



Detecting High-Risk Pregnancies And Premature Births: A Comprehensive Survey

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Citation Mohit Lal Sah et.al (2024). Detecting High-Risk Pregnancies And Premature Births: A Comprehensive Survey...*Educational Administration: Theory and Practice*, 30(4), 646-652 , Doi: 10.53555/kuey.v30i4.1529

ARTICLE INFO

ABSTRACT

High-risk pregnancy detection is important for maternal and fetal health in regions having limited access to medical resources. Our solution presents identification for resource-limited settings using Artificial neural networks ANNs for predicting high-risk pregnancies early and precisely. Which enables improved health outcomes and timely intervention. ANN model design, implementation, evaluation, and addressing healthcare challenges with resource limitation. High-risk pregnancy may cause several issues including lifelong health disabilities. We aim to diminish the consequences of high-risk pregnancies and test systems for their reliability and accuracy. Expert ANN system and back propagation algorithm which shows results with a 0.98 accuracy rate. We utilized a dataset comprising 172 medical records from patients, featuring 17 input parameters, and encompassing 5 distinct output classes. These classes included normal early pregnancy as well as four categories denoting various pregnancy disorders. Through a rigorous training and testing process, our experiment demonstrated the feasibility of applying an Artificial Neural Network (ANN) to predict pregnancy disorders. Notably, our model achieved an accuracy rate of approximately 78.248%. This achievement was attained through meticulous parameter tuning: a learning rate of 0.1, input layers with 17 neurons, 5 neurons at output layer, layers that are hidden with multiple neurons i.e., 50 and an error value of 0.01.

Keywords: High-risk pregnancies, resource-limited environment, Artificial Neural Network, ANN

1. INTRODUCTION

Getting a healthy baby is all couples dream. Every patient woman has a unique experience that is different from each other during pregnancy. Being aware of pregnancy is an important factor in overcoming the risk of premature birth for prediction as well as disorders of early birth based on physical symptoms. To determine pregnancy disorder expert system, recommend and provide a solution. Technology grows with time its adoption Infoware contains methods, facts, and theories [1]. Expert system in artificial intelligence transfers knowledge to solve problems and make decisions [2]. The artificial neural network of algorithms adapts to the behavior of living things. In the ANN algorithm human neuron is copied for prediction [3]. This is because the ANN algorithm predicts various cases [4]. Due to abnormalities in chromosomes, perinatal death may occur in low-income countries and is common in prosperous societies [5]. Families with limited resources have a high risk of pregnancy termination chromosomal abnormalities due to resource-limited environment [6]. That is why it is important to consider high-risk pregnancies to be identified timely. Risk increases with advancement in age. Widespread screening decreases multiple biochemical live birth incidents which is not feasible for low-income countries. Ultrasound screening is done due to differences in aneuploid fetuses but not specific [7]. The relative individuals find ratios that combine background factors to calculate the risk of trisomy in pregnancies [8]. Aneuploidy screening offered for more than 2 decades in the public health sector. High-cost serum

screening is not possible in karyotyping performed in tertiary centers. Routine ultrasound is acknowledged and available in South Africa [9]. 2 approaches for screening and detection of abnormalities as the sole consideration. In rural areas hospital lacks healthcare from hospitals to measure preventing risks in best solution so needs to be understood better. Detecting labor early is a key factor for moderating the impact high risk pregnancy and attaining best birth outcomes along with health risk reduction. It could help in saving one-fourth of babies. Artificial neural network ANNs adopt human behavior more of human neuron adapted using ANN for prediction. Women need awareness for decision of birth and pregnancy. Countries develop designed schemes for medical factor that reduce nonelective cesarean section depend upon criteria of medical and intrusion [10]. ANN studies Mas-Cabo identify MLP along preterm labor evidence by electro-hysterogram for labor induction success. Similarly, placenta cell classification using ANN. Similarly, authors used for placenta cell classification in early first trimester disorder detection prediction during development in pregnancy and cesarean delivery risk evaluation [11]. The SVM used to solve detection issues using margins and kernel trick for improved prediction based on computerized decision methodology developed in fetal heart rate classification, labor prediction, and risk evaluation on linked algorithm [12]. Electrical activity in EHG signal data is trained for high and low risk pregnancy data [13]. Advanced Artificial neural network is focused for labor detection using EHG dataset. ML classifier use dataset having 300 records that include 38 of them at high risk. Signal processing techniques extracts raw signal records to perform well than other.

2. LITERATURE REVIEW

Artificial neural networks in healthcare are reviewed. High risk pregnancy detection focused on well-resourced settings leaving a gap in addressing . many present studies focus on setting that are well resourced for addressing deficiencies in healthcare in resource limited area. Artificial Neural network analyze medical data make predictions. Whereas it is still not much explored in field of high-risk pregnancy. The ANNs works in MLP, NLP and DL in clinical dataset to made aid easy and prediction fast using SVM and ANN. Learning could be taken as nodes processing for neuronal processes of physiology. Nonlinear regression and discriminative methods require information related to the phenomenon. Physio Net High risk EHG for term and preterm database achieved 90\% accuracy, 80\% Area under the curve and 90\% as specificity [14]. Labor detection through another machine learning technique that combines HR and EHR dataset by applying on pregnant women dataset [15]. High and low risk cases are also identified by SVM, auto regressive model by using feature extraction where, achieved 95\%, 99\% and 97.1\% as sensitivity, specificity, and accuracy respectively [16]. A wearable electrode device that uses AgCl₂ electrode application for monitoring EHG signal. Health status is analyzed by status data for mHealth provider by SVM, Naïve Byes, KNN, GB and DT with accuracy of about 94\%, and 92\% sensitivity. 85\% of accuracy is achieved in Naïve bayes, specificity of 84\% and sensitivity of 80\% [17]. Back propagation layer based on NIA algorithm using Artificial Neural Network for classification and detection which improves high risk detection of labor of about 70.82\% accuracy. TPEHG database from signals compared thirty cepstral using sequential forward selection and fisher discriminant [18]. MLP classifies neural network with best classification results. Another technique based on KNN classification auto regressive modelling used wavelet transformation techniques. Which is divided into three groups. The unsupervised method based on statistical analysis and wavelet transformation that adapted fisher test along k mean method [19]. EHG signal show accuracy of about 88.6\% in support vector machine that classify fusion division rule including RBF [20]. Convolutional neural network CNN predicts Icelandic 16-electrode electro hysteroqram database and physio Net database. 14016 of 24 length segments are created from first database that normalize image pixels to 482x482 pixels. 5-fold cross validation of 98\% accuracy and 93\% accuracy in first and second one database respectively. CTG dataset for MLP detection-based classification methods i.e., Decision tree, k nearest neighbor SVM with 90\% above accuracy. Ensemble learning is also used in some studies based on RF with final candidates LightGBM hybridized with Gaussian Naive bayes modeled by calculating k fold cross validation with accuracy of about 95\%. Deep learning classification is used for prediction where F measure and recall up to 90\% in model implemented based on ANN for CTG data classification [21]. Previous work in ML methods such as classifier, hybrid approaches predict high risk pregnancies with compared to prove ANN and LSTM methods of Machine learning.

Nature inspired algorithm used in medical care areas. ACO algorithm proposed to rebuild electrocardiogram ECG signals. Performance optimization methods and several state of art algorithm used ECG signals construction using arrhythmia database. Swarm intelligence algorithm reconstructed ECG signals with higher accuracy. Data mining discussed by Hedeshi and Abadeh discusses data mining DM techniques to be efficient for CDSSs [22]. PSO algorithm suggested using fuzzy rules for heart disease identification using a coronary disease dataset [23]. Where the boosting mechanism determines weights from the training set and newly extracted rules for misclassified instances. The performance of the method detects coronary artery disease disorder at an acceptable rate of accuracy. AIS is applied by researchers using immune system and memory-related characteristics for learning disease diagnosis [24]. The smart model combines the AIS approach to Gas for diagnosing using the smart model combination. Gas was adopted to learn the process of inferring antibody population evolution in various health datasets where results describe promising accuracy useful for diagnostic tools for health problems. They are efficient in solving a variety of challenges such as optimization. Another

model using GAs recognizes older adults to provide knowledge for experts by wrist-worn sensors. Accelerometers use primary sensor in heart rate acquisition [25]. The best fusion weights based on GAs selection showed the algorithm achieved accuracy as of classifiers. Another automated magnetic resonance image algorithm for improvement was proposed [26]. Optimization techniques inspired by clustering proposed support health experts for pathological processes through clustering and optimization techniques. Several optimization techniques suggest sensitivity and specificity values for system performance improvement along with experience of user quality QoE through optimization algorithms [27]. E-health systems use mobile cloud environments for announcement system delays as open issues [28]. Many conventional and stochastic models are discussed that showed these could not address subjective user responses regarding announcement delay. Analyzation of fundamental nature-inspired algorithms solves gaps in response time and performance assessment including literature as a contribution to the proposal in the paper and supports its novelty and innovation.

3. METHODOLOGY

The methodology used for this phenomenon is specific to high-risk pregnancy and lacks a perinatal loss, interpretation approach guided by theories considered relevant to the project. The phenomenology attempts to uncover structures that lack a gender framework and require an appropriate feminist lens. feminism depends upon race, generation, and sexual orientation. Feminism majorly depends upon value, recognition, and desire to cause social change. High-risk maternity charts distributed to women at appointments. A phenomenological study evaluated perinatal loss following high-risk pregnancy. The study evaluated the research question to be structured on preliminary methodology through data collection accomplished and documented where evaluation standards ensure commitment. The phenomenological analysis identifies the labeling of participants followed by grouping and labeling. The analysis process began with careful attention to interviews. Voice and non-verbal communication provide additional meaning. The PSO algorithm optimizes globally for nonlinear continuous functions. The fact that sharing information among others offers evolutionary advantages in development. Which is based on social behavior. Particles pass by search space and share information to transmit. PSO applies continual problems where particle position and velocity are found.

Data collection contains a resource-limited environment. Local health facilities ensure data relevancy. Data comprises maternal and fetal parameters that allow them to comprehend patterns. Specialized dataset tailor resource-limited setting. The dataset incorporates maternal health history clinical measurements ultrasound findings i.e., blood pressure, and weights. Data collection Adheres to ethical considerations and patient privacy. The framework uses 5 datasets obtained from the Physio Net repository. Icelandic electrode signals from 2008 to 2010 have a recording of 300 signals, preterm EHG has 24 recordings, and CTU-CHB has 552 CTG recordings of 90 min length from 2010 to 2012. Another database has 5h 42m EHG signals. The ANN model comprises an input and output layer that are hidden. Neurons having activation function and learning rate of effective learning gave security of data TL techniques on pre-trained models and enhanced performance. In parallel ANN processes are just like the biological brain works. Signals received by neurons transmit nearby signals. Input layer along electrical signal from dendrites to other cells. Incoming signals do summation from neurons passed to the next layers if strong enough via axons. Backpropagation uses updated weights in the backward process and algorithm in the backpropagation algorithm. It follows weight initialization then epochs setting by learning rate and target error. Initiate epochs 0 and MSE by 1 as activation function. Maximum epochs and target MSE performed for epochs less than maximum epochs.

Domain knowledge incorporation processes data techniques to address missing values and normalize features. Resource limitation stops data augmentation strategies such as imputation of data and feature scaling tailored to an available dataset such as in WFDB format. Data is converted into CSV using Rdsmp. Data is extracted column-wise and split into 30 min lengths. 7271 of 30 min datasets extracted having 40\% and 60\% pattern and no-pattern ratio respectively. Boolean and numeric values configure learning processes for improving training time, prediction, performance and hyperparameter.

SD stands for standard deviation and FD stands for final decision. Boolean and numeric values set to configure learning process by improving training time, prediction time and performance hyperparameter. Grid search technique tune parameter to calculate optimum hyperparameter by exhaustive search that saves time and resources. Decision trees start from root node. Every node gave test attributes until reached leaf nodes where RF leads to more accurate results. Performance improvement applies ensemble techniques to detect subsets where parallel implementation is performed which is independent. It minimizes model overfitting issue. SVM achieved accuracy of input data type and robustness due to Vapnik learning statistics to classify and detect. Dataset overfitting avoids prediction of maximize precision in optimization. ANN units process neural layers that are organized in fault tolerance, robustness and processing parallel. Topologies classify according to supervised and unsupervised layers connection types. It is described by Rosen blat where input parameter receives and propagate to output layer through back propagation layer which is most widely accepted network compared to gradient descent algorithm. distributed backward layers run again and again to correct output. Topologies train backpropagation method and hidden layers require time for computation. Training cycle for determining epochs for neural network. Batch size is determined through network weights. Grid searches classify correctly 86\% and 90\% cases. Naïve bayes used widely for applications having fast learning and

testing. Bayesian rules designed probability theorem. DL models learns from high level features. pregnant women are at high risk have certain features and characteristics i.e., smoker, diabetic issue cause complications. It consists of seven layers comprised of neuron known as nodes taken by superpower layers comprising three input, output, and hidden layers. Training is performed speedily by rectified linear unit due to its simplicity in computation. In case input x is lower than 0 is set as 0 . Else set to x and calculate for prediction using logistic sigmoid ranging between 0 and 1 . And calculated as $S(x) = 1 / (1 + e^{-x})$ during compilation of optimizer model. Loss is minimized by optimization such as RMSprop, Stochastic gradient and Adam descent. Error predicted by loss function such as mean squared error, categorical entropy ranges from 0.0 to 1.0 learning rate. ANN phases pass forward network of NN using activation and backtrack tune neural network using optimizer learning rate and loss function in one complete phase termed as iteration.

Selection of features from records taken personalizes Mean frequency, Median frequency, and peak frequency of records by women that are pregnant. Five databases choose features. To avoid bias in five databases we choose more features. for avoiding database biasness features such as Amplitude, frequency, MDF, women age is chosen to give more accurate results such that obesity status is not reported. Model designing is more important for accurate prediction which consist of input layer to receive patient data for feature extraction to enhance generalization of dropout layers and batch normalization is incorporated. Fine tuning and transfer learning explored for existing models. Data processing architecture neural network for EHG signal for identifying contraction we use hyper parameter setting and searching model ANN.

Artificial neural network use data processing for EHG signal to identify contractions by using hyper parameter setting on data and searching model ANN. Grid search tuning technique use for optimizing model hyper parameter searching layer optimizes activation and loss function. Number of layers are 2, 3, 4 and 5 where 16, 32, 64, 128 and 256 neurons are present. Optimizers such as RMSprop, and Adam. Loss function such as BCE use search range setting. Experiments such as grid search experiments have four hidden layers 128 nodes uses sigmoid at output and Relu for hidden layers and 20 to 50 epochs of batch size with learning rate of 3×10^{-4} . Hidden layers use common activation function for binary classification sigmoid function for output layer.

4. EVALUATION AND PERFORMANCE METRICS

Metrics such as accuracy specificity and sensitivity are employed to access ROC predictions. Model ability to distinguish among high and low risk is quantified. Evaluation of ANN is crucial for its validation. Methodology evaluation is performed for accurate resource performance. Two-dimensional matrix rate classifies performance based on data test. CM give predicted number of class while correctly representing rows values and wrongly predicted values. Predicted number of columns correctly represents CM values. Columns gives predicted numbers of each class while row represents correctly and wrong prediction. Performance calculates of framework obtained through 30% validating testing and 70% training.

Classifier effectiveness in predicting high and low risk labor is measured by accuracy. Correct predictions and total predictions made are measured through proportion of predictions. It is found through sum of true positive and true negative values. Misclassification MisCl represents instances percentage between high and low risk values. Misclassification is measured through sum of false positive and false negative. Recall R called true positive rate TPR classifies ability to predict high risk instances by proportion of true positive out of summation of TP and FP. Precision quantifies percentage of accurate predictions by the classifier for instances belong to high risk or low risk labor class. Formula for precision is given by sum of true positive, true positive and false positive. False positive rate is percentage of classifier that predicts high and low risk instances when they are different. FPR is summation of False positive, and true negative. Receiver operating characteristic perform evaluation for binary classification algorithm represent algorithm. it represents TPR and FPR for AUC statistical values ranging from 0 to 1 for measurement of performance. Classifier probability is chosen randomly higher than in negative instances higher value represents higher performance. Here, TP represents True Positives, and PP represents Precision.

5. RESULT

Evaluation performed show capability of ANN model for detecting pregnancies. Evaluation show ANN model capability for detecting high risk pregnancies in resource limited setting. Performance of model measure through AUC ROC that identify efficiently. Performance presents smart devices of resource at start middle and end of 30 min length. Signals are sent through one device to other through Bluetooth device. Confusion matrix for ML, DT, RF, SVM, NB classifier. We compared decision rates based upon preference and accuracy requirement. RF compared with related studies however all results could not be classified. AUC achieved confusion matrix for model that improved prediction of risk from collected data sessions. ANN predictions improved 95% to 98% from 0.04 - 0.01 and FNR 0.03 - 0.01 . whereas FNR reduced to 50% from 75% . Both models have same rate of AC. This tells likelihood of model related to model by margin of 11.2% . necessity for analysis of model underscores comprehensiveness ultimately employment of deep learning approach yield outcome to the adequacy of dataset problem. The observation underscores the necessity for more comprehensive CNN model performance and employment of deep learning yielded favorable outcomes.

Conceivable outcomes of dataset render undemand for ML models. The potency of DL data generates dependable outcomes. Imperative data is sustainable to the outcomes through deep learning that explored forthcoming delve of big data realm surrounding EHG data synthesis. The patient record analysis comprises 172 data points partitioned to facilitate distinct training and testing the data ratio. Dataset employed for training and testing split into 90 and 10 percent split, 80 and 20 percent split, 70 and 30 percent split, 60 and 40\% split finally 50 and 50 percent split. Diverse scenes comprehensively examine allocation of varied data for training and testing the efficiency and generalization of ML model and algorithms. Configuration serves specific purpose that evaluate 100\% model capacity for memorization and 90\%-10\% provide balanced assessment for generalization. Configuration serves a specific purpose where direct memorization of model capacity evaluates scenario and 90 to 10\% split give balance generalized assessment. Subsequent split progressively challenges model adaptability for unseen data for diminishing training availability example. The intricate split adapts model to unseen data due to diminishing availability of training example. Divisions offer insights to intricate trade off among overfitting and generalized research that guide optimal training data aligned with overarching objectives. Conducting analyses involve experimental phase of data pre-processing and tuning. Experimental phase conduct outcome of data processing parameter tuning. Optimal model selection guide accuracy encompassing the performance of various datasets for testing. LGBM and RF exhibits performance among models particularly in term of AUC and F1 scores metrics achieving 0.99 and 0.98 respectively. LightGBM demonstrates accuracy at 0.99 compared to RF 0.98 emerged as most suitable method. The predicted outcome LGBM highlight remarkable accuracy of f1-score and AUC value nearing perfection at 0.99. Models display minor deviation by predicting incorrectly only 12 instances as non-normal out of entire dataset. Deep learning exhibits enhanced performance in third featuring induced preprocessing of data and its optimal efficacy with high dimensional dataset.

6. DISCUSSION

The research discusses the implications of an Artificial Neural Network (ANN) model for detecting high-risk pregnancies in resource-limited settings. It acknowledges limitations such as data availability and overfitting risk. The study thoroughly evaluates various ANN models, considering overfitting and generalization dynamics. Remarkably, the research demonstrates the superiority of machine learning models like LightGBM and Random Forest, which outperform deep learning counterparts such as LSTM and ANN, particularly in terms of accuracy and F1-Score metrics. Deep learning shows potential when dealing with data preprocessing involving multicollinearity, indicating nuances in its effectiveness. The findings highlight the importance of dataset characteristics in influencing model outcomes and advocate for further exploration of dataset diversity and algorithm intricacies to enhance prediction accuracy.

In conclusion, the research underscores the ANN model's significant capability in identifying high-risk pregnancies in resource-limited settings. The model's performance metrics, including accuracy and AUC-ROC, emphasize its proficiency in detecting potential high-risk cases, with potential benefits for healthcare practices in constrained environments. The study also analyzes resource consumption, provides insights into decision-making processes, and evaluates the suitability of the Random Forest classifier. The balanced dataset composition enhances the reliability of the findings. Despite certain limitations, the proposed scheme shows promise.

7. CONCLUSION

In this study, an Artificial Neural Network (ANN) model's robust ability to identify high-risk pregnancies in resource-limited settings is demonstrated. The model's accuracy and AUC-ROC metrics confirm its proficiency in detecting potential high-risk cases, which has significant implications for constrained healthcare environments. Despite lower accuracy rates compared to a comparative study, in-depth analysis reveals distinctive advantages, with AUC being the highest, strengthening its performance superiority. Enhanced ANN predictions, reduced misclassifications, and improved FNR values collectively highlight the model's effectiveness. The study emphasizes the importance of dataset diversity and adequacy for exceptional deep-learning outcomes.

The research introduces a comprehensive framework for continuous monitoring of expectant mothers at high risk of complications. This framework combines wireless communication (WBS) and smartphones for cost-effective and dependable home-based monitoring. The primary objective is to utilize Artificial Neural Network algorithms to identify impending labor by closely monitoring uterine electro-hysterogram (EHG) contractions. The system sends alerts to pregnant individuals when signs of labor emerge. The study analyzed 7271 sets of uterine EHG contraction data, showing that the deep learning ANN model outperformed the machine learning random forest (RF) classifier in terms of accuracy and reliability.

The research concludes with a summary of the proposed approach's effectiveness in using ANNs for high-risk pregnancy detection in resource-limited environments. It underscores the potential of technology to address healthcare disparities and provide accessible and timely care to vulnerable populations. Overall, the study addresses the global concern of premature births and presents a promising solution for identifying high-risk pregnancies and ensuring timely intervention.

8. REFERENCES

1. M. A. Ramdhani, H. Aulawi, A. Ikhwana, and Y. Mauluddin, "Model of green technology adaptation in small and medium-sized tannery industry," *Journal of Engineering and Applied Sciences*, vol. 12, no. 4, pp. 954-962, 2017.
2. A. Hermawan, "Jaringan Saraf Tiruan Teori dan Aplikasi," Andi, Yogyakarta, 2006.
3. S. Oreski, D. Oreski, and G. Oreski, "Hybrid system with genetic algorithm and artificial neural networks and its application to retail credit risk assessment," *Expert systems with applications*, vol. 39, no. 16, pp. 12605-12617, 2012.
4. Y. Kara, M. A. Boyacioglu, and Ö. K. Baykan, "Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the Istanbul Stock Exchange," *Expert systems with Applications*, vol. 38, no. 5, pp. 5311-5319, 2011.
5. C. Prins, G. Theron, D. Steyn, L. Geerts, and G. De Jong, "Total perinatally related wastage at Tygerberg Hospital—a comparison between 1986 and 1993," *S Afr Med J*, vol. 87, pp. 808-814, 1997.
6. R. J. Snijders, K. Sundberg, W. Holzgreve, G. Henry, and K. H. Nicolaides, "Maternal age- and gestation-specific risk for trisomy 21," *Ultrasound in Obstetrics and Gynecology: The Official Journal of the International Society of Ultrasound in Obstetrics and Gynecology*, vol. 13, no. 3, pp. 167-170, 1999.
7. K. Nicolaides, "Screening for chromosomal defects," *Ultrasound in Obstetrics and Gynecology*, vol. 21, no. 4, pp. 313-321, 2003.
8. R. Smith-Bindman, W. Hosmer, V. A. Feldstein, J. J. Deeks, and J. D. Goldberg, "Second-trimester ultrasound to detect fetuses with Down syndrome: a meta-analysis," *Jama*, vol. 285, no. 8, pp. 1044-1055, 2001.
9. L. Geerts, A. Theron, D. Grove, G. Theron, and H. Odendaal, "A community-based obstetric ultrasound service," *International Journal of Gynecology & Obstetrics*, vol. 84, no. 1, pp. 23-31, 2004.
10. A. D. R. Fernández, D. R. Fernández, and M. T. P. Sánchez, "Prediction of the mode of delivery using artificial intelligence algorithms," *Computer Methods and Programs in Biomedicine*, vol. 219, p. 106740, 2022.
11. D. S. a. Maylawati, M. A. Ramdhani, W. B. Zulfikar, I. Taufik, and W. Darmalaksana, "Expert system for predicting the early pregnancy with disorders using artificial neural network," in 2017 5th International Conference on Cyber and IT Service Management (CITSM), 2017: IEEE, pp. 1-6.
12. A. Al Housseini, T. Newman, A. Cox, and L. D. Devoe, "Prediction of risk for cesarean delivery in term nulliparas: a comparison of neural network and multiple logistic regression models," *American journal of obstetrics and gynecology*, vol. 201, no. 1, pp. 113. e1-113. e6, 2009.
13. J. Alberola-Rubio et al., "Prediction of labor onset type: Spontaneous vs induced; role of electrohysterography?," *Computer methods and programs in biomedicine*, vol. 144, pp. 127-133, 2017.
14. M. Altini, E. Rossetti, M. J. Rooijackers, and J. Penders, "Towards non-invasive labour detection: A free-living evaluation," in 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2018: IEEE, pp. 2841-2844.
15. P. Fergus, I. Idowu, A. Hussain, and C. Dobbins, "Advanced artificial neural network classification for detecting preterm births using EHG records," *Neurocomputing*, vol. 188, pp. 42-49, 2016.
16. G. Fele-Žorž, G. Kavšek, Ž. Novak-Antolič, and F. Jager, "A comparison of various linear and non-linear signal processing techniques to separate uterine EMG records of term and pre-term delivery groups," *Medical & biological engineering & computing*, vol. 46, pp. 911-922, 2008.
17. P. S. La Rosa, H. Eswaran, H. Preissl, and A. Nehorai, "Multiscale forward electromagnetic model of uterine contractions during pregnancy," *BMC medical physics*, vol. 12, no. 1, pp. 1-16, 2012.
18. W. L. Maner and R. E. Garfield, "Identification of human term and preterm labor using artificial neural networks on uterine electromyography data," *Annals of biomedical engineering*, vol. 35, pp. 465-473, 2007.
19. B. Moslem, B. Karlsson, M. O. Diab, M. Khalil, and C. Marque, "Classification performance of the frequency-related parameters derived from uterine EMG signals," in 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2011: IEEE, pp. 3371-3374.
20. B. Moslem, M. Khalil, M. O. Diab, A. Chkeir, and C. Marque, "A multisensor data fusion approach for improving the classification accuracy of uterine EMG signals," in 2011 18th IEEE International Conference on Electronics, Circuits, and Systems, 2011: IEEE, pp. 93-96.
21. D. Ayres-de-Campos, C. Costa-Santos, J. Bernardes, and S. M. V. S. Group, "Prediction of neonatal state by computer analysis of fetal heart rate tracings: the antepartum arm of the SisPorto® multicentre validation study," *European Journal of Obstetrics & Gynecology and Reproductive Biology*, vol. 118, no. 1, pp. 52-60, 2005.
22. R. Veloso et al., "Categorize readmitted patients in intensive medicine by means of clustering data mining," *International Journal of E-Health and Medical Communications (IJEHMC)*, vol. 8, no. 3, pp. 22-37, 2017.
23. N. G. Hedeshi and M. S. Abadeh, "Coronary artery disease detection using a fuzzy-boosting PSO approach," *Computational intelligence and neuroscience*, vol. 2014, pp. 6-6, 2014.

24. C. Liang and L. Peng, "An automated diagnosis system of liver disease using artificial immune and genetic algorithms," *Journal of medical systems*, vol. 37, no. 2, pp. 1-10, 2013.
25. S. Chernbumroong, S. Cang, and H. Yu, "Genetic algorithm-based classifiers fusion for multisensor activity recognition of elderly people," *IEEE journal of biomedical and health informatics*, vol. 19, no. 1, pp. 282-289, 2014.
26. A. Vishnuvarthanan, M. P. Rajasekaran, V. Govindaraj, Y. Zhang, and A. Thiyagarajan, "An automated hybrid approach using clustering and nature inspired optimization technique for improved tumor and tissue segmentation in magnetic resonance brain images," *Applied Soft Computing*, vol. 57, pp. 399-426, 2017.
27. L. Zhou, "QoE-driven delay announcement for cloud mobile media," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 27, no. 1, pp. 84-94, 2016.
28. L. Zhou, "Mobile device-to-device video distribution: Theory and application," *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, vol. 12, no. 3, pp. 1-23, 2016.