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Fetal Hypoxia Detection using CTG Signals and CNN Models

Aswathi Mohan P P [1], *Uma V* [2]

[1] *Research scholar, Department of Computer Science, Pondicherry University, Puducherry, India*

[2] *Asssociate professor, Department of Computer Science, Pondicherry University, Puducherry, India*

Emails: aswathimohan.academic@gmail.com, umabskr@gmail.com

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Abstract

Hypoxia is a significant condition causing oxygen deficiency in the fetal blood and accounts for more than 23% of perinatal and infant mortality worldwide in a calendar year. Therefore, these circumstances require more efficient methods for prompt detection of hypoxic condition. Cardiotocography (CTG) is the most common technique used to assess fetal well-being and hypoxic complications. Newly, signal processing techniques bring out an innovative horizon for processing the CTG signals. Herein, we are exploring the usefulness of CTG signals by converting them to Recurrence Plots (RP) and classifying using deep learning models for the more accurate detection of hypoxia. A comparative study of VGG16, ResNet and CNN models is done on the RP data. VGG16 achieved better result with an accuracy of 82.02%.

1. Introduction

As per the report of the United Nations Children's Fund (UNICEF), in 2021, 140 million babies are born in a calendar year. Approximately 2.8 million newborns and pregnant women die annually, or around one death occurs every 11 seconds, and one stillbirth occurs every sixteen seconds. The fetal death rate is high and there is a need to establish good health for the fetus and mother during pregnancy and labour. A widely used technique to monitor the fetal heartbeat and uterine contractions during pregnancy and labour is CTG (Cardiotocography) (Václav et al.). It is recorded through the fixing of an ultrasound transducer on the abdomen of pregnant women. The technique of CTG is also named Electronic Fetal Monitoring (EFM). It is a prominent diagnostic technique to evaluate maternal and fetal well-being at both the antepartum and intrapartum stages. Usually, the antenatal period is after 28 weeks of pregnancy. The CTG data has two lines, viz. the upper line represents FHR in beats per minute, and the lower line represents uterine contraction. Fetal Heart Rate (FHR) evaluation during labour can help in determining hypoxia, which can lead to newborn academia. The FHR can be used for early determination of pathological state. It may assist obstetricians in anticipating future complications and prior inference of permanent harm to the fetus.

Although, techniques have evolved for CTG analysis, the wrong inference from the FHR recordings causes half of the fetus's death. Previously, CTG signal was examined by visual analysis, and it is a typical analysis done by experienced medical practitioners on the recorded morphological structure of FHR provided by the CTG signals. The characteristics of FHR are baseline, baseline variability, tachycardia, bradycardia, acceleration, and deceleration. The nature of uterine contraction and the period of contractions are the parameters usually considered for inference in visual inspection (Sbrollini et al.).

In 1986, the International Federation of Gynecology and Obstetrics (FIGO) (Ayres-De-Campos and Bernardes) introduced general guidelines governing the analysis of morphological features of CTG. Although comprehensive guidelines were made available in this field, poor interpretations of the CTG are repeatedly occurring now since, the precision of the determination from the CTG traces is more dependent on the knowledge and experience of the practitioners. The accurate assessment of signals cannot be guaranteed from the visual examination of a practitioner. Hence, in order to achieve the automatic interpretation of CTG trace patterns, researchers need to address the problem with machine learning and deep learning algorithms (Warrick et al.).

In this work, attempt has been made to detect hypoxia using deep learning models. The CTG signals are converted to RP, and various CNN models are used to detect the abnormality. The significance of this work is that the CTG signals are directly interpreted and RP representing the features are generated. So, the manual feature extraction phase is avoided and thereby the proposed system achieves comparative results as tabulated in Table 3.

This paper is arranged as follows. Section 2 includes a comprehensive analysis of the related works. Section 3 provides a short glimpse of the CTG signals. Section 4 describes the dataset and methods used by the proposed system. Section 5 discusses about the experimental results obtained. Section 6 concludes the paper.

2. Related works

In 2018, Cömert Z et al. (Cömert, Kocamaz, and Subha) presented a transfer learning-based intelligent system to interpret hypoxia instances from the heart signal data. Short-time Fourier transformation (STFT) was used to convert the CTU-UHB signal dataset to frequency domain images and then classified fetal health status using CNN.

Zhidong Zhao et al. (Zhidong et al.) proposed an RP Computer-Aided Diagnosis system to predict hypoxia. Converted Ctg signal to corresponding RP and used Basic CNN model for the prediction, achieved an accuracy of 98.69%.

Fasihi, M et al., in 2021, presented 1D-CNN, a Shallow architecture designed to improve prenatal assessment accuracy. This model has effectively minimized the complexity and produced better results (Zhidong et al.).

In 2023, a CNN-RNN unified framework (Liang and Lu) was introduced by Hauwen et al. for the efficient classification of cardiotocography and achieved an accuracy of 95.15%, sensitivity is 96.20%, and specificity is 94.09% respectively. In 2023 (Magesh and Rajakumar) magesh et al. introduced a new ensemble feature extraction model for fetal arrhythmia prediction.

Yu lu et al. (Liang et al.) used 1D-CNN and GRU hybrid model on CTG signal to predict fetal hypoxia and achieved an accuracy of 96%.

3. CTG Signal

CTG is a promising diagnostic technique for monitoring fetal well-being during pregnancy and labour.

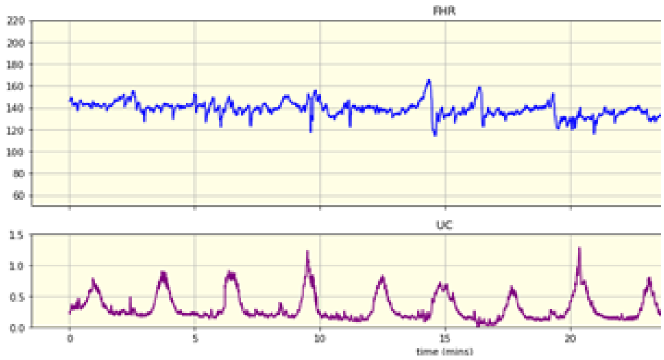

FIGURE 1. **CTG signal**

The cardiotocographic machine has two intricate sensors, called toco probe and cardio probe. These two transducers will be meticulously positioned on the mother's abdomen to collect valuable data. The toco probe is used to track uterine contractions, and the cardio probe diligently records fetal heart rate. CTG is a commonly used during two critical periods, namely antepartum and intrapartum. Antepartum means the prenatal period; during this period, the fetal heart rate is recorded for twenty minutes with a speed of 3cm/min. In antepartum, only FHR can be recorded. Conversely, during intrapartum, as the mother progresses through the stages of labour, both uterine contractions and fetal heart rate are recorded in CTG. Schematic representation of the aforementioned signals are shown in figure 1.

In order to analyze CTG records, healthcare professionals typically focus on the features identified by the International Federation of Gynecology and

Obstetrics (FIGO). Among these features, the most important features are:

3.1. Fetal Heart Rate (FHR) Baseline:

This refers to the consistent, prolonged segment of the fetal heart rate on a CTG recording. The normal range for FHR baseline is between 110 and 160 beats per minute (bpm). If the bpm is lower than the normal range, it is called bradycardia, and if it is higher than 160 bpm, it is known as tachycardia.

3.2. Beat-to-Beat Variability:

This refers to the normal fluctuations in the FHR that occur with each beat. It is a sign of a healthy fetal nervous system and oxygenation, and reduced variability can be an indicator of fetal distress.

4. Materials and Methods

4.1. Methods

The visual assessment of the FHR has affected inter and intra-observer variability (Osrin and Prost). The vulnerable interpretation of the visual assessment of FHR is the primary cause of the numerous caesarean sections. The computer aided assessment is done to overcome the troubles of visual interpretation of the FHR. The CTG data available are always in signal form. Usually, those signals consist of some noise and variables. The signal processing is used for the extraction of essential features from the raw CTG signal in computer aid assessment. Pre-processing is the crucial step of signal processing. It removes unwanted noise in signals and improves the quality of data.

4.1.1. Signal Pre-processing

During the recordings of the CTG signal, the FHR signal often contains numerous artifacts or spikes because of maternal and fetal movements or transducer displacement. This noise affects the extracted features and the performance of the final classification. Hence, noise has to be eliminated before further analysis to obtain a relatively pure signal for more accurate results. FHR includes two kinds of noise: spiky artifacts and missing values. FHR value of 0 and continuing for more than 15 s is eliminated directly; or else, it is linearly interpolated (Yang et al.). As extreme points, the signal value greater than 200 bpm is also removed. Detection of the gap and outlier and interpolation are the preprocessing steps.

4.1.2. Recurrent plots

It is a technique used to represent phase space trajectories visually (Mathunjwa et al.). The phase space means the possible states of a system at a given time interval. Furthermore, the trajectories mean system evolution over a period. According to dynamics theorem, phase space reconstruction is the prime step in examining FHR signals. Visualizing phase space is much more complicated since it does not have low-level dimensions to be represented. The RP can display the recurrence of multiple-dimensional space phase trajectories in two dimensions. The computation of a square matrix is a significant step in visualization. Equation (1) represents the numerical expression of the RP.

$$Ri,\ j = \Theta(\varepsilon i - \parallel xi - xj \parallel),\ i,\ j = 1, \ldots .N \quad (1)$$

In above equation, ε_i denotes the cut off distance and Θ is the Heaviside function. Θ is one if x greater than zero and Θ is zero when x less than zero. x_i and x_j are the ascertained subsequence at each point. ll . ll Is the Euclidian norm.R_{ij} = 1(i=1…N), The RP contains a black line along with a diagonal line, which signifies the recurrence line with an angle of II/4. The trajectory mending is performed using entire recurrence points. The recurrent plot consists of three parameters, time delay, distance threshold and embedding dimension, and those parameters can be adjusted. If the time delay is too long, it will lead to irrelevance, and if too small, then RP may cause redundancy. As like time delay, embedding dimension also needs to be absolutely tuned. The one-dimensional CTG time series data can be embedded into the m dimension using properly determined time delay and embedded dimension.

4.1.3. Convolutional neural network

Convolutional Neural Network is a deep learning model commonly used to process image data. CNNs are created with the intention of automatically learning and extracting information. It consists of three layers, called the convolutional layer, the pooling layer and the fully connected layer. The convolutional layer extracts the feature from the input image, and the pooling layer resizes the feature map and it follows one or more fully connected layers, that carry out the final classification.

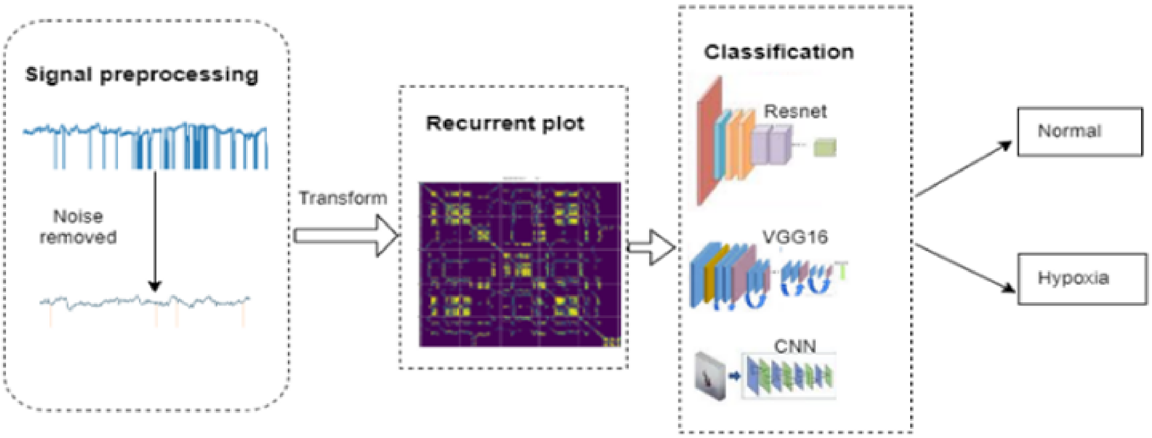

FIGURE 2. **Architecture of the CTG classification system**

4.1.4. ResNet

Residual Network is designed to address the vanishing gradient problem of deep neural networks. ResNet contains a skip connection between layers which allows the network to learn residual functions. ResNet is composed of the residual block. Each block contains numerous convolutional layers and skips connections. Residual blocks are stacked together to form overall ResNet architecture.

4.1.5. VGG16

VGG16 is a deep convolutional neural network with sixteen layers. Among the sixteen layers, thirteen are convolutional layers, and three are fully connected layers. It uses 3x3 filter and a max pooling after each convolutional layer. The small filter size allows the network to have a significantly sizeable receptive field without increasing the number of parameters. Max pooling reduces the spatial dimension of the feature map.

4.2. Dataset

In this work, publicly available CTG-UHB (Mathunjwa et al.) is used. The CTG-UHB is an open-access database consisting of 552 intrapartum CTG recordings collected from obstetric wards of the University hospital in Berno during the period of April 2010 to August 2012. All records were sampled 4 Hz. In the collected instances, 447 are normal, and 105 are hypoxic. Abnormality can be detected with the PH value of the umbilical cord blood (Chudáček et al.). If the PH value is below than 7.15, it is classified as hypoxia or otherwise normal (Deng et al.) (Krupa et al.). The ratio of normal and hypoxic cases is 4:1 in the CTG-UHB dataset. The asymmetry of the dataset will reduce the performance of the model. Due to the limited size of the dataset, the algorithms of deep learning can not be used effectively. In order to overcome this issue, the CTG signal is converted into a corresponding recurrent plot. To monitor the fetal heart rate, 20 minutes of CTG signals are required.

The longest signal in the CTG-UHB dataset is 90 minutes. Therefore, one CTG signal can be changed into multiple two-dimensional Recurrent plots. In a ratio of 4:1, 1675 normal and 550 hypoxic instances in the 2225 recurrent plots are created from the 552 datasets. The dataset is partitioned into training set, validation set and test set, as mentioned in the below table.

5. Results and Discussion

A total of 2225 Recurrent plot is created from 552 preprocessed CTG signal. In this work, CNN models are trained on an intel core 2.30 GHz processor (i7-12650H) and 16 GB RAM. The proposed work is implemented with Python. We trained VGG16, ResNet and CNN with enhanced RP image dataset. The parameters of the models are tuned for better performance. The learning rate is set to 1x10 $^{-3}$, and L2 regularization is used to reduce overfitting. The training and testing loss of VGG16 is shown in figure 3.

As shown in figure 3, the loss rate is minimized with increasing iteration. Figure 4 depicts VGG16's training and testing accuracy.

The training and validation loss of CNN is illustrated in figure 7, and accuracy is shown in figure

TABLE 1. Performance comparison

Author	Dataset	Input form	Feature extraction	Feature selection	Classifier	Performance
Comert et al. 2018 (Zhao et al.)	CTU-UHB	CTG signals	Morphological, linear, nonlinear, IBTF feature, STFT and GLCM	-	ANN	Sensitivity=68.52% Specificity=70.29%
Zhidong et al.,2020 ("Memory-based Intelligent Auxiliary Diagnosis of Fetal Health")	CTU-UHB	CTG signals	Morphological, linear and nonlinear	statistical test and AUC	Adaptive boost-ing	Sensitivity=92% Specificity=90%
Paul Fergus et al.,2020 (Fergus et al.)	CTU-UHB	CTG signals	1DCNN	-	MLP	Sensitivity=80% Specificity=79% AUC=86%
Rongdan Zeng et al.,2021 (Zeng et al.)	Physionet	Digitalized signal forms	-	-	Ensemble Cost-sensitive SVM	Sensitivity=59.3% Specificity=78.3% Quality index=68.1%
Nida Aslam et al.,2022 (Aslam et al.)	Mendeley Data Private (Azienda Ospedaliera Universitaria-Federico II)	Digitalized signal forms	-	-	RF, SVM, KNN and GB	Accuracy =97% F1-score = 98%
Our work	CTU-UHB	CTG signals	RP+VGG16 Rp + ResNet Rp + CNN	- -	FC Layer FC Layer FC Layer	Accuracy=82.02% Specificity=85.81% Sensitivity=69.10% Accuracy=76.47% Specificity=89.91% Sensitivity=50.01% Accuracy=73.47%S pecificity=69.21% Sensitivity=52.02%

TABLE 2. Dataset partition

Training set	Validation set	Testing set
1866	210	149

8.

In our study, the performance of the model is assessed using accuracy, sensitivity and specificity. The predicted outcome is categorized into True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). In table 3 listed the Accu-

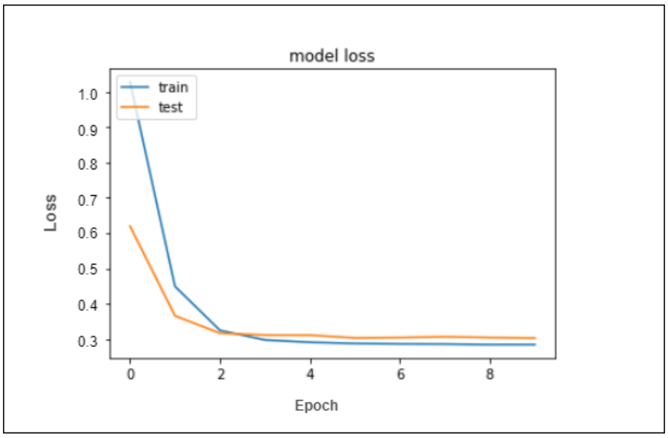

FIGURE 3. Loss rate of VGG16 classifier

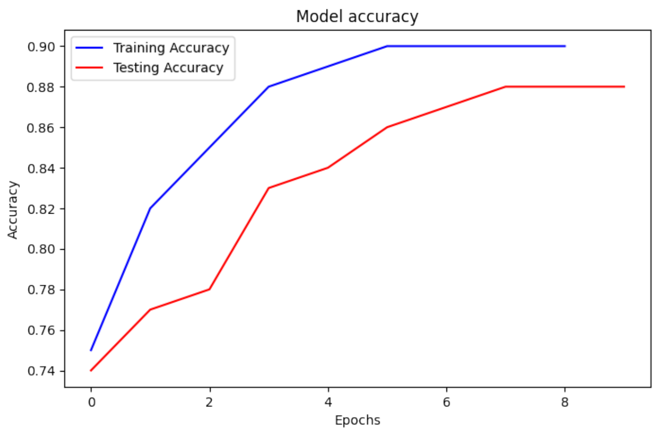

FIGURE 4. Accuracy of VGG16

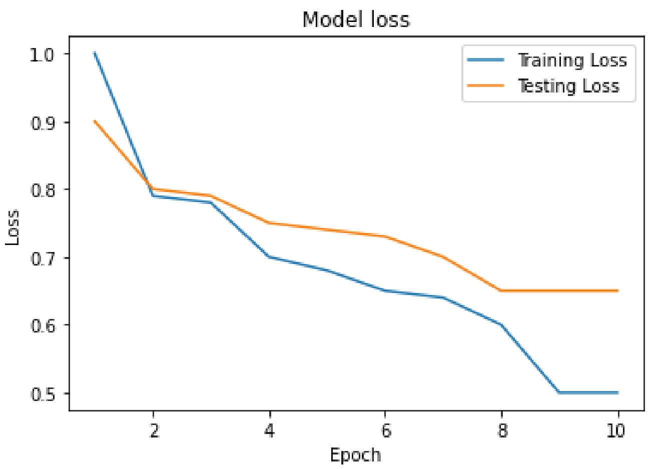

FIGURE 5. Loss rate of ResNet classifier

racy Specificity and Sensitivity of our work.

$$Sensitivity = TP/(TP + FN) \tag{2}$$

$$Specificity = TN/(TP + TN) \tag{3}$$

$$Accuracy = (TP + TN)/ \\ (TP + FP + TN + FN) \tag{4}$$

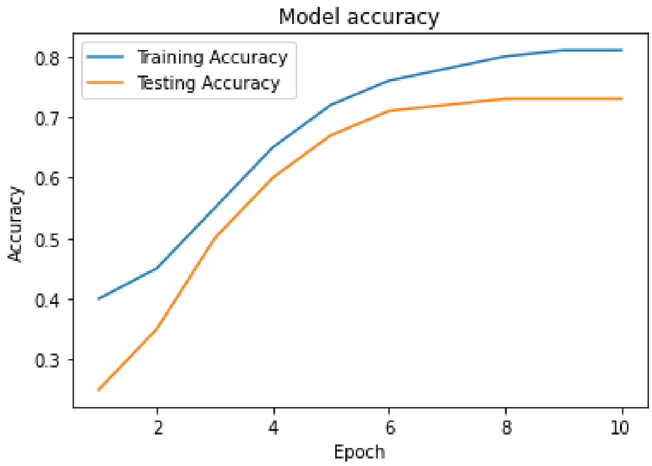

FIGURE 6. Accuracy of ResNet classifier

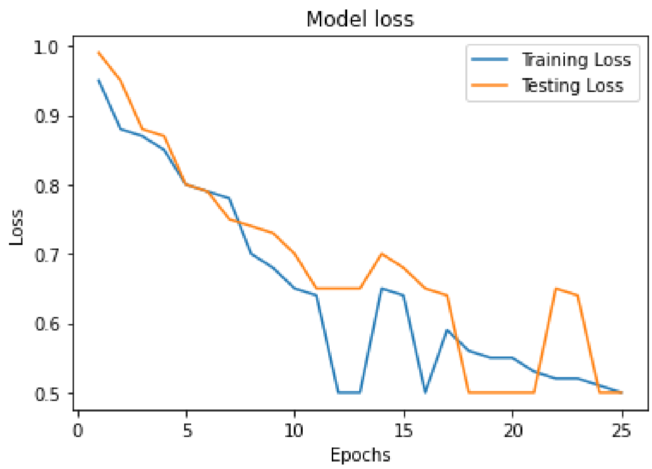

FIGURE 7. Loss rate of CNN classifier

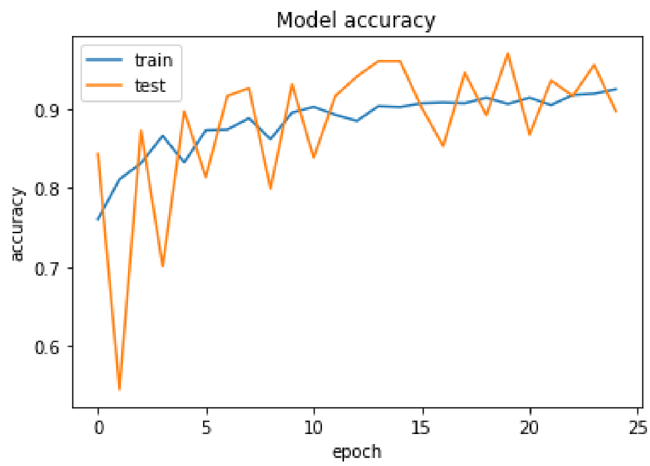

FIGURE 8. Accuracy of CNN

The performance of the CNN models is listed in Table 3. VGG16 achieved the best result with an accuracy of 82.02%, Sensitivity of 69.10% and Specificity of 85.81%. We have compared our work

TABLE 3. Performance of models

	VGG16	ResNet	CNN
Accuracy	**82.02%**	76.47%	73.47%
Specificity	85.81%	**89.91%**	69.21%
Sensitivity	**69.10%**	50.01%	52.12%

with the existing work and comparison results are shown in Table 2. Among the existing systems that takes CTG signals as input, our model performs better than (Fergus et al.) (Zeng et al.) in terms of specificity. Achieving higher specificity is a desired characteristic of any health care monitoring system. In this aspect, our system is achieving better results.

6. Conclusion

CTG signals are used to monitor fetal health. Visual analysis of CTG is subjective to the knowledge and experience of the practitioners. An objective examination method of CTG is essential. We proposed a hypoxia detection method using RP and VGG16. A publicly available CTG-UHB data set is used for our study. Noises and artefacts present in the signal is removed using signal preprocessing techniques. After that, Recurrent plots are generated from signals. It is a tool to represent the time series data visually. A comprehensive experiment has been done on the final RP image dataset using optimized VGG16 configuration. We obtained Acc, Sp, and Se are 82.02%,85.81% and 69.10% respectively.

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