Standard Scaler Python package is used to normalize the CTG data. By calculating the f-score along with bringing it into the same range, the Standard Scaler adjusts the data, facilitating computation and comparison.

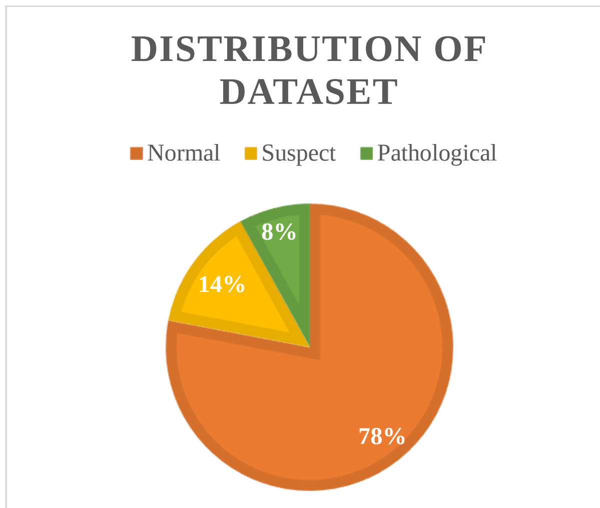

Fig. 3. Categorization of fetal health dataset.

TABLE I. Attributes from the Dataset

Attribute	Description and Unit	Mean	Std	Min	Max
Baseline value	Beats per minute	133.3039	9.840844	106	160
Accelerations	Accelerations per second	0.003178	0.003866	0	0.019
Fetal movement	Fetal movements per second	0.009481	0.046666	0	0.481
Uterine contractions	Uterine contractions per second	0.004366	0.002946	0	0.015
Fetal health	Fetal state class (0: normal (N); 1: suspect (S); 2: pathological (P))	-	-	0	2

TABLE II. RESULTS OF PROPOSED BARXG MODEL

Category	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Normal	0.98	0.98	0.96	0.97
Suspect	0.93	0.88	0.84	0.85
Pathology	0.90	0.87	0.86	0.86

Table II summarizes the results of the proposed BARXG model for the categorization of fetal health. The total accuracy provided by the proposed BARXG model was 98.2%. Precision, recall, and F1-score outperformed for each of the three classes. The accuracy of the forecast for healthy fetal cases is 98%, that of suspected fetus cases is 93%, and that of pathological fetus cases is 90%.

B. Performance Evaluation

For comparison the SVM, Random Forest Classifier, LGBM, EHG methods performance is compared with the proposed BARXG model. Precision, recall, F1-score, and accuracy were utilized as segmentation of the driver drowsiness evaluation criteria for comparison. The model was evaluated using these parameters. They are shown below:

A frequently used indicator to assess the effectiveness of categorization tasks is accuracy. The accuracy is computed by dividing the total number of predicts by the number of right predictions. It is described using an Eq. (15).

$$Accuracy = \frac{RN+RP}{RP+AP+RN+AN} \tag{15}$$

where, 'RN' means true negative; 'RP' means true positive; 'AP' means false positive; 'RN' means true negative; 'AN' means false negative.

A classification model's positive predictions are evaluated using a measure called precision. When false positive mistakes are expensive or undesired, it is especially crucial. To compute precision, use the formula below Eq. (16).

$$Precision = \frac{RP}{TP+FP} \tag{16}$$

where, 'RP' represents true positive and 'FP' represents false positive.

Recall, sometimes referred to as sensitivities or real-positive rate, is a statistic used to evaluate a classification model's capacity to accurately identify every relevant occurrence of a given class. The following Eq. (17) is used to calculate recall.

$$Recall = \frac{RP}{RP+AN} \tag{17}$$

The F1 score is a statistic that combines accuracy and recall to give a fair evaluation of the effectiveness of a classification model. It is especially helpful when you're trying to balance reducing inaccurate results (precision) and avoiding false negatives (recall) while maintaining accuracy. Eq. (18), which calculates the F1 score, is as follows.

$$F1\ score = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{18}$$

The suggested model's accuracy is displayed in Table III. It compares the suggested approach's accuracy (98.2%) with existing approaches' recall (96.7%), precision (97.7%) and F1-score (98%) values. The proposed methodology, BARXG outperforms the currently used methods, Random Forest classifier (93%), EHG (88%), SVM (84%), Voting classifier (95%) and LGBM (96%), in terms of accuracy (98.2%) and precision (97.7%).

Fig. 4 depicts the graphic depiction of the performance metrics of proposed with existing approaches. The proposed BARXG method demonstrates the highest accuracy across all five categories Random Forest Classifier, EHG, SVM, Voting Classifier, LGBM, with 98.2% high accuracy. On tiny or noisy datasets, Random Forests may overfit, which will lower their capacity for generalization effectiveness. EHG is an invasive technique for measuring fetal growth since it requires affixing sensors onto the uterine wall. Because of their computational complexity, SVMs could not scale well to very big datasets. The variety of a Voting Classifier's base models determines how effective it is. It might not result in appreciable gains if the basic models are comparable. For LGBM models, hyperparameter tuning can be complex and time-consuming.

Fig. 5 shows the training and testing accuracy of proposed BARXG model. During training, the BAT Algorithm-Driven RNN-XGBoost model for fetal health classification performed well, with a training accuracy of almost 99%.

Nonetheless, it retained strong extrapolation to novel data, with an approximate 98% testing accuracy. This suggests that the model is a viable method for assessing fetal health in real-world clinical situations as it is capable of learning effectively via the training data and produce precise predictions on previously encountered cases.

TABLE III. PERFORMANCE METRICS OF PROPOSED BARXG MODEL IS EVALUATED WITH EXISTING METHODS

Method	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
SVM [18]	84	86	88	85
EHG [13]	88	87	86	86
LGBM [19]	96	95	94	95
Voting Classifier [12]	95	94	93	94.8
Random Forest Classifier [20]	93	91	92	94
Proposed BARXG Model	98.2	97.7	96.7	98

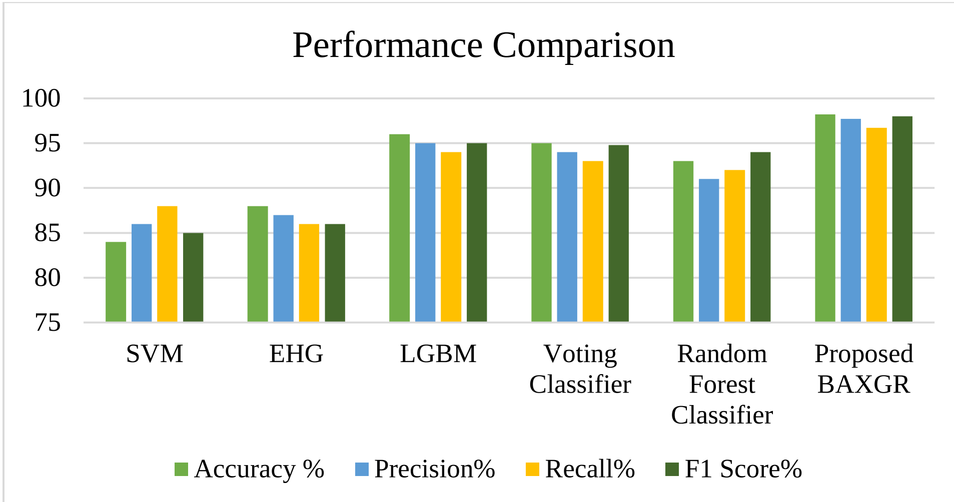

Fig. 4. Graphical depiction of the performance metrics of proposed BARXG with existing approaches.

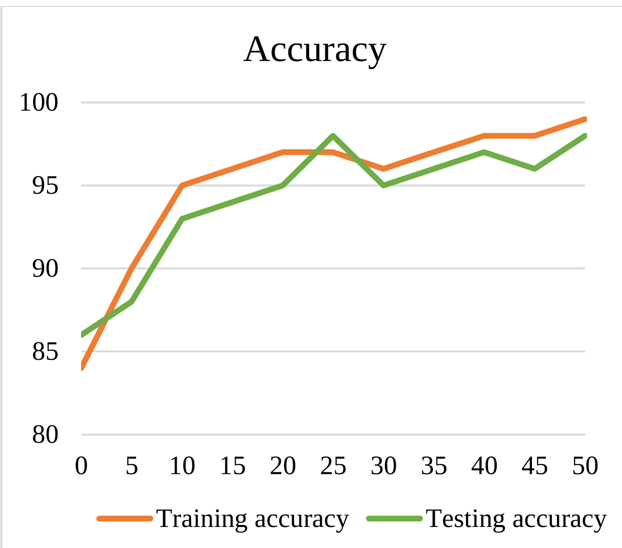

Fig. 5. Graphical depiction for training and testing accuracy of proposed BARXG model.

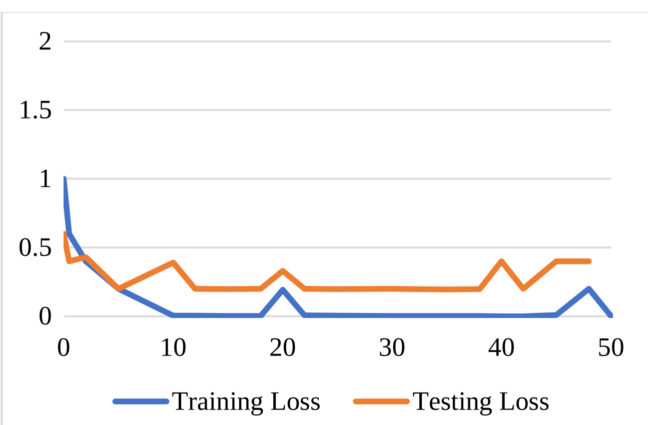

Fig. 6. Graphical depiction for training and testing loss of proposed BARXG model.

Fig. 6 shows the training and testing loss of the proposed model. The main goal of this model's training phase is to use the Bat Algorithm to fine-tune the RNN and XGBoost models' parameters. During the testing phase, the model's generalization skills are evaluated by analysing how well it performs on untested data. This step involves computing the testing loss.

The accuracy of the model and its ability to generalize to new, untested fetal health data are measured by the testing loss. The testing loss evaluates the model's capacity to produce accurate predictions on fresh, untested data, ultimately determining the efficacy of this novel approach in fetal health classification. The training loss is minimized by optimizing model parameters using the Bat Algorithm.

C. *Discussion*

Recurrent neural networks (RNNs) and XGBoost in combination with the Bat Algorithm (BA) show promise as a way to categorize fetal health in pregnancy monitoring. The accuracy of prediction of the XGB-RNN model is improved by the creative application of BA for parameter optimization. BA modifies model parameters by mimicking the echolocation behaviour of bats, which may enhance the precision of fetal health forecasts. The combination of XGBoost's gradient boosting and RNNs' sequence modelling allows for the effective processing of time-series data, such as fetal monitoring records. With the help of BA, this innovative method provides insights into complex data patterns, which could improve our comprehension of the dynamics of fetal health. Further research could improve scalability by addressing adaptability issues and convergence rates in a variety of data distributions, as well as handling bigger datasets and real-time processing. Larger datasets will be used in future research to assess BARXG's adaptability and continuous processing capabilities. The Bat Algorithm's continued adaptation to a variety of datasets and its implementation into healthcare systems are important future directions. A few of the research limitations are that enormous datasets may not scale well, validation of continuous processing is required, and the Bat Algorithm may not be as flexible with various data distributions. In order to classify fetal health throughout pregnancy monitoring, BARXG's wider application will need to carefully validate and take these factors into consideration when investigating extension in various healthcare environments.

VI. Conclusion and Future Scope

In conclusion, a potential advancement in the field of maternal-fetal medicine is the investigation concerning the Bat Algorithm-Driven XGB-RNN for optimal fetal health categorization in pregnancy monitoring. Fetal health assessment becomes more potent and precise when the synergistic powers of XGBoost and RNNs are combined with the optimization inspired by nature of the Bat Algorithm. This method's benefits—such as enhanced precision, reliable analysis of time series, and clinical applicability highlight its potential to transform pregnancy monitoring and enhance outcomes for pregnant women and their unborn babies. It is obvious that the knowledge gathered by refining and validating this approach will have a significant influence upon clinical practice, ultimately resulting in healthier pregnancies and better care for the mother and fetus. Future improvements, thorough clinical validation, and continuous development will be necessary as this research develops in order to fully realize the potential of this novel strategy, which will ultimately help pregnant women and their kids as well as improve the present level of healthcare in the area of pregnancy monitoring. Maternal-fetal medicine may be profoundly impacted by more validation and clinical practice integration of this strategy. Working together with organizations and healthcare practitioners is essential to guaranteeing the method's efficacy in practical settings. It is crucial to investigate strategies for elucidating the model's predictions. Because they can comprehend and confirm the reasoning behind each categorization, healthcare professionals' trust may be increased through the development of interpretable models.

References

[1] L. Davidson and M. R. Boland, “Enabling pregnant women and their physicians to make informed medication decisions using artificial intelligence,” J Pharmacokinet Pharmacodyn, vol. 47, no. 4, pp. 305–318, Aug. 2020, doi: 10.1007/s10928-020-09685-1.

[2] O. E. F. Shaw and J. Y. Yager, “Preventing childhood and lifelong disability: Maternal dietary supplementation for perinatal brain injury,” Pharmacological Research, vol. 139, pp. 228–242, Jan. 2019, doi: 10.1016/j.phrs.2018.08.022.

[3] E. S. Green and P. C. Arck, “Pathogenesis of preterm birth: bidirectional inflammation in mother and fetus,” Semin Immunopathol, vol. 42, no. 4, pp. 413–429, Aug. 2020, doi: 10.1007/s00281-020-00807-y.

[4] K. Yammine, M. Eric, and C. Assi, “Variations and morphometrics of palmaris longus in fetuses: a meta-analysis of cadaveric studies,” Surg Radiol Anat, vol. 42, no. 3, pp. 281–287, Mar. 2020, doi: 10.1007/s00276-019-02391-9.

[5] C. M. J. Tan and A. J. Lewandowski, “The Transitional Heart: From Early Embryonic and Fetal Development to Neonatal Life,” Fetal Diagn Ther, vol. 47, no. 5, pp. 373–386, 2020, doi: 10.1159/000501906.

[6] A. Mehbodniya et al., “Fetal health classification from cardiotocographic data using machine learning,” Expert Systems, vol. 39, no. 6, p. e12899, Jul. 2022, doi: 10.1111/exsy.12899.

[7] M. G. Signorini, N. Pini, A. Malovini, R. Bellazzi, and G. Magenes, “Integrating machine learning techniques and physiology based heart rate features for antepartum fetal monitoring,” Computer Methods and Programs in Biomedicine, vol. 185, p. 105015, Mar. 2020, doi: 10.1016/j.cmpb.2019.105015.

[8] M. Chaturvedi, S. Agrawal, and S. Silakari, “An Investigation into Techniques used for Fetal Health Classification,” CSEIJ, vol. 12, no. 1, pp. 35–42, Feb. 2022, doi: 10.5121/cseij.2022.12105.

[9] L. M. Daly, F. M. Boyle, K. Gibbons, H. Le, J. Roberts, and V. Flenady, “Mobile applications providing guidance about decreased fetal movement: Review and content analysis,” Women and Birth, vol. 32, no. 3, pp. e289–e296, Jun. 2019, doi: 10.1016/j.wombi.2018.07.020.

[10] X. Zhao, X. Zeng, L. Koehl, G. Tartare, and J. De Jonckheere, “A Wearable System for In-Home and Long-Term Assessment of Fetal Movement,” IRBM, vol. 41, no. 4, pp. 205–211, Aug. 2020, doi: 10.1016/j.irbm.2019.11.003.

[11] R. Abiyev, J. B. Idoko, H. Altıparmak, and M. Tüzünkan, “Fetal Health State Detection Using Interval Type-2 Fuzzy Neural Networks,” Diagnostics, vol. 13, no. 10, p. 1690, May 2023, doi: 10.3390/diagnostics13101690.

[12] M. Al Duhayyim, S. Abbas, A. Al Hejaili, N. Kryvinska, A. Almadhor, and H. Mughal, “Ensemble Learning for Fetal Health Classification,” Computer Systems Science and Engineering, vol. 47, no. 1, pp. 823–842, 2023, doi: 10.32604/csse.2023.037488.

[13] D. Hao, J. Peng, Y. Wang, J. Liu, X. Zhou, and D. Zheng, “Evaluation of convolutional neural network for recognizing uterine contractions with electrohysterogram,” Computers in Biology and Medicine, vol. 113, p. 103394, Oct. 2019, doi: 10.1016/j.compbiomed.2019.103394.

[14] M. Mesbah et al., “Automatic fetal movement recognition from multi-channel accelerometry data,” Computer Methods and Programs in Biomedicine, vol. 210, p. 106377, Oct. 2021, doi: 10.1016/j.cmpb.2021.106377.

[15] J. A. L. Marques et al., “IoT-Based Smart Health System for Ambulatory Maternal and Fetal Monitoring,” IEEE Internet Things J., vol. 8, no. 23, pp. 16814–16824, Dec. 2021, doi: 10.1109/JIOT.2020.3037759.

[16] M. T. Alam et al., “Comparative Analysis of Different Efficient Machine Learning Methods for Fetal Health Classification,” Applied Bionics and Biomechanics, vol. 2022, pp. 1–12, Apr. 2022, doi: 10.1155/2022/6321884.

[17] A. de . Campos et al., “Fetal Health Classification.” Accessed: Oct. 21, 2023. [Online]. Available: https://www.kaggle.com/datasets/andrewmvd/fetal-health-classification

[18] C. V. Ananth and J. S. Brandt, “Fetal growth and gestational age prediction by machine learning,” The Lancet Digital Health, vol. 2, no. 7, pp. e336–e337, Jul. 2020, doi: 10.1016/S2589-7500(20)30143-6.

[19] V. Nagabotu and A. Namburu, “Fetal health classification using LightGBM with Grid search based hyper parameter tuning,” ENG, vol. 18, Jul. 2023, doi: 10.2174/1872212118666230703155834.

[20] S. Das, H. Mukherjee, K. Roy, and C. K. Saha, “Fetal Health Classification from Cardiotocograph for Both Stages of Labor—A Soft-Computing-Based Approach,” Diagnostics, vol. 13, no. 5, p. 858, Feb. 2023, doi: 10.3390/diagnostics13050858.