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Research Article

Mutual Information Grey Wolf Optimized and Gradient Derivative Recurrent Network Pregnancy Growth Data Analysis

D.Sudha[1], P. Sujatha[2]
[1,2] Department of Computer Science,
Vels Institute of Science, Technology & Advanced Studies, Chennai, Tamil Nadu, India
[1]sudha041285@gmail.com, [2]suja.research@gmail.com

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ABSTRACT

Introduction: Cardiotocography (CTG) is a clinical procedure that is utilized in tracing and measuring the extremity of fetal discomfort. Fetal health involves prediction of fetus health condition during pregnancy. Despite CTG is being the most frequently utilized equipment to keep track of and gauge the fetus health, the high rate of false positive results because of visual analysis appreciably contributes to unnecessary surgical delivery or delayed arbitration. By employing sophisticated techniques like, Artificial Intelligence (AI) and Deep Learning (DL) can boost the fetal health classification accuracy. Nevertheless, hardly any studies have concentrated on analyzing mutual dependence between features and non-linear transformation to the generated features making it potential in learning and performing more complicated tasks (i.e. predictive data analysis)

Objectives: To enhance maternal-fetal health and assist clinical decision-making by creating a more reliable and accurate AI-based fetal health classification system.

Methods: Mutual Information Grey Wolf Optimized Gradient Derivative Recurrent Network (MIGWO-GDRN) for pregnancy growth data analysis is proposed. The MIGWO-GDRN method is split into two parts, namely, feature selection and classification. First, the samples obtained from the Fetal Health Classification dataset as input are subjected to the Mutual Information-based Grey Wolf Optimization-based (MIGWO) feature selection model. The MIGWO optimizes the parameters by reflecting mutual dependence between two features aids in improving Pregnancy Growth Data Analytics accuracy. Second with the optimal selected features and the chief controlling features for classification being fetal heart rate, fetal movement and uterine contractions a DL method called, Backpropagated Gradient Derivative-based Recurrent Neural Network model (BPDRNN) is designed. The Backpropagated Gradient here allows to measure derivatives by means of three unique features: uterine contractions, fetal heart rate, and fetal movement respectively.

Results: From analysis, it is inferred that the MIGWO-GDRN method acquired an improved precision, recall and accuracy with minimal false positive and training time. This shows the improved performance of proposed pregnancy growth data analytic method

Conclusions: MIGWO-GDRN is presented for analyzing pregnancy growth data in order to improve the fetal health categorization procedure. The total performance results show that the provided MIGWO-GDRN technique achieves higher precision, recall, and accuracy with less training time and false positive rate when compared to existing methods.

Keywords: Cardiotocography, Artificial Intelligence, Deep Learning, Mutual Information, Grey Wolf Optimization, Backpropagated Gradient Derivative, Recurrent Neural Network

INTRODUCTION

Globally in 2012 there were roughly 213 million births. As far as the developing nations are concerned, 23 million women were pregnant, whereas, in the case of poor countries, nearly 190 million women were pregnant. Also as per the report by the World Health Organization (WHO) nearly, 830 women die per from issues related to pregnancy.

Both mothers and their unborn children are at danger for consequential health issues and even death owing to pregnancy in today's contemporary conditions. Cardiotocography (CTG) tests manual analysis, a traditional method among obstetricians is considered as both laborious and time consuming. Owing to this the evolution of effective classification of fetal health becomes crucial for optimizing medical resources and minimizing time.

In [1] machine learning(ML) models were applied to address essential fetal health classification in an accurate and precise manner. The objective here remained in exploring, designing and analyzing machine learning models potential of classifying fetal health in an accurate and precise manner employing CTG data. Despite improvements observed in terms of accuracy and precision however the training time was not focused. SHapley Additive exPlanations (SHAP) were proposed in [2] with the objective of implementing the decision support tool for not only boosting live-birth rates but also to reduce time-to-pregnancy in an extensive manner. Though precision and recall involved in pregnancy analysis was focused, the false positive rate was not concentrated.

An arbitrary method for predicting outcome during the first trimester of pregnancy employing baseline demographic data and serially acquired blood samples was proposed in [3] with improved precision. However the training time involved was not focused. The applications and challenges involved in application of machine learning (ML) algorithms for pregnancy analysis were presented in [4]. Advanced data analysis and role in pregnancy care employing ML techniques were investigated in [5] with improved accuracy. Despite improvements in accuracy however the false positive rate was not focused.

In [6], a mechanism utilizing ML and DL techniques to circumvent the results of premature birth was proposed. By utilizing this combination of ML and DL techniques resulted in the improvement of accuracy. However the training time was not focused. Over the past few years, unfavorable pregnancy results have received more and more awareness globally. In addition more than 8 million new-born babies have birth deficiencies globally every year. As a result prediction of pregnancy results stays a pivotal research topic as it may minimize birth deficiency and boost population quality.

A DL algorithm which is potential in both detecting and classifying unfavorable pregnancy outcomes was proposed in [7]. With this there resulted in the classification improvement. Here a multi-layer neural network was trained for accurate results detection. Advanced mathematical methods like, independent component analysis and singular value decomposition was presented in [8] with the intent of detecting fetal health analysis. Despite improvement in accuracy the precision factor was not focused. A holistic review on ML techniques for predicting difficulties in pregnancy was investigated in [9].

It is apprehended that the patients with immune-abnormal co-pregnancies are said to be at the risk of adverse pregnancy outcomes. Conventional pregnancy risk management mechanisms produced prediction abilities with several drawbacks. In [10], ML techniques were proposed in [11] with the objective of analyzing risk factors and designing miscarriage risk prediction methods for patients with abnormal pregnancies. As a result improvement was observed both in terms of precision and accuracy. However the training time was not focused. A systematic review of pregnancy data analytics for premature birth prediction employing ML techniques was investigated in [12].

Fetal death rate is said to be high and there is a requirement to institute good health for both the fetus and mother during the time of both pregnancy and labor. An extensively utilized method for monitoring fetal heartbeat and uterine contractions during pregnancy is CTG. Deep learning methods were applied in [13] with the intent of detecting fetal hypoxia. Yet another method employing deep neural network architecture that takes into consideration the Bidirectional LSTM(BiLSTM) was designed in [14] to analyze maternal health during pregnancy.

Woefully the absence of efficient diagnostic methods hinders or obstructs timely medical administration. To be more specific, In fact, arbitration is only required for intervention and is only necessary for treating contractions. Multichannel entropy features and machine learning techniques were applied in [15] for assessing pregnancy. Yet another method to focus on the precision and recall aspects employing principal component analysis was proposed in [16] that with the aid of stacked ensemble voting classifiers aided in the improvement of F1-score considerably.

Machine learning methods were applied in [17] to predict pregnancy related complications with the objective of boosting prediction accuracy. However due to the inexperienced nature of the operator fetal biometric results are compromised. To address this issue, a deep learning method was proposed in [18] with the aid of statistical analysis that in turn resulted in the improvement of true positive rate. A systematic review on AI and machine learning techniques were investigated in [19] to boost pregnancy outcome. Also prediction of gestational diabetes was presented in [20]. Moreover, machine learning techniques were applied in [21] [22] to focus on both the accuracy, precision aspects in addition to the AUC curve. A systematic review on fetal health monitoring employing AI and machine learning techniques was presented in [23]. A systematic review to predict pregnancy outcomes using machine learning was investigated in [24]. Also a real time maternal fetal clinical environment for automatic classification was presented in [25].

With the incorporation of convolutional neural networks not only aided in minimizing computational cost but also boosted classification accuracy. Yet another deep representation of learning employing Mann-Whitney was proposed in [26] to reduce error rate. Also chromosomal enhancing analysis mechanism employing deep learning based AI was presented in [27] with faster convergence rate. Digitization and classification for abnormality detection employing Empirical Mode Decomposition was presented in [28]. Here the utilization of the support vector machine resulted in the improvement of average accuracy score. A hybrid CNN method was proposed in [29] for detecting fetal heart rate. By employing principal component analysis resulted in the improvement of overall accuracy. Deep neural network based classification was presented in [30] for CTG classification with improved accuracy.

Here we present an improved pregnancy growth data analytics method for robust fetal health classification using a method called, Mutual Information Grey Wolf Optimized Gradient Derivative Recurrent Network (MIGWO-GDRN). The proposed Mutual Information Grey Wolf Optimization-based (MIGWO) feature selection obtains or selects optimal features with minimal training time and convergence speed. Backpropagated Gradient Derivative-based Recurrent Neural Network (BPDRNN) classifier on the other hand identifies the fitness using Gradient Derivative optimization function. The MIGWO-GDRN method results of the optimization for fetal health classification using fetal health classification dataset are compared with the state-of-the-art methods for validation. A summary of existing methods, technology employed, advantages, limitations and the dataset in use are provided in Table 1.

Table 1 Existing methods summary

Reference	Work	Methodology	Advantages	Drawbacks	Dataset used
[1]	Fetal health classification	Machine learning model	Precision, recall, accuracy	Training time	CTG dataset
[2]	SHAP	Pregnancy analysis	Precision, recall, accuracy	False positive rate	Embryo
[6]	Labor detection to monitor pregnant women	Machine learning and deep learning	Accuracy rate	Training time	Term-Preterm EHG Database (TPEHGDB)
[7]	Adverse pregnancy outcome detection	Deep learning	Accuracy, recall, F1-score	Precision	National Free Pre-Pregnancy Check-ups (NFPC)
[10]	Pregnancy miscarriage risk prediction	Deep learning	AUC	Training time	Real time
[11]	Maternal health risk classification	Synergy of ANN and random forest	Precision, recall, accuracy	Training time	Maternal health risk dataset
[14]	Maternal health risk prediction	Ensemble learning	Accuracy	False positive rate	Real time dataset
[15]	Early assessment of pregnancy progression	Machine learning	Accuracy	Precision and training time	EHG dataset
[16]	Prediction of material health	PCA features and TREE net	Precision, recall and	False positive rate	cardiotocography dataset

	risk		accuracy		
[22]	Prediction of gestational diabetes	Bayesian optimization and ML	Sensitivity and specificity	Accuracy	Real time

OBJECTIVES

Taking into consideration the above performance metrics and to address the above said gaps, in this work a method called, Mutual Information Grey Wolf Optimized Gradient Derivative Recurrent Network (MIGWO-GDRN) for pregnancy growth data analysis to ensure time and minimize false positive rate is proposed. The essential contributions of MIGWO-GDRN method are listed below,

- To improve the training time with minimal false positive rate for efficient pregnancy data analysis, MIGWO-GDRN method is proposed. The MIGWO-GDRN method is introduced by applying the mutual information based fitness function and Gradient Derivative-based Recurrent Neural Network contrary to existing work that used machine learning techniques.
- To reduce the training time with minimal false positive rate, relevant and robust feature selection is obtained using Mutual Information Grey Wolf Optimization-based (MIGWO) feature selection.
- To improve the precision, recall and accuracy, Backpropagated Gradient Derivative-based Recurrent Neural Network (BPDRNN) classifier is employed that uses Gradient Derivative optimization function on the basis of the desired result and the actual result for the corresponding sample respectively.
- The performance is evaluated through extensive simulations for different performance metrics like, precision, recall, accuracy, training time and false positive rate with fetal health data and validated with the state-of-the-art methods.

METHODS

Deep learning, a division of machine learning, has exceptional calibers like the potentiality to select high level features employing a general-purpose learning procedure. Pregnancy data analysis for fetal health classification employing deep learning relies on two extensive complicating facets. The first facet depends on the mutual dependence between features in the process of selecting pertinent features from the raw fetal health dataset. The second facet is the false positive involved in fetal healthcare classification. Both facets must be complicated enough that the information cannot be predicted easily.

The objective of the proposed Mutual Information Grey Wolf Optimized Gradient Derivative Recurrent Network (MIGWO-GDRN) is to minimize false positive rate, training time and improve overall precision and accuracy involved for pregnancy growth data analysis. The work flow is presented in figure 1 which includes feature selection and classification.

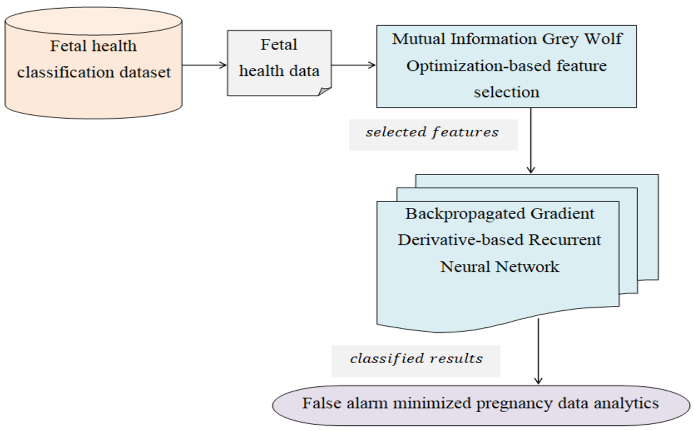

Figure 1 Block diagram of Mutual Information Grey Wolf Optimized Gradient Derivative Recurrent Network (MIGWO-GDRN)

As illustrated in the figure 2, the proposed MIGWO-GDRN method, the fetal health data for pregnancy data analytics is initially subjected to Mutual Information Grey Wolf Optimization with the intent of obtaining robust selection of features. Second the selected features are subjected to Backpropagated Gradient Derivative-based Recurrent Neural Network (BPDRNN) classifiers with the intent of classifying the health of the fetus into normal, suspect or pathological in an accurate and precise manner.

Mutual Information Grey Wolf Optimization-based (MIGWO) feature selection: This model employed in our work aims to improve Pregnancy Growth Data Analytics accuracy by optimizing the parameters by reflecting the mutual dependence between two features. The hierarchical construction of MIGWO model consists of four different parts, alpha, beta, delta and omega via fitness levels of the wolves. The predatory behavior of wolves essentially encloses the operation of pursuing and closing in on the prey, prey movement tracing and finally, triggering an attack on the prey. In the proposed model, triggering an attack on the prey forms the selection of the best features for Pregnancy Growth Data Analytics. Here, Least Mean Mutual Information (LMMI) is selected as the optimization objective function for determining the fitness levels. In the Mutual Information Grey Wolf Optimization-based (MIGWO) feature selection for pregnancy data analytics, the population of candidate solutions is denoted by a group of wolves (i.e., features) that communicate with one another (i.e., correlate with one another) and fine tune their locations (i.e., either discarding or including) based on the activities of the groups alpha, beta, and delta wolves. In this work, the fitness levels of the wolves or features are utilized in classifying them as alpha, beta, or delta.

The wolf or the feature possessing the highest fitness resultant value selected as the alpha wolf or alpha feature, the second-best wolf or feature is considered as the beta wolf or beta feature and finally the third-best wolf or feature is regarded as the delta wolf or delta feature respectively. These wolves or features are indispensable owing to the reason that they aid in directing the search the other wolves or features receive. Least Mean Mutual Information (LMMI) is considered to calculate the fitness value. Figure 2 shows the structure of the Mutual Information Grey Wolf Optimization-based (MIGWO) feature selection model.

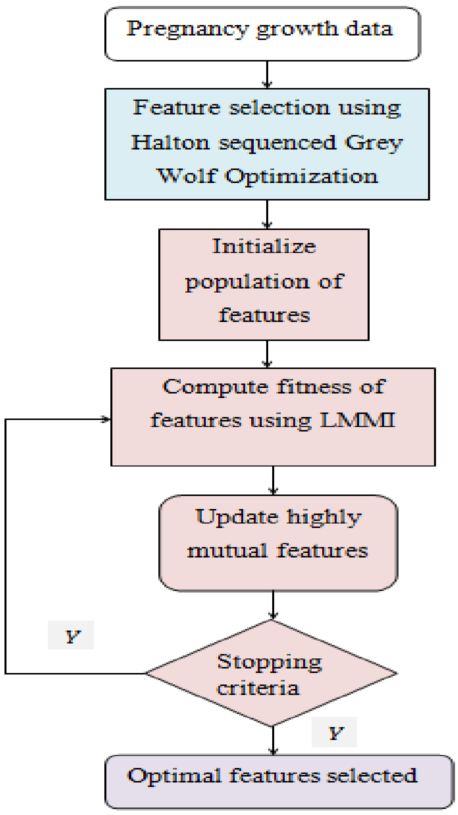

Figure 2 Structure of Mutual Information Grey Wolf Optimization-based (MIGWO) feature selection model

As shown in the figure 2, the selection of features for pregnancy predictive data analytics using MIGWO is as follows. The first step remains in initializing the population of wolves or the total number of features from the given dataset with arbitrary positions utilizing arbitrary numbers. Each wolf or feature denotes a candidate solution and the objective remains in identifying the optimal solution.

The second step on the other hand defines initial value for '$A = 2$' and encircle the prey. The third step remains in measuring each wolf's or each feature's fitness by applying the MIGWO to its corresponding position and the fitness here denotes the quality of the solution. The fourth step is to identify the wolves or the features with the first-highest, second-highest and third-highest wolves or features utilizing the fitness values of wolves or features.

Fifth step updates the positions of the remaining wolves or features in the dataset. The sixth step selects the best optimal solution by taking into consideration the mean value of three wolves or three features. In this manner the positions of the features are fine tuned to investigate the solution space and converge toward better solutions.

To start with the population initialization is performed based on arbitrary position using arbitrary numbers using the pregnancy growth data analytics is performed using fetal health classification dataset extracted from https://www.kaggle.com/datasets/andrewmvd/fetal-health-classification, University of California Irvine Machine Learning Repository. The input vector formulated as given below.

$$IV = \begin{pmatrix} S_1F_1 & S_1F_2 & .. & S_1F_m \\ S_2F_1 & S_2F_2 & .. & S_2F_n \\ .. & .. & .. & .. \\ S_mF_1 & S_mF_2 & .. & S_mF_n \end{pmatrix} \tag{1}$$

With the above initialized population 'IV' and '$iter$' denoting the current iteration for two coefficient vectors (i.e., features $P, Q \in F$) 'P', 'Q', then the distance 'Dis' between grey wolf or feature position vector '$F_{(iter)}$' and the prey position or feature prey position vector '$F_{p(iter)}$' is formulated as given below.

$$Dis = \left(Q\ F_{p(iter)} - F_{(iter)}\right) \tag{2}$$

$$F_{p(iter+1)} = F_{p(iter)} - P.Dis \tag{3}$$

From the above equations (2) and (3) the distance is evaluated for each set of input vector 'IV' consisting of 'm' samples and 'n' features. Next, the number of elements in 'A' is minimized from '2' to '0' employing the random number 'RN' in the interval '$[0,1]$' is mathematically represented as given below.

$$P = 2ARN_1 - A_1 \tag{4}$$

$$Q = 2RN_2 \tag{5}$$

From the above equations (4) and (5) 'RN_1' and 'RN_2' denotes random numbers between zero and one and a congruent element falls from two to zero with the increase in the iterations. Next, each wolf's or each feature's fitness is measured by applying the Mutual Information Grey Wolf Optimization to its corresponding position as given below.

$$MI(P, Q) = \sum_{a \in P} \sum_{b \in Q} f(P, Q) \log \frac{f(P,Q)}{f(P)f(Q)} \tag{6}$$

From the above equation (), '$f(P, Q)$' represent joint probability density functions of 'P' and 'Q', '$f(P)$', '$f(Q)$' represent the edge probability density functions of 'P' and 'Q' respectively. With the resultant Mutual Information Grey Wolf Optimization results, the alpha, beta and delta features administer the omega features in their identification of the prey (i.e., feature selection) and the omega features recomputed the feature prey position on the basis of the best estimates of the alpha, beta and delta features to arrive at the optimal features.

$$Dis_{\alpha} = (Q_1F_{\alpha} - F) \tag{7}$$

$$Dis_{\beta} = \left(Q_2F_{\beta} - F\right) \tag{8}$$

$$Dis_{\delta} = (Q_3F_{\delta} - F) \tag{9}$$

Next the wolves or the features with the first-highest, second-highest and third-highest wolves or features are identified. The fitness level of each feature is mathematically stated as given below.

$$F_1 = F_\alpha - P_1.Dis_\alpha \quad (10)$$

$$F_2 = F_\beta - P_2.Dis_\beta \quad (11)$$

$$F_3 = F_\delta - P_3.Dis_\delta \quad (12)$$

From the above results finally, the best optimal solution is arrived at by taking into consideration the mean value of three wolves or three features as given below.

$$FS = F_{(iter+1)} = \frac{F_1+F_2+F_3}{3} \quad (13)$$

From the above equation (13) results the optimal features '$F_{(iter+1)}$' are selected for further processing. The pseudo code representation of structure of Mutual Information Grey Wolf Optimization-based (MIGWO) feature selection is given below

Input: Dataset 'DS', Samples '$S = \{S_1, S_2, \dots, S_m\}$', Features '$F = \{F_1, F_2, \dots, F_n\}$'
Output: robust feature selection

Initialize '$m = 2127$', '$n = 22$', '$A = 2$', '$RN_1, RN_2 \in [0,1]$'
Begin
For each Dataset 'DS' with Samples 'S' and Features 'F'
//Population initialization
Initialize population as given in equation (1)
Evaluate distance between grey wolf or feature position vector and prey position or feature prey position vector as given in equations (2) and (3)
 	
For each coefficient vector 'P' and 'Q'
Encircle prey position or feature prey position vector as given in equations (4) and (5)
Evaluate feature's fitness by applying Mutual Information Grey Wolf Optimization as given in equation (6)
Identify wolves or features with the first-highest, second-highest and third-highest wolves or features as given in equations (7), (8) and (9)
Measure fitness for each feature as given in equations (10), (11) and (12)
Evaluate best optimal solution as given in equation (13)
Return features selected 'FS'
End for
End for
End

Algorithm 1 structure of Mutual Information Grey Wolf Optimization-based (MIGWO) feature selection

As given in the above algorithm, initially a group of grey wolves or features is arbitrarily generated from the dataset and they are split into four social hierarchies taking into consideration their objective function values from best to worst, namely, 'α', 'β', 'δ' and 'ω'. Next, the optimization process is performed by 'α' under the cooperation with 'β' and 'δ' by circling the prey. Followed by which 'ω' and other features move towards the prey, gradually minimizing the distance between them and the prey, and finally obtaining optimal features.

Backpropagated Gradient Derivative-based Recurrent Neural Network (BPDRNN) classifier: So far, cardiotocography (CTG) is the only cost efficient tool accessing pregnancy data analysis and continuous fetal health monitoring. Despite the tremendous amount of growth in the CTG automation, it still remains a demanding signal processing task. Complicated and arbitrary fetal heart rate patterns are imperfectly deciphered. Specifically, the accurate elucidation of the suspected cases is impartially low by both visual and automated mechanisms. Moreover, the first and second phase of labor generates very distinct fetal heart rate (FHR) dynamics. Hence a powerful classification method takes both stages into consideration independently.

In this section with the optimal selected features the objective remains in predicting fetal health status during pregnancy and detect fetal anomalies or conditions as early as possible therefore permitting for the administration and benefitting both mother and child. With the chief controlling features for classification being fetal heart rate, fetal movement and uterine contractions a Deep Learning (DL) method called, Backpropagated Gradient Derivative-based Recurrent Neural Network model (BPDRNN) is designed.

The Backpropagated Gradient here allows to measure the derivatives required when optimizing an iterative analysis procedure by classifying the data analysis by means of three unique features: uterine contractions, fetal heart rate, and fetal movement respectively. Figure 3 shows the block diagram of Backpropagated Gradient Derivative-based Recurrent Neural Network (BPDRNN) classifier model.

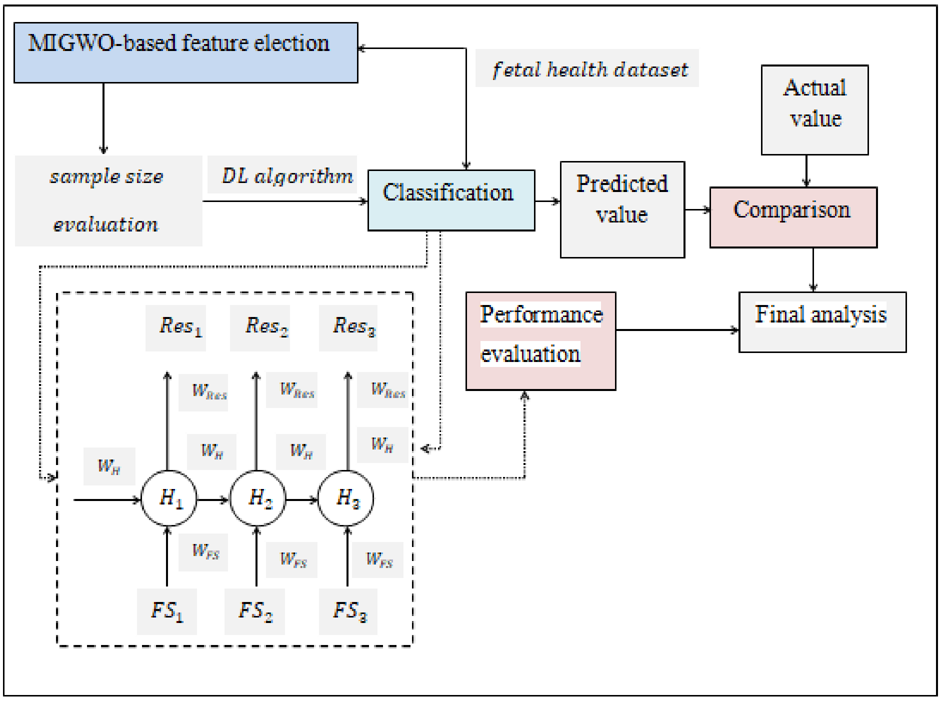

Figure 3 Block diagram of Backpropagated Gradient Derivative-based Recurrent Neural Network (BPDRNN) classifier

As illustrated in the figure 3 , the Fetal Health is an information system utilized in medical diagnosis where the paramount objective aims in forecasting fetus health state employing a diversification of specifications acquired from CTG Scanning. The task necessitates exploring recordings of CTG to encapsulate the fetal heart rate (FHR) and uterine Contractions in addition to the selected features and employing this data in predicting fetal health status as normal, suspicious or pathological for pregnancy data analysis. The complication declaration for classification of fetal health classification directs to create a DL Backpropagated Gradient Derivative-based RNN model that utilizing features selected along with the sample CTG data can accurately and precisely classify fetal health condition.

Also ‘H_1’, ‘H_2’, ‘H_2’ represents the hidden states at time ‘t_1’, ‘t_2’ and ‘t_3’ respectively and ‘W_H’ is the corresponding weight. Moreover, ‘FS_1’, ‘FS_2’ and ‘FS_3’ represent the inputs of fetal health at time ‘t_1’, ‘t_2’ and ‘t_3’ and ‘W_{FS}’ is the weight matrix correlated with it. Finally, ‘Res_1’, ‘Res_2’ and ‘Res_3’ are the resultant outputs at time ‘t_1’, ‘t_2’ and ‘t_3’ respectively and ‘W_{Res}’ is the correlated weight matrix associated with it.

The Backpropagated Gradient Derivative-based RNN comprises numerous arranged activation function units one for each time step. Each unit has an internal state also referred to as the hidden state denotes the previous knowledge of the fetal health state that the network presently holds at a given time instance. This hidden state is fine tuned at every time instance to denote the fine tuned results in the knowledge of the network about the past knowledge of the fetal health state. Then the hidden state is fine tuned utilizing the following recurrence relation as given below.

$$H_t=f(H_{t-1}, FS_t) \tag{14}$$

From the above equation (14) ‘H_t’ and ‘H_{t-1}’ signifies the current state and previous state of the input state ‘FS_t’ (i.e., features selected) respectively. Then the formula for applying activation function permitting to learn and represent complicated patterns in the data is as given below. Also employing back propagation for predicting the output utilizing not only the current knowledge of fetal health state but also considering those based on the previous knowledge of fetal health the hidden state is represented as given below.

H_t= 〖AF〗_1 (W_FS 〖FS〗_t+W_H H_(t-1)) (15)

From the above equation (15), 'W_H' and 'W_FS' signifies weight at recurrent and input neurons respectively. Finally the mathematical formulates for evaluating the output is stated as given below.

〖Res〗_t= 〖AF〗_2 (W_Res H_t) (16)

From the above equations (15) and (16) results '〖AF〗_1', '〖AF〗_2' represent the activation function activated at distinct time instance. Finally, Gradient Derivative optimization function is employed in minimizing the loss function during model training. The error employing Gradient Derivative optimization function is mathematically formulated as given below.

E_k=(〖DR〗_k- 〖AR〗_k)^2 (17)

(∂E_k)/(∂W_Res)=(∂E_k)/(∂ 〖Res〗_k).(∂ 〖Res〗_k)/(∂W_Res) (18)

From the above equations (17) and (18) the error 'E_k' is formalized based on the desired result '〖DR〗_k' and the actual result '〖AR〗_k' for the corresponding 'k-th' sample respectively. Also from the above equation 'E_k' is a function of '〖Res〗_k' and '〖Res〗_k' is a function of 'W_Res'. So we differentiate '〖Res〗_k' with respect to 'W_Res'. The pseudo code representation of Backpropagated Gradient Derivative-based Recurrent Neural Network (BPDRNN) classifier is given below

Input: Dataset 'DS', Samples '$S = \{S_1, S_2, \dots, S_m\}$', Features '$F = \{F_1, F_2, \dots, F_n\}$'
Output:

Initialize '$m = 2127$', '$n = 22$', '$A = 2$', features selected 'FS'
Begin
For each Dataset 'DS' with Samples 'S' and features selected 'FS'
Formulate hidden state utilizing the recurrence relation as given in equation (14)
Formulate back propagation for predicting the output as given in equation (15)
Evaluate resultant output as given in equation (16)
If '$Res_t = 0$'
Then classified result is normal
End if
If '$Res_t > 0$ and $Res_t \leq 0.5$'
Then classified result is suspect
End if
If '$Res_t > 0.5$'
Then classified result is pathological
End if
End for
End

Algorithm 2 Backpropagated Gradient Derivative-based Recurrent Neural Network (BPDRNN) classifier

As given in the above algorithm with the objective of reducing the false positives involved in fetal health classification for pregnancy data analytics, Backpropagated Gradient Derivative function with Recurrent Neural Network is applied. With this objective first, with the sample instances and features selected as input, the hidden state is formulated using recurrence relation. Next, by employing Backpropagation evaluates the gradient of a loss function iterating backward from the last layer to circumvent redundant calculations of intermediate terms therefore not only reducing the training time but also minimizes the false positive rate significantly. Finally with the back propagated results the classified outcomes of normal, suspect or pathological condition is obtained in an accurate and precise manner.

RESULTS

In this section, performance evaluation and validation of the proposed method Mutual Information Grey Wolf Optimized Gradient Derivative Recurrent Network (MIGWO-GDRN) for pregnancy growth data analysis is presented. Detailed comparison with two existing methods, machine learning model [1] and SHapley Additive exPlanations (SHAP) [2] are analyzed and validated in Python high-level general-purpose programming language with the aid of fetal health classification data set extracted from https://www.kaggle.com/datasets/andrewmvd/fetal-health-classification. The validation is performed in an Intel Core i5- 6200U CPU @ 2.30GHz 4 cores with 4 Gigabytes of DDR4 RAM. Simulations are analyzed using four performance parameters, precision, recall, accuracy, training time and false positive rate. To ensure fair comparisons similar sample data are utilized from fetal health classification data set for all the three methods, MIGWO-GDRN, machine learning model [1] and SHapley Additive exPlanations (SHAP) [2] respectively for pregnancy health data analysis pertaining to fetal health classification using the same dataset.

Performance analysis of precision, recall and accuracy: Precision is referred to as the ratio of fetal health samples considered for simulation that were predicted correctly (i.e., normal as normal or suspect as suspect or pathological as pathological) and is measured in the form of model precision score. In other words, precision is denoted as the positive predictive score and is mathematically represented as given below.

$$Pre = \frac{TP}{TP+FP} \tag{19}$$

From the above equation (19), precision 'Pre', is measured by utilizing true positive rate 'TP' (i.e., normal fetal health as normal) and false positive rate 'FP' (i.e., suspect samples as normal samples). The second performance metric recall measures the method's accuracy in pregnancy data analytics for fetal health classification predicting positives as differentiated from actual positives and is formulated by means of model recall score. This evolves from precision that takes into consideration how many of the total number of pregnancy data analytics for fetal health classification predictions produced by the methods are truly positive. In this manner the methods prospective in identifying positive instances are denoted by high recall score as given below.

$$Rec = \frac{TN}{TN+FP} \tag{20}$$

From the above equation (20), recall rate 'Rec', is estimated by taking into consideration the true positive rate 'TP' (i.e., detection of pathological sample as pathological sample) and the false negative rate 'FN' (i.e., pathological sample as normal samples). Third, the method accuracy is mathematically represented as the ratio of true positive 'TP' and true negative 'TN' to all the positive and negative observations, symbolizing one of the most extensively utilized performance metrics for fetal health classification. Accuracy rate is mathematically stated as given below.

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \tag{21}$$

From the above equation (21), the accuracy represents the frequency of times pregnancy data analytics for fetal health classification predicted a result accurately out of all the predictions it made. Table 2 given below lists the comparative results of three distinct performance metrics in terms of precision, recall and accuracy employing the proposed Mutual Information Grey Wolf Optimized Gradient Derivative Recurrent Network (MIGWO-GDRN) and two existing methods, machine learning model [1] and SHapley Additive exPlanations (SHAP) [2].

Table 2 Comparison table of precision, recall and accuracy using proposed MIGWO-GDRN and two existing methods, machine learning model [1] and SHAP [2]

Samples	**Precision**			**Recall**			**Accuracy**		
	MIGWO-GDRN	machine learning model	SHAP	MIGWO-GDRN	machine learning model	SHAP	MIGWO-GDRN	machine learning model	SHAP
100	0.94	0.91	0.88	0.98	0.97	0.96	0.93	0.88	0.82
200	0.92	0.88	0.85	0.85	0.81	0.78	0.91	0.85	0.75
300	0.9	0.85	0.8	0.92	0.83	0.81	0.90	0.82	0.72
400	0.87	0.82	0.78	0.9	0.8	0.75	0.89	0.83	0.70
500	0.85	0.81	0.75	0.87	0.83	0.77	0.89	0.81	0.69
600	0.83	0.78	0.71	0.83	0.8	0.74	0.85	0.80	0.65
700	0.85	0.8	0.74	0.81	0.75	0.71	0.83	0.82	0.68

800	0.87	0.82	0.75	0.83	0.77	0.73	0.85	0.83	0.73
900	0.89	0.84	0.77	0.87	0.79	0.75	0.87	0.84	0.75
1000	0.9	0.85	0.79	0.9	0.81	0.77	0.89	0.85	0.77

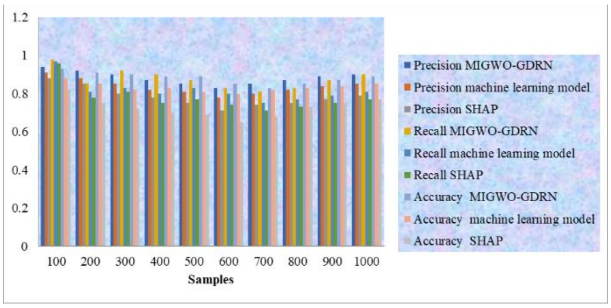

Figure 4 Graphical representations of precision, recall and accuracy

Figure 4 given above illustrates the graphical representations of three distinct performance parameters, precision, recall and accuracy employing the three different methods, proposed MIGWO-GDRN and two existing methods, machine learning model [1] and SHapley Additive exPlanations (SHAP) [2]. Also three different count classes, namely normal, suspect and pathological count were used for detailed analysis.

To perform simulation a sample set of 1000 three different count classes while performing fetal health classification towards pregnancy data analytics were employed and accordingly its validation is carried out utilizing three performance parameters namely, precision, recall and accuracy using the proposed MIGWO-GDRN and two existing methods, machine learning model [1] and SHAP [2]. Here, second different hypotheses were made. The first hypothesis was that the proposed methods precision, recall and accuracy were instituted to be comparatively better than [1] and [2].

The second hypothesis was that increasing the fetal health samples obtained as samples for input did not increase or decrease the resultant values of precision, recall and accuracy. To be more specific, the precision, recall and accuracy were neither found to be inversely or directly proportional to the samples of fetal samples provided as input. The reason for the improvements of precision, recall and accuracy would be attributed to the application of Backpropagated Gradient Derivative-based Recurrent Neural Network (BPDRNN) classifiers. By applying this algorithm, recurrence relation was initially applied to formulate the sample instances and the features selection. Followed by which Backpropagation was applied to measure the gradient of a loss function to alleviate redundant calculations.

Finally with the back propagated results the classified outcomes of normal, suspect or pathological condition were obtained in an accurate and precise manner. This in turn improved the precision rate of pregnancy growth data analytics using the proposed MIGWO-GDRN method by 6% upon comparison to [1] and [2] and 13% upon comparison to [1] and [2]. In a similar manner the recall rate of fetal heath classification for pregnancy growth data analytics using the proposed MIGWO-GDRN method was found to be improved by 7% upon comparison to [1] and [2] and 13% upon comparison to [1] and [2] respectively. Finally the accuracy factor was said to be enhanced utilizing the proposed MIGWO-GDRN method by 6% upon comparison to [1] and [2] and 22% comparison to [1] and [2].

Performance analysis of training time: Second in this section the training time in pregnancy growth data analytics towards fetal health classification for three different methods are analyzed. While validating and analyzing fetal health classification fetal samples a proportional amount of time is said to be consumed and this is measured in terms of milliseconds. The training time is mathematically represented as given below.

$$TT = \sum_{i=1}^{m} S_i * Time(Res_t) \quad (22)$$

From the above equation (22) training time 'TT' is measured on the basis of the samples involved in the simulation process 'S_i' and the pregnancy growth data analytics towards fetal health classification time into either normal samples or pathological samples '$Time\ (Res_t)$'. Table 2 given below tabulates the comparative analysis of performance metric in terms of training time employing the proposed MIGWO-GDRN method and two existing methods, machine learning model [1] and SHAP [2]. Table 3 given below tabulates the comparative results of three distinct performance metrics in terms of training time using the proposed MIGWO-GDRN and two existing methods, machine learning model [1] and SHAP [2].

Table 3 Comparison table of training time using proposed MIGWO-GDRN and two existing methods, machine learning model [1] and SHAP [2]

Samples	Training time (ms)		
	MIGWO-GDRN	machine learning model	SHAP
100	1.2	1.8	2.3
200	1.45	1.95	2.45
300	1.65	2.05	2.55
400	1.93	2.15	2.8
500	2	2.3	3
600	2.15	2.45	3.15
700	2.35	2.52	3.35
800	2	2.25	3
900	1.75	2	2.85
1000	1.55	1.85	2.55

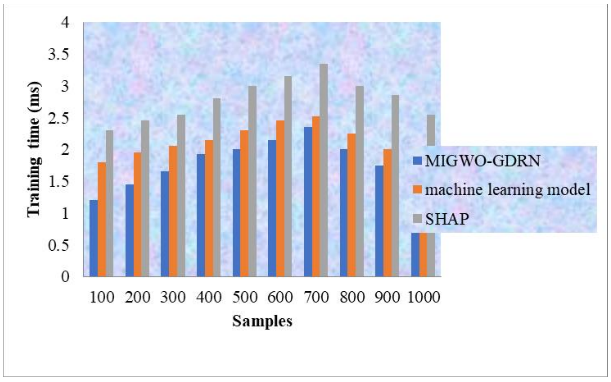

Figure 5 Graphical representation of training time

Figure 5 given above shows the training time graphical representation using the proposed MIGWO-GDRN method and two existing methods, machine learning model [1] and SHAP [2]. To make certain impartial comparison and simulation analysis between the proposed and two existing methods, fetal health samples were obtained from the fetal health classification dataset for three different count qualities (i.e., normal or suspect or pathological) of fetal health samples. From the above results two hypotheses were made.

Initially, the training time consumed in analyzing and validating fetal health samples for pregnancy data analytics employing the proposed MIGWO-GDRN method was found to be comparatively better than [1] and [2] for all the 10000 fetal samples performed for 10 simulation runs. Second, increase in fetal samples has no associations with the performance metric training time, i.e., increasing the fetal sample size did not increase the overall training time, hence confirming the objective of performance improvement even for large fetal sample size.

The rationale for minimum time consumed in training time was due to the application of Mutual Information Grey Wolf Optimization-based (MIGWO) feature selection algorithm. By applying this algorithm, initially each wolf's or each feature's fitness is measured by applying the Mutual Information Grey Wolf Optimization with respect to raw fetal samples.

Followed by which the features with the first-highest, second-highest and third-highest wolves or features were identified for further processing. With this the overall training time using the proposed MIGWO-GDRN method was found to be less by 16%, 36% when compared to [1] and [2].

Performance analysis of false positive rate: Finally in this section the false positive rate or false alarm ratio involved in pregnancy growth data analytics is measured. False positive rate is evaluated as the probability or falsely rejecting the null hypothesis for pregnancy growth data analysis. The false positive rate is measured as given below.

$$FPR = \frac{FP}{FP+TN} \tag{23}$$

From the above equation (23) false positive rate 'FPR', is measured based on the false positive 'FP' rate (i.e., normal samples as suspect) and true negative rate 'TN' (i.e., suspect samples as suspect) respectively. Table 4 given below lists the false positive rate using the three methods, MIGWO-GDRN, machine learning model [1] and SHAP [2].

Table 4 Comparison table of false positive rate using proposed MIGWO-GDRN, machine learning model [1] and SHAP [2]

Samples	False Positive Rate		
	MIGWO-GDRN	machine learning model	SHAP
100	0.18	0.27	0.36
200	0.2	0.28	0.37
300	0.22	0.29	0.38
400	0.25	0.3	0.39
500	0.15	0.25	0.3
600	0.12	0.21	0.27
700	0.1	0.18	0.25
800	0.15	0.2	0.26
900	0.2	0.22	0.28
1000	0.22	0.24	0.29

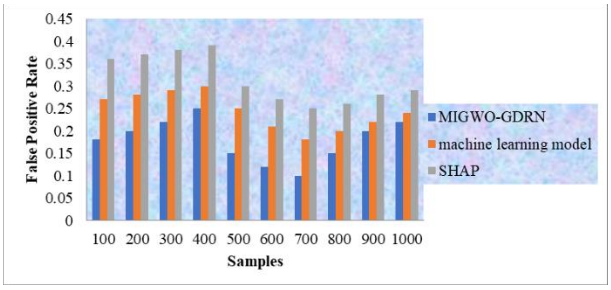

Figure 6 Graphical representation of false positive rate

Figure 6 given above shows the performance of the proposed MIGWO-GDRN method on 1000 different fetal samples along with the existing works, machine learning model [1] and SHAP [2]. It can be seen that the false positive rate is neither increasing nor decreasing with the increase in the fetal samples provided as input. From this result it is inferred that increasing the fetal samples does not compromise the prespective of falsely rejecting the null hypothesis. Also from the above result the false positive rate using the proposed MIGWO-GDRN method was found to be reduced upon comparison to [1] and [2]. The reason behind the minimization of false positive rate employing the proposed MIGWO-GDRN method was due to the application of Gradient Derivative-based Recurrent Neural Network based classifiers during the classification process. By applying this gradient derivative function is employed in reducing the loss function (i.e., reducing false alarm) during model training. This in turn minimizes the false positive rate using the proposed MIGWO-GDRN method 27% upon comparison to [1] and 43% compared to [2] respectively.

CONCLUSION

Pregnancy difficulties paramount influence women and give rise to prospective threats to the developing child's health. Early recognition of these difficulties is paramount for life-saving arbitrations. As a result the evolution of effective pregnancy data analytics for fetal health classification becomes pivotal for optimizing both medical resources and minimizing time. Several healthcare monitoring industries have started employing deep learning with the intent of improving both precision and accuracy. In this work a suitable method called, Mutual Information Grey Wolf Optimized Gradient Derivative Recurrent Network (MIGWO-GDRN) for pregnancy growth data analysis is to further improve the fetal health classification. First the raw fetal health samples from fetal health classification data were obtained and subjected to Mutual Information-based Grey Wolf Optimization-based (MIGWO) feature selection model for obtaining robust selection of features for further processing. Several performance metrics, including precision, recall, accuracy, training time, and false positive rate, were measured experimentally in detail using different numbers of fetal samples for the matching fetal sample data. The overall performance results illustrate that the presented MIGWO-GDRN method achieves higher precision, recall and accuracy with minimum training time and false positive rate upon comparison to the conventional methods.

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