Original Article

Building A Deep Learning Model Using Grammian Angular Field Encoding Of Time-Series Cardiotocography Images

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DOI: 10.47750/pnr.2022.13.S09.269

Abstract

Fetal well being and safe pregnancy has been the yearning of almost everyone. Cardiotocography is a technical means of recording the fetal heart rate and uterine contractions of mothers. These signals help in monitoring the fetal distress and also classify the fetal as being safe or unsafe. These time-series signal dataset is preprocessed using interpolation method to remove the missing beats. Inspired by the monumental success of computer vision field, these preprocessed fetal signal data are encoded into images using Grammian Angular Field, representing some temporal correlation between each time point. This proposed work employs data augmentation strategies on the CTH-UHB Intrapartum dataset and these encoded images are fed to a Convolutional Neural Network, a deep learning algorithm. The paper experiments with both Grammian Angular Summation Field and Grammian Angular Difference field and the resultant images are supplied to a pretrained Capsule neural network for training. CNN can successfully capture the spatial and temporal dependencies in an image and the features learnt from this transfer learning network are utilized for classifying the fetal as being normal, abnormal or suspicious. The work achieves a good predictive performance by understanding the sophistication of the images better.

Index Terms Cardiotocography, Grammian Angular Field, Convolutional Neural Network, Capsule Network

1. Introduction

Cardiotocography is one of the way by which the state of fetal is monitored at various times of pregnancy. CTG records the fetal heart rate and the uterine contractions of mother. As humans are subjected to interpret the signals in different ways, inter-observer variability exists in the prediction of fetal health state. So, an effective way to automate and predict these signals has been a challenging research topic. International Federation of Gynecology and Obstetrics (FIGO) has defined the guidelines for interpreting the data based on the crucial parameters such as Baseline Fetal Heart Rate, Variability, Accelerations and Deceleration. The fetal is classified as Normal or Abnormal or Suspicious according to the FIGO guidelines and based on the pH value. The article is laid as out as follows: Section 2 enlists the related works done and Section 3 provides a brief description of the dataset, Section 4 focus on the Methodology and the results, discussions and analysis are made in the Section 5. Section 6 provides the concluding remarks.

2. Review of Literature

A huge amount of work has been taken up by researchers for ascertaining the fetal health state. Few of the related works has been summarized in this section with due importance to methodology and performance.A significamt amount of work has been done with the CTH-UHB cardiotocography dataset. Tereza Janíčková et al., (2014) proposed a novel method called SAX that performed feature cluster analysis. Angela Agostinelli et al. came up with a statistical baseline assessment of FHR as it is essential to fix the baseline parameters in the Cardiotocography data. [11] Zafer comert and Adnan Fatih Kocamaz (2016) used Grey Level Co-occurance matrix features to classify the signals. In this context, GLCM was obtained by transforming the STFT spectrogram representing the time frequency field into an 8-bit gray-level image and new features like contrast, correlation, energy, and homogeneity were obtained after GLCM was normalized. In 2017, Zafer Cömert Adnan Fatih and Kocamaz projected a segmentation method adopting extreme machine learning.[4] Sbrollini et et al., (2018) developed an automation system to extract signals from CTG images. In 2018, Zafer Comert et al., investigated Image Based Time features using different window length on the FHR signals.[4] Zafer Comert et al., further developed an analytical model combining IBTF features and genetic agorithms for determining fetal hypoxia. [7] Zafer Comert et al (2019) proposed a deep convolutional neural network using transfer learning approach to classify the signals as normal or abnormal.[13] Zhidong Zhoa et al., (2019) proposed a novel Computer-aided diagnostic system integrated with advanced deep learning algorithm using recurrence plot.[12]

3. The DataSet

The 552 recordings from the Open Access Intrapartum CTG dataset collected at the University Hospital in Brno, Czech Republic is used in this work. Out of 9164 recordings, 552 records are chosen and it is utmost 90 min long and they start 90 min on the onset of labour. This time series data also comes with some biomarkers like pH value, APGAR score etc. The signals are classified as Normal, Suspicious and Pathological based on the pH values. The class distribution in the dataset is [N S P]=[437,68,44].

4 .Methodology

The Fetal Heart Rate sampled at 4Hz for duration of 15 minutes of Stage -2 of delivery is obtained from the CTG-UHB repository. In this work, the FHR signals alone is considered for detecting the fetal hypoxic nature. These one dimensional temporal data can be visually encoded as 2 dimensional images using some encoding mechanism and the images obtained can further be trained to learn the feature of a truly hypoxic nature of data. With the increasing popularity of the Computer Vision techniques and Deep Learning, automated interpretation of these encoded images can provide the results with high degree of accuracy. This research article uses the Grammian Angular Summation Field to encode the time series data and feeds the image input to Capsule Network for building a predictive model

4.1 Grammian Angular Field

A Grammian Angular Field is an image obtained from a time series, representing some temporal correlation between each time point. Gram Matrix Structure is a good 2D representation of the univariate time series data. Polar encoding of the data is followed by a Gram Matrix like operation on the resulting angles. This kind of visual inspection of temporal data is best suited as it preserves the temporal dependency of fetal heart beat. The CTH-UHB dataset that contains the time series Fetal Heart Rate is encoded as Grammian Angular Field Images. The FHR value is expressed as angles and the corresponding time is represented as radius. The Gram Matrix formed by the inner product of the points at two different times are used to form the images as presented in Fig 2.

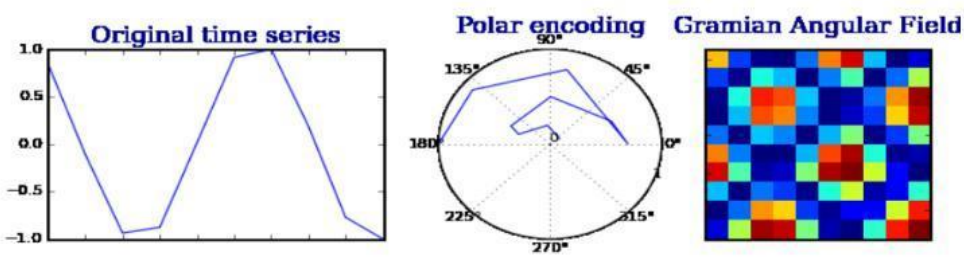
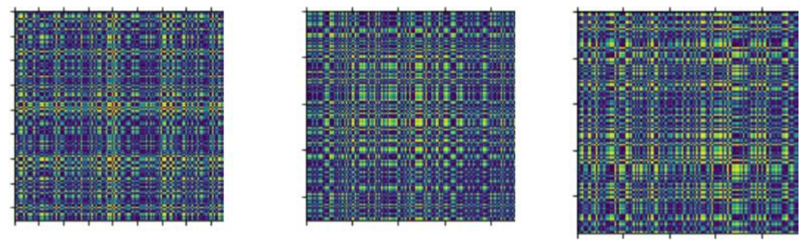
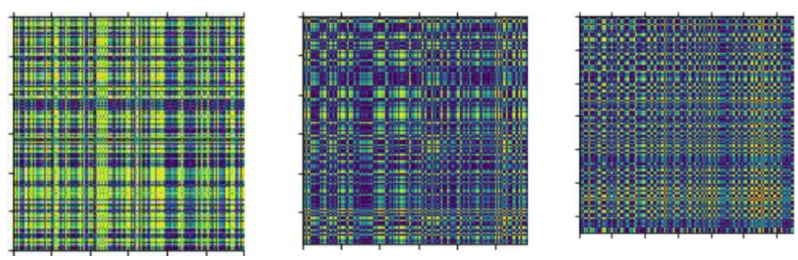


Fig 1: Grammian Angular Field Conversion



1001.dat 1033.dat 1079.dat



1001.dat 2043.dat 1211.dat

Fig 2: Grammian Angular Field Encoded Images

4.2 Capsule Network

Capsule Networks (CapsNet) are the networks that are able to fetch spatial information and more important features so as to overcome the loss of information that is seen in pooling operations. Although the performance of CNN algorithms are good, they miss the essential information during the pooling process. Capsule network overcomes this drawback as it gives a vector as output that keep track of the change in features along the direction. The four main components of Capsule Network are Matrix Multiplication, Scalar Weighting of Input, Dynamic Routing Algorithm and Squashing Function. The Capsule Network architecture comprises of 6 layers, of which the first 3 layers are called encoders where the task is to convert the input image into a vector and the last 3 layers are called decoders are used to reconstruct the image using that. Capsule Network uses dynamic routing between Capsules in layers to pass the information from one layer to another.

4.3 Algorithm

Algorithm: GAFEncode-Capsule (D,N)

1. Load the time series FHR dataset

1. Remove outliers in the signals that are greater then 210 and less than 100.
2. Read each signal data and use mean to impute missing beats
3. For each record in the Dataset D,repeat steps 5.1 to 5.2
4. Convert the time serie into polar coordinates

   4.1 Normalize the serie using Min-Max Scaler

   4.2 Transform the scaled series into Polar Coordinate as :

   (i) The value of FHR is expressed with the angle and the corresponding timestamp will be the radius, given by the equation 1

$$\begin{cases} \phi_i & = \arccos(x_i) \\ r_i & = \frac{i}{N} \end{cases} \quad \text{(i)}$$

   (ii) The Grammian Angular Summation Field is computed as ,

$$\text{GASF} = [\cos(\varphi i + \varphi j\ )] \quad (2)$$

   (iii) The Gram Matrix (N*N) is computed as a dot product as given by the equation 3

$$G = \begin{pmatrix} \cos(\phi_{1,1}) & cos(\phi_{1,2}) & \cdots & cos(\phi_{1,n}) \\ \cos(\phi_{2,1}) & cos(\phi_{2,2}) & \cdots & cos(\phi_{2,n}) \\ \vdots & \vdots & \ddots & \vdots \\ \cos(\phi_{n,1}) & cos(\phi_{n,2}) & \cdots & cos(\phi_{n,n}) \end{pmatrix} \quad (3)$$

   4.3 These Gram matrices are converted to images.

5. These encoded images are fed to deep learning Pretrained Capsule Network for building the model.
6. Build model is validated and the performance metrics is recorded.

Table 1: Algorithmic Steps

5. Results and Discussions

The pre-processed FHR time-series signals were transformed into 2d Grammian Angualr Filed encoded image dataset. These images are fed to an Capsule Network CNN for training. A snapshot of the progress of training is presented in Fig 3. The final iteration yields an accuracy of 85.19%. It can be apparently seen from the plot of the training that as the iteration advances, the ACC increases. The different input and hyper parameters options used for the training are summarized,

Image Size: 28*28; Filter Size :5 ; No.of Filter : 5 ; Nested Layers : 4; Epochs : 10 ;

Max Pooling : 2*2 ; Activation Function: RELU; Optimizer : ADAM; Loss function: Categorical

Cross Entropy ; Batch Size : 75; Output Layer Size : 2 (Binary Classification); Activation

at Output Layer : Softmax Classification

ImageSet : GAF Images
Total: 543
Network : Capsule Network

Use tf.where in 2.0, which has the same broadcast rule as np.where Train on 380 samples, validate on 163 samples Epoch 1/10

55/55 [==============================] - 1s 22ms/step - loss: 1.0336 - acc:

0.5091 - val_loss: 0.8047 - val_acc: 0.8519 Epoch 2/10

55/55 [==============================] - 0s 966us/step - loss: 0.7570 -

acc: 0.8545 - val_loss: 0.5991 - val_acc: 0.8519 Epoch 3/10

55/55 [==============================] - 0s 907us/step - loss: 0.6293 -

acc: 0.8545 - val_loss: 0.5320 - val_acc: 0.8519 Epoch 4/10

55/55 [==============================] - 0s 887us/step - loss: 0.6034 -

acc: 0.8545 - val_loss: 0.5665 - val_acc: 0.8519 Epoch 5/10

55/55 [==============================] - 0s 961us/step - loss: 0.6056 -

acc: 0.8545 - val_loss: 0.5991 - val_acc: 0.8519 Epoch 6/10

55/55 [==============================] - 0s 883us/step - loss: 0.5346 -

acc: 0.8545 - val_loss: 0.6022 - val_acc: 0.8519 Epoch 7/10 55/55
[==============================] - 0s 909us/step - loss: 0.5753
-

acc: 0.8545 - val_loss: 0.5865 - val_acc: 0.8519 Epoch 8/10

55/55 [==============================] - 0s 944us/step - loss: 0.6136 -

acc: 0.8545 - val_loss: 0.5626 - val_acc: 0.8519 Epoch 9/10

55/55 [==============================] - 0s 929us/step - loss: 0.5622 -

acc: 0.8545 - val_loss: 0.5488 - val_acc: 0.8519 Epoch 10/10

55/55 [==============================] - 0s 953us/step - loss: 0.5936 -
acc: 0.8545 - val_loss: 0.5488 - val_acc: 0.8519

Fig 3: Snapshot of Capsule Network Training Process

6. Conclusion

This work explored the possibility of using Grammian Angular Field encoding on the time series Fetal Heart Rate dataset, leveraging the deep learning algorithm of Capsule Network. As the temporal dependency of the data is preserved and the direction between the two temporal points are also maintained, this algorithm can be of greater importance for building a predictive model for classification of fetal hypoxic state. The work was carried out on low resource environment with Single CPU hardware resource with a dataset size being 552 signal data. In future, the dataset can be augmented and the model can be built on a large voluminous dataset, so that the accuracy can be improved to a stunning level. Though Capsule Network is still evolving and it is complex in nature and computationally expensive, these networks reveals the concrete features in the images. It removes the black box in the Neural Networks concepts and eliminates the drawbacks met in the Convolutional Neural Network algorithm.

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