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Knowledge Management System for Fetal Movement during Pregnancy

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Abstract

During pregnancy period the inconsistent fetal movement complications or decreasing causes fetal death and stillbirth. Development of knowledge management system model for decreased fetal movement facilitates the diagnosis of the pregnancy complication from large medical dataset. Prevention of decreasing fetal movement during gestation at trimester period is the main task of the study in medical diagnosis system.The more suitable data mining algorithm such as Wrapper based Genetic Algorithm, Artificial neural Network and Support vector machine had been used for building the model. The study addressedthat improving pregnant women care quality due to decreasing fetal movement (DFM) using stacking method. Combining performance of both algorithm maintain the best solution that scored 99.2% accuracy.

***Key Words*:**Pregnancy, Fetal Movement, Knowledge Management system, prediction, Model, Classification, Data mining, ANN, SVM, Stacking.

1 Introduction

Pregnancy is an epoch during which descendants in womb properly develop inside a woman [1]. Fetal health is the symptom of appropriate growth of the fetus in the gravid woman's uterus during the gestation period. During pregnancy fetal unwell, illness, placental problems and decreasing fetal movement are the sign of potential problem.Fetal movement is the indication of the woman contact with her baby and fetus wellbeing during gestation period. Lack of blood and oxygen supply during pregnancy causes fetal distress can be the symptoms of decreasing fetal movement. The study has been reported that trimesters period of pregnancy is exposure to the risks arise from drugs causes preterm birth [2]. Pregnancy complications increase the risk of maternal and infant death, and are associated with unfortunate birth outcomes .Inconvenient maternal parameters and inconsistent fetal movement may causes fetal death [[3]. The electronic information of FHR and UC has been collected from ultrasound and maternal pressure transducer that monitor the fetal health condition [6]. Around the world 10% of pregnant women suffer from high blood pressure that leads to stress, impairment, and death of as the World Health Organization (WHO) studies report [7]. This affects the babies in uterus to get insufficient blood circulation, which reduces proper fetus movement. Data mining and machine learning algorithms were used for maximizing performance of choosing classifier that builds an accurate learning model for predicting the risk based on CTG dataset [8]. Healthcare sector stores large amount of information about patients and their medical conditions [11].The babys Fetal Heart Rate and UC are collected using CTG techniques that stored previous abnormalities identification and provides the obstetrician to predict future risks [17]. Problem of Fetal wellness during late pregnancy probably association of weak fetal movements with a range of adverse pregnancy outcomes such as fetal growth restriction, and fetal death. The aim of the study is that identifying the more significant fetal movement feature from the available medical dataset to provide accurate diagnosis decision of the decreasing fetal movement.

Related work

In this study several Machine Learning data mining algorithms have been studied for the solution of decreasing fetal movement during pregnancy period. Decreasing in fetal movement has been reported as the sign of fetal wellness in abdominal ECG measurement tracking system studies [1]. In most pregnant women inconsistent and disordered movement of fetus leads both life to death at trimester period. Similarly, the use of some sort of medication during pregnancy exposes to vary accident in most pregnant women [2]. However, another author argued that the importance of hybrid data mining algorithm to a build model for pregnant women, health risk prevention, which caused by parameter inconsistency changes during pregnancy [3].The proper dataset consisting of relevant number of parameters and applying the hybrid approach my help for better prediction of fetal growth during pregnancy. Similarly, in other studies eight algorithm accurate prediction response of all was examined by using 10-fold cross validation [4]. ANN is applied with high accuracy for very large and complex data set. The theoretical concepts of fetal movement through summative context analysis method have been declared to solve inconsistent decreasing of fetal movement [5]. The Oral conversation between obstetricians and patient about the gestational state of the women cannot properly exert the factors that cause complications during the pregnancy. However, a new method has been explored to improve genetic algorithm feature selection for clinical features from the CTG dataset to diagnosis the fetal well-being [6]. Also, the popular acknowledged classifier, SVM has been proposed to solve the nonlinear and binary or multiclass classification problem. In similar way new algorithm has been reported to improve the performance of the Doppler uterine artery experiment in high-risk of blood supplying to the fetus during pregnancy [7]. Uterine contraction complication that was fired fromGestational Diabetes Mellitus disease only cause death of maternal and infant during gestation period [2][8]. In the studies [9] ANN method has been preferred for prediction of hypertension disease. High computation cost and long learning rate of ANN enforce extending the model to deep learning networks. In order to improve fetal risk prediction response hybrid approaches of SVM with the other attributes reduction method has been discussed [10]. SVM has been one of the most over-optimistic classifier methods and the genetic algorithm (GA) was demonstrated to reduce the number of features that maximize the classifier performance [11]. Also In the study [12]. Support Vector Machine and Genetic Algorithm has been used to find an optimized and reduced feature set in order to improve the performance of the Multi classification system on fetal movement CTG dataset taken from UCI Machine Learning Repository. SVM is a latest classification method that classifies any data into binary or multi classes by searching the best hyper plane that classify the data under proper category [13]. The studies [16] has been suggested that different data mining techniques to carry out accurate achievement that comfort pregnancy outcomes by predicting degree of risk. GA was preferred for giving a better feature subset whereas a linear SVM was chosen as the classifiers to investigate the relationship between features and adverse outcome [18]. Predicting the risk mitigation based on the model and for particular patient trend was the limitation of the paper. Moreover, GA and ANN has been examined for high power of optimal feature selection and global model respectively [19].If in pregnant women her body does not properly process food for use and distribute for the fetus as energy that fully affect uterine contraction [20]. In paper [21],a novel work on clinical dataset has been proposed that select relevant features in classification of ovarian cancer by applying genetic algorithm. The study provides further research to find optimal breast cancer predictive model that reduce the death of mass women in the world [22]. Hypertension is one of the causes of DFM [23].Obstetricians has a high responsibility about advising and awering basic information of fetal movement to the pregnant women [24]. Ensemble techniques that may help to provide better outcomes for fetal movement classification has been suggested in another paper [25]. Fetal movement has long been of interest to the medical and scientific communities as a possible measure of fetal health and of neurobehavioral development [26].In [27] paper investigation applicability of ensemble method and hybrid machine learning methods has been proposed to predict the terrorist groups attacks in Middle East & North Africa. The External impacts of maternal factors in fetal body movement and breathing system were reported in [28]. Wrapper based feature selection with cross validation and correlation based attribute selection has been proposed in [29]. Fetal movement assessment is widely used as a method of routine surveillance of the well- being of unborn babies that reduces the risk of stillbirth, fetal growth restriction, fetal distress and perinatal mortality [30]. A reduction of fetal movements causes concern and anxiety, both for the mother and obstetrician that is difficult to interpret because it is a subjective complaint by the mother [31].CTG is a simultaneous recording of FHR and UC that is the most common diagnostic techniques to evaluate maternal and fetal well-being during pregnancy and before delivery scored 97.9 accuracy using 21 attributes of CTG [32]. The ensemble methodology is to build a predictive model by integrating multiple models which can be used for improving prediction performance has been proposed [33]. The main goal of this study was employing a new hybrid technique for developing an accurate classifier model to predict fetal health during pregnancy period.

Knowledge Management System (KMS)

The study Aim is to build Knowledge Management System model which is capable of predicting decreased fetal movement problem. This work is unique that specifically deal with decreased fetus movement problem diagnosis using stacking method. Outcome of the designed KMS are:

Developing a classifier model that can predict the fetal movement

Predict accurately result of the classifier model

Fetal Movement Facts and its Classification concepts

Biomechanical aspects of fetal movements describe that fetus can move in flexible constrained physical environment where volunteer movement high limited as fetal size increase and amniotic fluid decrease [3]. To assure ultrasound and fetal CTG the knowledge management system model designed to enable continuous monitoring and detect risks of decreasing fetal movements during pregnancy

Knowledge Management system Model architecture

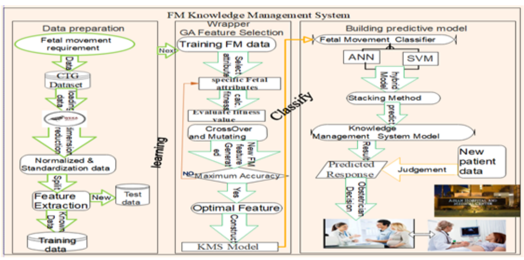

Figure 1: KMS for Fetal movement Architecture

Methodology and Tools

Dataset design

Ultrasound method is the earliest analysis of a pregnant woman with DFM to identify normal CTG or if any suspected risk factors. The assessing of abdominal circumference on ultrasound to detect the growth restricted fetus whereas Doppler measurements should be used as a screening tool. CTG dataset consists of 4252 instances with 22 original attributes which are multivariate data types [3].

Fetal Movement Data preparation

Reducing actual size of the CTG Dataset and choosing relevant fetal movement attributes or remove the irrelevant are the initial tasks in CTG data pre-processing. The Dataset contains 34 attributes originally which are collected from the pregnant women.At first the feature reduced out of 34 to 22 attributes .On the second steps the 22 attributes reduced to 13 attributes for the final predictive classification of the fetal movement.The Optimal feature set selection realizes that the capability of generalization better than the original feature set.

Table 1: Fetal Movement CTG instances attributes

Rank		Attributes	Data types
1.	LB	FHR baseline (beats / minute)	Numerical
2.	AC	Accelerations Per Second	Numerical
3.	FM	Fetal Movements Per Second	Numerical
4.	UC	Uterine Contractions Per Second	Numerical
5.	DL	Light Decelerations Per Second	Numerical
6.	DS	Severe Decelerations Per Second	Numerical
7.	DP	Prolonged Decelerations Per Second	Numerical
8.	ASTV	Abnormal Short Term Variability Percent	Numerical
9.	MSTV	Short Term Variability Mean Value	Numerical
10.	ASLTV	Abnormal State Long Term Variability Percent	Numerical
11.	Variance	Histogram Variance Value	Numerical
12.	Class	Class Of Heart Rate	Numerical
13.	NSP	Class Label (Normal, Suspect, Pathological)	Nominal

Data Mining Techniques

Data mining and machine learning algorithms were used for maximizing performance of choosing classifier that builds an accurate learning model for predicting the risk based on CTG dataset [7]. Data mining algorithms have potential usually to perform decreased fetal movement classification and visualization tasks that facilitate decision-making.

Classification algorithm approaches

In this study a suitable classification algorithm SVM, ANN and stacking ensemble method was assigned to develop a predictive model for decreased fetal movement from the pre-classified dataset. MajorTasks in decreased fetal movement predictive classification:-

1. Building KMS model by using attributes trained by SVM and ANN.

2. Prediction of the model performance from unknown class label.

Fetal movement Feature Selection

The goal of fetal movement attribute selection is to select a subset of fetal attributes without significantly affecting the overall quality of the model. Wrapper method is capable of selecting best fitting attributes which depends on Genetic Algorithm rule.

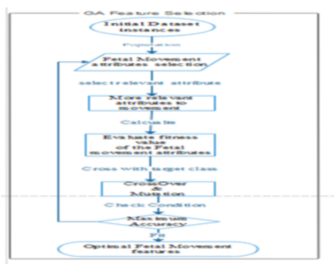

Figure 2: GA Feature Selection Operation flow

Fitness function design

To evaluate quality of the fetal movement attributes that fulfil the selection criteria from the original CTG dataset. The attributes that minimizes objective function depends on the fitness values of the two individual parent which exchange genes to generate new attributes and children selected by the chosen algorithm [9].

$$F = VCA * A * N \frac{1}{\sum} A_i \tag{1}$$

Where i=1, F- Fitness, A - accuracy, VCA -assigned weight value for classification accuracy, N - number of the attributes, Ai - summation of values of each attributes (i=1, N).The fitness of KMS Model to the fetal movement data that we used to estimate model parameters based on the new decreased fetal movement data during trimester.

Algorithm and Techniques

Artificial Neural Network (ANN)

ANN model uses back propagation learning methods for training the model to predict complex nonlinear medical data efficiently [7]. To minimize the error between the network's class prediction and the actual class label of original data set a set of weights are required.

$$Vj(n) = \sum_{i=1}^{p} (Wji * xi + T) \tag{2}$$

Activation function:

$$Yj(n) = \frac{1}{1 + exp(-Vj)(n)} \tag{3}$$

Support Vector Machine

SVM was used to construct hyper planes in a multidimensional space that separates cases of different class labels. Nonlinear kernel functions help in order to integrate data into a suitable form that tends to split the data [17]. To achieve optimal result RBF kernel used indecreasing fetal movement classification because of generalization and low computational cost.

To Isolating hyperplane fetal movement training data must satisfying the following condition,

$$WTX + b = 0(4) \tag{4}$$

$$W^T X^i + b >= 1 foralli \tag{5}$$

The goal is to get hyperplane (W, b) with maximal separation between closest data points which fulfil the above criteria.

Stacking Ensemble Method

Stacking is a technique whose purpose is to achieve the highest generalization accuracy in predicting decreasing fetal movement classification. Stacking is a heuristic method that simultaneous mixing of n classifiers where all executed simultaneously.The main factors that differentiate stacking method are combining method and Ensemble size [34]:

1. Input fetal movement training data
2. Combine using ensemble classifier to train at base level(SVM)
3. Construct new fetal dataset prediction
4. Learn fetal data again at meta level classifier (ANN)

5. Predict the outcome

2 Experiment and discussion

The practical Diagnosis of decreasing fetal movement (DFM) had been classified by SVM and ANN with Wrapper method feature selection using ensemble method called stacking. In this study reducing the number of attributes by feature selection and increasing number instances provides great changes in performance accuracy compared to most early studies. Statistics for KMS

Root Mean Squared Error: measure of the differences between value (Sample and population values) predicted by a model and the values actually observed.

$$RMSE = \sqrt{\sum_{i=1}^{n}(xi - xi)^2} \tag{6}$$

Cross Validation (CV)

In the decreasing fetal movement diagnosis specific part of training and testing set not considered by this method [3]. In 10-fold the dataset is divided into 10 teams of uniform length, whereas 9 teams used for building the model and 1 reserved for validation [13][15].

Accuracy

Accuracy rate is the percentage of test set samples that are correctly classified by the model. If the attributes fit, the required goal for the diagnosis to classify the Unknown decreased fetal movement data accurately. The Test set must be independent of training set to avoid over fitting.

$$accuracy = 100 * \frac{Tpositive + Tnegative}{Tpositive + Tnegative + Fpositive + Fnegative} \tag{7}$$

Confusion matrix (CM)

Performance of KMS model classification evaluated using the fetal movement data in the matrix. Precision: fetal movement classifier exactness or quality

$$precision = \frac{Tpositive}{Tpositive + Fpositive} \tag{8}$$

Recall: fetal movement classifier completeness.

$$Recall = \frac{Tpositive}{Tpositive + Fnegative} \tag{9}$$

Specificity: It shows the ration of negative test result

$$Specificity = 100 * \frac{Tnegative}{Tnegative + Fpositive} \tag{10}$$

Sensitivity: It indicates the rate of Positive test result

$$Sensitivity = 100 * \frac{Tpositive}{Fnegative + Tpositive} \tag{11}$$

True positive rate:correctly identified fetal movement class False positive rate:incorrectly identified fetal movement class

Experiment and Discussion Methods

In conducting the experiment two models are efficient in the diagnosis of decreased fetal movement using the percentage split of 80:20 of the CTG data set.

Table 2: building KMS model

Using	Classifier	Normalization	RMSE	Accuracy
Training set	SVM	Applied	0.035	98.5
	ANN	Not Applied	0.0569	98.81
Using Cross	------	---------	-----	------
Validation	SVM	Applied	0.1092	98.2
	ANN	Not Applied	0.1079	98
	Stacking	Not applied	0.0751	99.2

SVM model achieved high performance on Cross Validation whereas ANN Model scored better performance on training set. The capability nature of analysing complex data leads ANN model to provide highest performance without data Normalization.

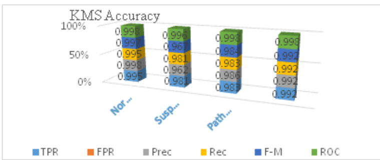

Figure 3: Details of Fetal Movement classification accuracy

Table 3: Classification of DFM Instance

	Number of Instance	Accuracy
Correctly Classified	4218	99.2
Incorrectly classified	34	0.8
Total Instance	4252	99.2

This table describe general algorithm performance in the classification.

3 Conclusion and Further work

In thisstudy knowing mandatory required fetal movement data, identify type of fetal movement knowledge to be discovered and facts about the knowledge are the main tasks. Accuracy of the Knowledge Movement System for Fetal Movement model are predicted by comparing unknown decreased fetal movement label of test sample with the classified result from the KMS model. The hybrid of SVM and ANN through stacking method scored 99.2 accuracy. In further studies creating up-to-date fetal movement dataset and developing mobile data mining will be the future works of the researcher for monitoring fetal movement to facilitate Obstetrician activity.

References

[1] M. J. Rooijakkers, C. Rabotti, H. De Lau, S. G. Oei, J. W. M. Bergmans, and M. Mischi, Feasibility Study of a New Method for Low-Complexity Fetal Movement Detection from Abdominal ECG Recordings, IEEE J. Biomed. Heal. Informatics, 2016.

[2] Y. Chen, L. H. Pedersen, W. W. Chu, and J. Olsen, Drug exposure side effects from mining pregnancy data, ACM SIGKDD Explor. Newsl., vol. 9, no. 1, p. 22, 2007.

[3] B. N. Lakshmi, T. S. Indumathi, and N. Ravi, An Hybrid Approach for Prediction Based Health Monitoring in Pregnant Women, Procedia Technol., 2016.

[4] H. Sahin and A. Subasi, Classification of the cardiotocogram data for anticipation of fetal risks using machine learning techniques, Appl. Soft Comput. J., vol. 33, pp. 231238, 2015.

[5] J. Warland and P. Glover, Fetal movements: What are we telling women?, Women and Birth, vol. 30, no. 1, pp. 2328, 2017.

[6] R. S., J. A.B., and M. H., A novel clinical decision support system using improved adaptive genetic algorithm for the assessment of fetal well-being, Comput. Math. Methods Med., vol. 2015, p. no pagination, 2015.

[7] P. T. Jadhav, R. Jadhav, K. Jadhav, and T. Naidu, Use of Doppler indices in prediction of Acute Fetal Hypoxia Proposed Staging System, vol. 0, pp. 2131, 2017.

[8] M. W. L. Moreira, J. J. P. C. Rodrigues, A. M. B. Oliveira, K. Saleem, and A. V. Neto, An inference mechanism using Bayes-based classifiers in pregnancy care, 2016 IEEE 18th Int. Conf. e-Health Networking, Appl. Serv. Heal. 2016, no. Dm, pp. 04, 2016.

[9] D. Lafreniere, F. Zulkernine, D. Barber, and K. Martin, Using machine learning to predict hypertension from a clinical dataset, 2016 IEEE Symp. Ser. Comput. Intell. SSCI 2016, 2017.

[10] V. Subha, D. Murugan, and A. M. Boopathi, A sian R esearch C onsortium A Hybrid Filter-Wrapper Attribute Reduction Approach For Fetal Risk Anticipation, vol. 7, no. 2, pp. 10941106, 2017.

[11] D. Senthilkumar and S. Paulraj, Prediction of Low Birth Weight Infants and Its Risk Factors Using Data Mining Techniques, Proc. 2015 Int. Conf. Ind. Eng. Oper. Manag., pp. 186194, 2015.

[12] S. Velappan, M. D, P. S, and M. B. A, Genetic Algorithm Based Feature Subset Selection for Fetal State Classification, J. Commun. Technol. Electron. Comput. Sci., vol. 2, no. February, p. 13, 2015.

[13] M. Altini et al., Variable-length accelerometer features and electromyography to improve accuracy of fetal kicks detection during pregnancy using a single wearable device, 2017 IEEE

EMBS Int. Conf. Biomed. Heal. Informatics, BHI 2017, pp. 221224, 2017.

[14] M.-L. Huang and H. Yung-Yan, Fetal distress prediction using discriminant analysis, decision tree, and artificial neural network, J. Biomed. Sci. Eng., vol. 05, no. September, pp. 526533, 2012.

[15] S. V and M. D, Opposition Based Firefly Algorithm Optimized Feature Subset Selection Approach for Fetal Risk Anticipation, Mach. Learn. Appl. An Int. J., vol. 3, no. 2, pp. 5564, 2016.

[16] E. Yilmaz and . Kilikier, Determination of fetal state from cardiotocogram using LS-SVM with particle swarm optimization and binary decision tree, Comput. Math. Methods Med., vol. 2013, 2013.

[17] B. N. Lakshmi, T. s. Indumathi, and R. Nandini, A Comparative Study of Classification Algorithms for Risk Prediction in Pregnancy, Int. Conf. Comput. Commun. Syst., pp. 4246, 2015.

[18] L. Xu, A. Georgieva, C. W. G. Redman, and S. J. Payne, Feature selection for computerized fetal heart rate analysis using genetic algorithms., Conf. Proc. IEEE Eng. Med. Biol. Soc., vol. 2013, pp. 4458, 2013.

[19] C. Vaghela, N. Bhatt, and P. U. Patel, A Survey on Various Classification Techniques for Clinical Decision Support System, Int. J. Comput. Appl., vol. 116, no. 23, pp. 9758887, 2015.

[20] M. Renuka Devi and J. Maria Shyla, Analysis of various data mining techniques to predict diabetes mellitus, Int. J. Appl. Eng. Res., vol. 11, no. 1, pp. 727730, 2016.

[21] P. Khare and K. Burse, Feature Selection Using Genetic Algorithm and Classification using Weka for Ovarian Cancer, Int. J. Comput. Sci. Inf. Technol., vol. 7, no. 1, pp. 194196, 2016.

[22] S. Bhalerao and B. Gunjal, Hybridization of Improved K-Means and Artificial Neural Network for Heart Disease Prediction, Int. J. Comput. Sci. Trends Technol., vol. 4, no. 3, pp. 5461, 2013.

[23] K. Sivakami and C. Application, Mining Big Data: Breast Cancer Prediction using DT - SVM Hybrid Model, Int. J. Sci. Eng. Appl. Sci., no. 5, pp. 418429, 2015.

[24] A. Linde, I. Rdestad, K. Pettersson, L. Hagelberg, and S. Georgsson, Better safe than sorryReasons for consulting care due to decreased fetal movements, Women and Birth, vol. 30, no. 5, pp. 376381, 2017.

[25] M. M. H. Khorshid, T. H. M. Abou-el-enien, and G. M. A. Soliman, HYBRID CLASSIFICATION ALGORITHMS FOR TERRORISM PREDICTION in Middle East and North Africa, vol. 4, no. 3, pp. 2329, 2015.

[26] N. C. Nowlan, Biomechanics of foetal movement, Eur. Cells Mater., vol. 29, no. 0, pp. 121, 2015.

[27] S. Ravindran, A. B. Jambek, H. Muthusamy, and S.-C. Neoh, A Novel Clinical Decision Support System Using Improved Adaptive Genetic Algorithm for the Assessment of Fetal Well-Being, Comput. Math. Methods Med., vol. 2015, no. January 2014, pp. 111, 2015.

[28] D. Sussman, S. J. Lye, and G. D. Wells, Impact of maternal physical activity on fetal breathing and body movement-A review, Early Hum. Dev., vol. 94, pp. 5356, 2016.

[29] S. Georgsson, A. Linde, K. Pettersson, R. Nilsson, and I. Rdestad, To be taken seriously and receive rapid and adequate care Womens requests when they consult health care for reduced fetal movements, Midwifery, vol. 40, pp. 102108, 2016.

[30] I. B. Aydilek and A. Arslan, A hybrid method for imputation of missing values using optimized fuzzy c-means with support vector regression and a genetic algorithm, Inf. Sci. (Ny)., vol. 233, pp. 2535, 2013.

[31] M. J. Jassawalla, Reduced fetal movements: Interpretation and action, J. Obstet. Gynecol. India, vol. 61, no. 2, pp. 141143, 2011.

[32] D. Jagannathan, A Comparative Assessment of Classification Algorithms for Cardiotocography Dataset, no. March, pp. 912, 2017.

[33] L. Rokach, Ensemble Methods for Classification, Data Min. Knowl. Discov. Handb., pp. 957980, 2005.