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OPTIMIZING FETAL HEALTH ASSESSMENT WITH AI-DRIVEN UMBILICAL CORD CLASSIFICATION VIA 2-D DOPPLER ULTRASOUND IMAGING

Dr. Aniket M Zope[1*], Dr. Uday M Zende[2], Dr. Snehil Kumar[3], Dr. Amol Gautam[4]
[1] Assistant Professor, Department of Radiodiagnosis, Symbiosis Medical College for Women &Symbiosis University Hospital and Research Centre, Symbiosis International (Deemed University), Pune, India. aniketzope88@gmail.com
[2] Assistant Professor, Department of Radiodiagnosis, Symbiosis Medical College for Women & Symbiosis University Hospital and Research Centre, Symbiosis International (Deemed University), Pune, India
[3] Assistant Professor, Department of Radiodiagnosis, Symbiosis Medical College for Women & Symbiosis University Hospital and Research Centre, Symbiosis International (Deemed University), Pune, India
[4] Professor, Department of Radiodiagnosis, Symbiosis Medical College for Women & Symbiosis University Hospital and Research Centre, Symbiosis International (Deemed University), Pune, India

Abstract
The fetal umbilical cord is an essential organ that connects the fetal to the placenta, supplying oxygen and food while removing waste. It is constructed of blood vessels that are enclosed in a gelatinous material. Ultrasound imaging provides real-time images of inside organs using sound waves, which helps in prenatal diagnosis and fetal development monitoring. In this research, we aim to develop a novel Artificial intelligence (AI)-driven umbilical cord classification model through 2-D Doppler ultrasound imaging. We proposed an innovative Dwarf Mongoose tuned Versatile Random Forest (DM-VRF) for classifying the umbilical cord based on ultrasound images. Initially, we gathered a dataset with 2-D Doppler ultrasound images, to train our model. Image Normalization algorithm is implemented to pre-process the gathered data. We extracted the crucial features from the processed data using a histogram of oriented gradients (HOG). This innovative approach leverages the significant behaviors of the DM algorithm to refine the performance and the accuracy of a classification model. The suggested approach is implemented in Python software, during the result analysis phase, we employed various parameters such as accuracy, Receiver operating characteristic (ROC), precision and recall to evaluate classification effectiveness. To determine the efficacy of the proposed approach, we performed a comparison study with other existing methods. The experimental findings show that the suggested model performs better than traditional methods for using image analysis to categorize the umbilical cord.
Keyword: Fetal Health, Umbilical Cord Classification, Dwarf Mongoose Tuned Versatile Random Forest (DM-VRF), 2-D Doppler Ultrasound Imaging

INTRODUCTION

Fetal health assessment in the umbilical cord category is crucial for prenatal treatment, ensuring the mother's and fetus's health during pregnancy. The umbilical cord aids in transferring nutrients and oxygen, identifying gestational risks requires knowledge of cord homes and classifications [1].

Traditionally, Fetal health assessment is typically based on ultrasound imaging and fetal heart rate tracking, which evaluate various factors such as cord diameter, duration, coiling and anomalies. These abilities enable scientists to predict and address potential issues affecting a fetus's health by classifying umbilical cords [2, 3].

The classification of umbilical cords allows for immediate intervention to reduce risks like twine compression, which can lead to stillbirth or excessive fetal pain. This assessment also helps to identify issues like chord anomalies or wire insertion anomalies, which can require specific delivery or monitoring methods [4].

Fetal health evaluation in the umbilical cord category is basically a proactive technique to ensure the notable possible consequences for the mom and the fetus. It offers precious insights into the dynamic interactions that arise among fetal health and umbilical cord developments for the duration of pregnancy [5, 6].

The objective is to develop an innovative artificial intelligence (AI)-driven umbilical cord categorisation model utilising 2-D Doppler ultrasound imaging.

RELATED WORKS

The study [7] classified cardiotocographic (CTG) information into three classes: normal, which required a guarantee, pathological and the usage of system mastering algorithms to predict fetal fitness. It uses K-nearest neighbors (KNN), multi-layer perceptrons, random forests (RF) and support vector machines (SVM) to evaluate the impact of parameters decided by using CTG on the health of the fetal. Performing feature engineering on CTG facts could provide even more benefits.

The research [8] was to develop machine learning models that use characteristics taken from CTG tests to forecast the health of the fetal. Evaluations were conducted on several machine learning techniques, including, RF, kNN, SVM, Gradient Boosting, Decision Tree (DT) and NN-MLP (Neural Network Multi-Layer Perceptron). The results show promising achievement by using several indicators.
The article [9] was to enhance fetal health. Voting classifier, logistic regression, RF, DT, SVM and KNN were used as classification techniques. A comparison of the findings revealed that the RF model produces the best outcomes.
The study [10] utilized seven algorithms that were contrasted to predict the health of the fetal XG Boost (XGB), SVM, RF, KNN and Artificial Neural Network (ANN). These algorithms' performance metrics use three consequences. The findings demonstrate that five out of seven algorithms work well with the highest accuracy.

METHODOLOGY
This section describes the dataset of 2-D Doppler ultrasound images of the fetal umbilical cord. Pre-processing using image normalization and histogram of Oriented Gradient for feature selection, we also discuss Dwarf Mongoose tuned Versatile Random Forest (DM-VRF) for optimizing fetal health assessment in umbilical cord classification.

3.1 Dataset
The data consists of a two-dimensional Doppler ultrasound image of the fetal umbilical cord obtained between 8 and 32 weeks of gestation. The image is classified into three categories: normo-coiling, hypo-coiling and hyper-coiling. An obstetrician is the one who labels the patients. There are 108, 34 and 9 images in the collection; in comparison to other classes, Hypercoiling has the least quantity of data [11].

3.2 Image Normalization Preprocessing
Image normalization is a process that standardizes pixel intensities across ultrasound scans, enhancing consistency as well as accuracy in assessing fetal growth and well-being. Nonlinear approximations are used to modify grayscale images, with translation as the first method. This method normalizes pixel values for each pixel at position (x, y) with pixel value z_{orig}.

$$z_{new} = z_{orig} - z_{back} \quad (1)$$

In linear approximation, $z_{back} = Ax + By + D$ and in nonlinear approximation, $z_{back} = Value(x, y)$ where $Value(x, y)$ is the nonlinear approximation value. Global shifting uses C, which is roughly equivalent to a white color value. Stretching modifies pixel values by increasing the pixel value.

$$z_{new} = \frac{z_{original}}{z_{back}} C \quad (2)$$

C is often set to 255, which makes the backdrop color white, to guarantee that the value does not exceed 255.

3.3 Enhancing Feature Extraction with Histogram Oriented Gradient (HOG)
Assessment of Fetal Health using the HOG is a tool that analyzes ultrasound images to accurately assess the health of the fetus by using orientation-based feature extraction. HOG is an appearance descriptor and it counts instances of gradient orientation in a portion of an image. The input image is divided into small square cells (in this case, 9×9) using HOG, which uses the centre differences to calculate the gradient direction or edge direction histogram. Normalization of the local histograms has occurred depending on contrast to increase accuracy, which indicates that HOG remains constant as illumination changes. HOG characteristics have been shown to be a useful descriptor for detection, due to its simple computations, associated with scale-invariant feature transform and LBP (local binary pattern).
3.4 Dwarf Mongoose tuned Versatile Random Forest (DM-VRF)
The Dwarf Mongoose tuned versatile Random forest (DM-VRF) is a new technique used in the categorization of umbilical cords as a part of fetal health assessment. This novel method promises improvements in perinatal care by the usage of machine learning techniques to increase accuracy and efficiency. DM-VRF is a technique that enhances performance by combining the flexibility of Random Forests with optimized parameters, making it effective in managing diverse data types.

3.4.1 Dwarf Mongoose Optimization (DMO)
Dwarf Mongoose Optimization improves fetal health evaluation by accurately classifying the umbilical cord, resulting in more efficient prenatal treatment.

3.4.1.1 Alpha Group approach
After initiating the population, the efficiency of every resolution is computed. A female alpha is chosen based on the probability value that is computed by Equation (3).

$$\propto = \frac{fit_i}{\sum_{i=1}^{n} fit_i} \quad (3)$$

The number of mongooses in the household is represented by the expression $n - bs$, where bs stands for babysitters and $peep$ for the vocalizations made by the dominating female to keep the family on track.

$$X_{i+1} = X_i + ph_i * peep \quad (4)$$

Equation (4) is followed by the sleeping mound, where ph_i is a uniformly distributed random number $[1, 1]$, but only after each iteration.

$$si_m = \frac{fit_{i+1} - fit_i}{\max\left[|fit_{i+1} - fit_i|\right]} \quad (5)$$

The average number of sleeping mounds found is given in equation (6).

$$\varphi = \frac{\sum_{i=1}^{n} si_m}{n} \quad (6)$$

The algorithm proceeds to the scouting phase when the child care exchange requirement is satisfied, where it considers the following food supply or resting mound.

3.4.1.2 Group of Scouts
In the scout group section is a nice sleeping mound. If the family ventures quite far during their foraging expedition. Equation (7) simulates the scout mongoose.

$$X_{i+1} = \begin{cases} X_i - CF * phi * rand\left[X_i - \vec{M}\right], & if \varphi_{i+1} > \varphi_i \\ X_i + CF * phi * rand\left[X_i - \vec{M}\right], & otherwise \end{cases} \quad (7)$$

Equation (8) is used to generate the CF value, Equation (9) calculates the $-\vec{M}$ value and the rand is a random value between 0 and 1.

$$CF = \left(1 - \frac{iter}{MAX_{iter}}\right)^{\left(2 * \frac{iter}{MAX_{iter}}\right)} \quad (8)$$

$$\vec{M} = \sum_{i=1}^{n} \frac{X_i * sm_i}{X_i} \quad (9)$$

Regular rotation of babysitters, who are typically members of the lower class of the group, is done to let the mother (alpha female) guide others of the group on daily hunts.

3.4.2 Versatile Random Forest (VRF)
The versatile random forest (VRF) incorporates a weighted voting mechanism based on the assurance rating of individual trees, improving upon the traditional method. This is obtained by the following formula:

$$\hat{y} = \arg\max \sum_{j=1}^{N} w_j I(y_i = k) \quad (10)$$

The weight w_j is computed based on the confidence core of each tree, which is described as the accuracy reduction obtained by dividing the data at each node of the tree during training. Allowing a more accurate tree to have a bigger impact on the final prediction, improves performance overall.

EXPERIMENTAL RESULT
Using Python programming and software like scikit-learn. The system was tested on an Intel Core i7 CPU-equipped PC, 16GB of RAM and Python 3.8. The effectiveness of the proposed and existing techniques was evaluated in terms of (accuracy, recall, ROC, and precision). Random forest (RF), Naïve Bayes (NB) and Ensemble Multiclassifier (EMC) [12] were the existing techniques compared with the proposed approach.
Accuracy
The total accuracy of a model or test's predictions is referred to as its accuracy. It represents the fraction number of incidents that were accurately predicted for all instances.

$$\text{Accuracy} = \frac{True\ Positive + False\ Positive}{Total\ instance} \quad (11)$$

ROC (Receiver operating characteristic)
The ROC curve visually displays the ratio of the false positive rate (specificity - 1) to the actual positive rate (sensitivity) at various threshold values. It illustrates the trade-off between sensitivity and specificity.
TPR (True Positive Rate)

$$TPR = \frac{True\ Positive}{False\ Negative + True\ Positive} \quad (12)$$

FPR (False Positive Rate)

$$FPR = \frac{False\ Positive}{True\ Negative + False\ Positive} \quad (13)$$

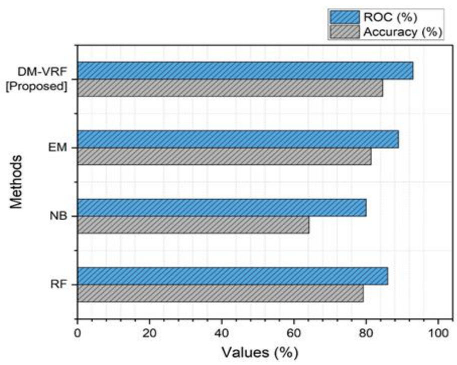

Figure 1: Outcome of Accuracy and ROC

Our proposed methods outperformed existing methods in optimizing fetal health assessment in umbilical cord classification, with an accuracy rate of 84.6% and ROC rate of 93%, indicating superiority in the field. The figure 1 shows the Outcome of Accuracy and ROC
Precision
The precision of optimistic forecasts is their accuracy. It expresses the ratio of successfully anticipated positive cases to all expected positive instance.

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (14)$$

Recall
Recall evaluates a test's ability to identify positive cases; it is also known as sensitivity. It is the ratio of all correctly projected positive cases to all genuine positive cases.

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (15)$$

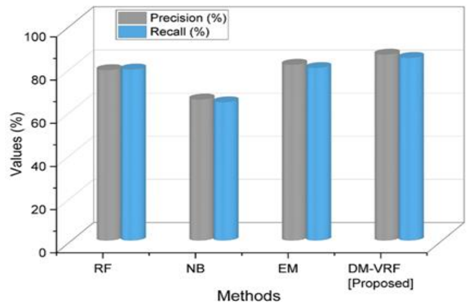

Figure 2: Outcome of Precision and Recall

Our proposed methods outperformed existing methods in optimizing fetal health assessment in umbilical cord classification, with a precision rate of 86.2% and a recall rate of 84.7%, indicating superiority in the field. The figure 2 shows the Outcome of Precision and Recall.

CONCLUSION
In this study, we presented a novel methodology for developing an AI-powered for classifying umbilical cords using 2-D Doppler ultrasound images. Comparing our proposed approach to traditional methods, the Dwarf Mongoose tuned versatile random forest (DM-VRF) performed superior in categorizing diverse kinds of umbilical cords. We gathered a collection of 2 dimensional Doppler ultrasound images and pre-processed the data using image normalization. Using the unique characteristic of the DM approach, the Histogram of oriented gradient (HOG) was used to extract significant features and improve classification accuracy. Our Python program solution evaluated features including accuracy, ROC, precision and recall of (84.6%, 93%, 86.2% and 84.7%) enabling robust analysis. Through comparisons with the proposed approach, our experimental result demonstrated the superiority of our suggested model image analysis-based umbilical cord classification proving with efficiency. The limited availability of varied ultrasound datasets might obstruct the generalization of the model.

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