Detecting Intrapartum Fetal Hypoxia from Cardiotocography Using Machine Learning

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Abstract

Intrapartum cardiotocography (CTG) can identify babies at risk of fetal hypoxia by detecting changes in fetal heart rate and uterine contractions during labour. However, variability in CTG interpretations affects intervention timings. Machine learning (ML) has been applied to this problem and has succeeded.

We proposed to use a 5-minute Apgar score as the benchmark for hypoxia in our ML algorithms as it has shown a high correlation with abnormal CTG and better clinical support decision-making than pH umbilical cord blood.

We used the CTU-UHB database containing 552 CTGs. We trained and compared five algorithms of decision tree (DT), random forest (RF), support vector machine (SVM), k-Nearest Neighbour (kNN) and artificial neural network (ANN). Performances were evaluated using precision, recall, F1 score and AUROC.

The ANN with four deep layers had the highest recall (100%), while the RF classifier had the highest F1 (97%), AUROC (99.73%) and precision (97%) (Table 1). The longest deceleration length is the most important feature among the 21 features.

Apgar scores can be used as a surrogate hypoxia marker for classifying CTG, making the model results more informative for clinical decision-making.

1. Introduction

Fetal hypoxia occurs when there is an interruption of constant oxygen supply to the baby during labour. Fetal hypoxic injury includes intrapartum stillbirth, neonatal encephalopathy, death, and disabilities [1-3]. While a level of hypoxic stress can be anticipated during labour when uterine contracts (UC), the main challenge is identifying the small number of babies where the natural physiological protective mechanisms fail to counteract the hypoxic stress [4]. Fetal monitoring during labour is crucial to prevent the devastating effects of fetal hypoxia on babies and families. However, it must also be discriminatory enough to minimise unnecessary interventions in the form of surgical birth (caesarean section) that carry risks to both mother and baby [5].

Cardiotocography (CTG) has been widely used as an electronic fetal monitoring device to indicate fetal wellbeing in the uterus during labour. It is attached to the mother's uterus and measures fetal heart rate (FHR) changes in conjunction with UC. Clinicians will classify if the fetus's condition is reassuring, non-reassuring or pathological [6]. Based on the classification, clinicians can take steps to reduce the effect of hypoxia, such as assisted birth, to minimise the harmful impact on newborns [7].

Since the introduction of CTG in 1970, research has shown inconsistencies in the interpretation of visual CTG amongst clinicians can result in a delayed response due to the time taken to achieve an agreement [8, 9]. Furthermore, some decision-making can be subjective and with some level of ambiguity which may contribute to discrepancies in CTG interpretation [10]. Due to the false positive cases – babies are deemed as hypoxic when they are not, there has been a fivefold increase in caesarean sections rates while cerebral palsy prevalence remains unchanged [11]

To tackle the shortcomings of visual CTG, computerised CTG was introduced to aid in decision-making for abnormal FHR by standardising interpretations allowing a quicker response to compromised fetuses. A randomised controlled trial and retrospective studies have shown that computerised CTG improved the quality of interpretations while minimising decision-making time [12]. However, a meta-analysis of six studies showed no significant improvement in fetal wellbeing between visual and computerised CTG in antenatal and intrapartum measurements [13].

Researchers who used machine learning (ML) on CTG data have demonstrated promising results in classifying fetal hypoxia. ML learning can improve fetal hypoxia detection while reducing interpretation variability between clinicians. Previous studies used varying pH umbilical cord blood levels to benchmark hypoxia and showed promising outcomes. Umbilical cord blood cord pH is taken immediately when babies are born, which does not reflect their ability to recover from birth stress [14]. Hence, we proposed using 5 minutes Apgar score as the surrogate marker of hypoxia in our ML algorithms. Low Apgar scores have shown a high correlation with hypoxic

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diagnosis and abnormal CTG. It is a routine, standardised measurement of babies' physiology and condition after birth, such as appearance, pulse, grimace, activity and respiration. Evidence showed that babies recover from birth stress, where there are differences in the Apgar score taken 1 minute and 5 minutes after birth. Studies have shown that low Apgar scores are associated with the diagnosis of hypoxia and cerebral palsy [15, 16]. Therefore, 5 minutes Apgar score after birth is a good indicator of whether babies can recover and is a better clinical decision than the pH of umbilical cord blood [17].

2. Methodology

2.1. Dataset

We used raw CTG from the CTU-UHB database, which consists of 552 CTG recordings sampled at 4Hz, and the recording was taken no longer than 90 minutes during labour (second stage of labour). CTG records were taken between 2009 and 2012 at the University Hospital in Brno, Czech Republic [18]. The Apgar score ranges from 0 to 10, where 0 is very unhealthy, and 10 is healthy. Our study used Apgar scores from 10 to 7 for healthy and 6 to 0 for hypoxic, where our model is trained to classify between these two categories.

2.2. Feature Extraction

We used both FHR and UC for this study. Before feature extraction, CTG signals were denoised to remove unwanted artefacts and missing recordings due to fetal and maternal movements. Missing beats were interpolated, and the signal was smoothed with moving mean.

For morphological features, we extracted acceleration, deceleration, average baseline and long and short-term heart rate variability of FHR in conjunction with UC as recommended by the National Institute for Health and Care Excellence guidelines for CTG interpretations [19]. For time domain, frequency domain and non-linear features, we only used FHR signals. We extracted 21 features, which were used to build the classification model.

2.3. Classification

We used Scikit-learn for modelling, and five ML classifiers were used to compare the performances, which include decision tree (DT), random forest (RF), support vector machine (SVM), k nearest neighbours (kNN) and artificial neural network (ANN). Due to the small sample size, we used oversampled using the Synthetic Minority Oversampling Technique (SMOTE) to increase the number of samples. The data was split into two subsets: train (70%) and test (30%). We performed a 5-fold cross-validation on the training set. GridSearchCV was used for hyperparameter tuning on the training subset to boost the model performances, where the best parameter was chosen for the final model [20]. The classification model was evaluated on a separate test subset.

2.4. Model Evaluation

We used the confusion matrix to measure the true positive (TP), true negative (TN), false positive (FP) and false negative (FN) values. TP represents the correct classification for positive samples, TN represents the correct classification of negative samples, FP represents the wrong classification for positive samples, and FN represents the wrong classification for negative samples [21]. We calculated precision, recall, F1 score and area under the receiving operator characteristics (AUROC) based on those values.

$$\text{Precision (P)} = TP / (TP + FP) \quad (1)$$

$$\text{Recall (R)} = TP / (TP+FN) \quad (2)$$

$$\text{F1 score} = 2 \times (P \times R) / (P + R) \quad (3)$$

3. Results

By using SMOTE, the dataset was increased from 552 to 1066. The oversampled group is the hypoxic Apgar scores, where the sample size increased from 19 to 533 subjects (figure 1). Based on the performance metrics, ANN with four deep layers, rectified linear unit activation and ADAM optimiser has the highest recall (100%). In contrast, the RF classifier has the highest F1 score (97.00%), AUROC (99.73) and precision (97.00%) (Table 1). Other results from different classifiers are all recorded in table 1. All five classifiers generally show promising results where most performance metrics score more than 75%, except for the F1 score, precision and AUROC for ANN. We identified the top three important features using the RF algorithm: longest FHR deceleration, Lempel-Ziv complexity (C) and the number of intrinsic mode functions (IMF). Other signal features that we extracted were mean, standard deviation, sample entropy, approximate entropy, long-term variability, short-term variability, total delta, power spectral density power of low frequency, movement frequency and high frequency, the ratio of low and high-frequency spectral density power, the ratio of low and combination of high and movement spectral density power, number of acceleration, number of deceleration, average baseline

and longest length of an acceleration.

Figure 1 shows the distribution between healthy and unhealthy babies in the training and test subset

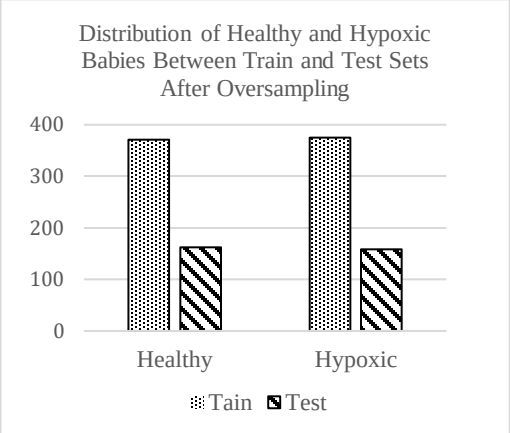
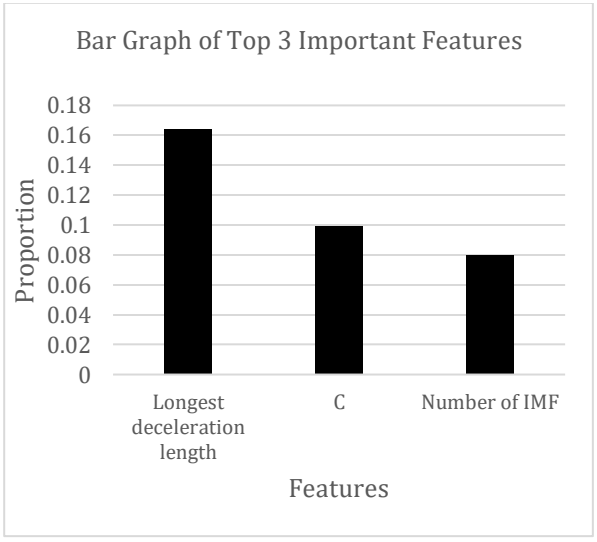


Table 1 shows the comparison of performances metrics between classifiers

Classifiers	P (%)	R (%)	F1 (%)	AUROC (%)
DT	93.0	88.0	90.0	94.8
RF	**98.0**	98.0	**98.0**	**99.8**
SVM	72.0	71.0	71.0	76.9
kNN	70.0	85.0	77.0	81.1
ANN	51.0	**100.0**	67.0	50.0

Figure 2 shows the top three important features calculated using the RF algorithm



4. Discussion

Compared with previous studies, our performances are as high as those that used pH levels as a surrogate marker for hypoxia [22, 23]. This indicates that Apgar scores are as good as pH levels in classifying hypoxia for this dataset.

Interestingly, two of the top features are from the time domain (longest FHR deceleration and average baseline), and one is from the non-linear domain (number of intrinsic mode functions) (figure 2). This shows that other domains of CTG help distinguish hypoxic fetuses compared to the traditional morphological changes suggested by clinical guidelines, and discrete signal processing techniques are crucial in interpreting CTGs.

One of the limitations of this study is the number of samples. While we employed oversampling techniques, the small sample size is still small for an ML study. Future studies would benefit from larger sample size and a mixture of geographical regions to increase model generalisability. Next, we oversampled the train and test set, where there is an equal number of healthy and hypoxic fetuses. However, in real life, the number of hypoxic fetuses is very small, demonstrating a severe imbalance between healthy and cases of hypoxia. Therefore, we need to create a detection model that can be implemented in real-life situations and is relevant in clinical settings. In addition, we tried to compare previous studies that used pH umbilical cord blood, and we found it difficult as previous studies used various pH benchmarks and selective performance measures when reporting their outcomes.

5. Conclusion

Our study shows that 5 minutes Apgar score can be used to distinguish between hypoxic and healthy CTGs for this dataset and achieved performances as high as studies using pH levels. Since Apgar scores reflect babies' ability to recover from intrapartum hypoxia, it is a more relevant surrogate marker to distinguish unhealthy babies. We can benefit from an external validation dataset to make our model clinically pertinent and more generalisable for the overall population. We also plan to integrate other obstetrics factors to improve classifications and make our model more clinically relevant.

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