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On the Use of Deep Learning Decompositions and Physiological Measurements for the Prediction of Preterm Pregnancies in a Cohort of Patients in Active Labor †

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Abstract: Preterm pregnancies are one of the leading causes of morbidity and mortality amongst children under the age of five. This is a global issue and has been identified as an area requiring active research. The emphasis now is to identify and develop methods of predicting the likelihood of preterm birth. This paper uses physiological data from a group of patients in active labor. The dataset contains information about fetal heart rate (FHR) and maternal heart rate (MHR) for all patients and electrohysterogram (EHG) recordings for the measurement of uterine contractions. For the physiological data analysis and associated signal processing, we utilize deep wavelet scattering (DWS). This is an unsupervised decomposition and feature extraction method combining characteristics from deep learning convolutions, as well as the classical wavelet transform, to observe and investigate the extent to which active preterm labor can be accurately identified from an acquired physiological signal, the results of which were compared with the metaheuristic linear series decomposition learner (LSDL). Additional machine learning algorithms are tested on the acquired physiological data to allow for the identification of optimal model architecture for this specific physiological data.

Keywords: pregnancy; preterm; signal processing; LSDL; signal decomposition; obstetric medicine; artificial intelligence; WHO; epidemic

1. Introduction

Preterm is an identified widescale epidemic which has been pointed out by the World Health Organization (WHO) as one of the leading causes of death in children under the age of five, globally. As a result, active work is ongoing towards effective means of diagnosis and care for mothers and fetuses who are subject to premature births and delivery, even though the underlying cause and physiological manifestation remains unknown [1–4]. A variety of means are currently employed towards the assessment of a potential preterm delivery which have been widely reported to be associated with a high degree of uncertainty stemming from the subjectivity of their data acquisition or the nature of data itself [1]. The use of physiological signals—particularly uterine contractions alongside machine learning-based pattern recognition—has seen a sharp increase in the literature reported in this area. Nsugbe et al. notably built on the work done in this area by proposing a cybernetic system which fosters a form of cyber-human collaboration in order to enhance proactive care strategies for preterm patients with active collaboration between clinicians and a prediction machine [3,5,6].

Work done by López-Justo et al. [7] from a group of patients showcases that other physiological signals, in addition to uterine contractions, can be utilized towards active inference and predictions of preterm births in pregnant patients. This work utilizes data from the published study by López-Justo et al. which spans uterine contractions, and fetus and maternal heart cardiac signals towards the prediction of a potential preterm birth in women in active labor using the deep wavelet scattering unsupervised feature extraction method [7,8]. This also builds on prior work where the linear series decomposition learner (LSDL) was investigated towards the prediction exercises [9–12].

Explicitly speaking, the contributions of this paper are as follows; the application of the DWS as a means of unsupervised feature extraction for the EHG, FHR and MHR physiological signals, the combination of the use of the LSDL followed by unsupervised feature extraction with the DWS, and Investigation of the prediction accuracies of the various machine learning models.

2. Materials and Methods

2.1. Dataset

The data used as part of this study comprises of physiological recordings from a number of patients and are from the published work of López-Justo et al. [7]. The data was collected from the "Mónica Pretelini Sáenz" Maternal-Perinatal Hospital, Toluca, State of Mexico, Mexico, where it also received ethical approval [7]. A preterm labor is defined as patient who delivered during the 32–36 weeks stage of gestation, while term labor refers to patients who delivered within 38–40 weeks of gestation [7]. As part of the assembly and call for patient volunteers, patients with twin pregnancies, gestational diabetes, hypertensive disorders, epidural blocking and degenerative diseases were not included in the study.

The heartbeat signals were recorded using the Monica AN24 system, designed by Monica healthcare, while the EHG data was recorded using a set of bipolar electrodes, where all of the data were acquired using a sampling rate of 900 Hz [7]. All acquired signals were post-processed with the MonicaSDK software. For the final analysis, 48 patients' data for the maternal heart beat (22 preterm and 26 term), and 45 patients (17 preterm and 28 term) for the fetus heartbeat were used.

The uterine contraction signal worked with an optimal single channel with the MonicaSDK software, where an envelope of the data was produced and subsequently downsampled with a 2-s epoch averaging scheme. The downselected files were chosen to ensure that a minimum of 4 s of uterine contraction were available for all files for the subsequent analysis, which resulted in 47 patients' data for the final signal processing exercise, of which 27 of the patients' data were term and 20 were preterm.

The SMOTE algorithm was employed for class balancing purposes, and a windowing scheme of 10 disjointed windows was used on the data, which divides each candidate signal into 10 equally sized windowed slices [13].

2.2. Signal Processing and Decompositions

2.2.1. DWS

This method enables a form of unsupervised feature extraction where the features can be said to be robust to factors such as translations, whilst being continuous altogether [14–18]. Parameters such as the wavelets and filters are preset, which reduces the overall computational load but breeds ground for uncertainties [14–18]. The method presents a merge of knowledge from convolutional neural networks (CNNs) alongside wavelet scatterings, where trade-offs are made whilst retaining their key properties [14–18]. A further strength of the method is its ability to work with a constrained amount of samples, due to its ability to extract features across all scales of decompositions which it conducts [14–18].

In terms of mathematical formulation, given a signal $f(t)$ being filtered with a low pass Ø with a wavelet Ψ which spans a range of frequencies identical to that of the signal, assume a low pass filter $\text{Ø}_{\text{J}}(t)$ which induces a localized translation invariance of the signal at a specific scale T, while the associated family of wavelets indices which possess an octave frequency distribution Q_k is represented as $\wedge_{\text{k}}$, and the multiscale high pass filter banks $\{\Psi_{\text{jk}}\}_{jk\in\wedge_{\text{k}}}$ are formed via a dilation of the wavelet [14–18]. The implementation of the DWS involves a combination of a deep CNN which iterates and convolves through the wavelets and nonlinear modules, as well as an averaging scaling function [14–18]. The Gabor wavelet was set as the mother wavelet utilized for signal decomposition, and as per related work, the invariance scale was set to 1 s, while the filter banks were set to 8 wavelets per octave in the first filter bank and 1 wavelet per octave in the second filter bank.

2.2.2. LSDL

The LSDL is a signal decomposition method which systematically separates a signal into component parts in order to minimize redundant components of the signal whilst maximizing the overall signal quality [9–11]. The LSDL is framed upon metaheuristic reasoning from the area of artificial intelligence and iterative signal decomposition using a select basis function from the area of signal processing. The founding study for the LSDL was based upon source separations of mixtures from acquired acoustic emissions signals which were non-linear and stochastic, where the LSDL showed better results than that of the classical wavelet decomposition [9–11]. The method has been applied in external case studies within the area of clinical medicine in areas spanning preterm pregnancies, early prostate cancer predictions, anesthesia depth prediction, rehabilitation medicine, and psychiatry, where the use of the LSDL for pre-processing of the signal was noted to enhance the prediction accuracies within the various highlighted areas [3,20–23].

The decomposition act is done in the time domain where a series of heuristics, alongside a linear basis function, is utilized towards the iterative separation of the signal. The identified optimal region in the signal, with respect to an embedded cost function, represents an area which contains optimal signal information with minimal redundancies within the signal. The embedded cost function used as part of the algorithm is the normalized Euclidean distance metric. For this paper, the optimal decomposition region for all signals alongside decomposition parameters are adopted from a prior related study, as can be seen in Nsugbe et al. [12].

2.2.3. LSDL-DWS

This case represents the merger of the two methods and involves the passing of the LSDL decomposed signal through the DWS algorithm for unsupervised feature extraction.

Machine Learning

The following machine learning models were adopted for use in this study: decision tree (DT), linear discriminant analysis (LDA), logistic regression (LR), support vector machines, i.e., linear SVM (LSVM), quadratic SVM (QSVM), cubic SVM (CSVM), fine Gaussian SVM (FGSVM), k-nearest neighbor (KNN), with k selected as 1 [20]. All models, as well as hyperparameters, were tuned and iterated using the MATLAB classification learner application, where the models were validated using a k-fold validation scheme with k chosen as 10.

3. Results

The classification accuracy was used to quantify the predictive performance of the models utilized for the various signals, as applied in previous studies.

3.1. EHG

The results for the EHG signals can be seen in Table 1, where first the DWS on its own was seen to exhibit a range of prediction accuracies, with the maximum seen to be the KNN model, therein showing the feasibility and applicability of the DWS towards being used for these kinds of exercises. In the second case, the LSDL pre-processed signal was passed through the DWS for unsupervised feature extraction, where the KNN model was seen to also be the optimal one, albeit with a slightly lower classification accuracy.

Table 1. Results of the EHG signals.

Model	DWS	LSDL-DWS
DT	78	74
LDA	75	73
LR	76	73
QDA	80	67
LSVM	79	73
QSVM	92	86
CSVM	86	91
FGSVM	95	87
KNN	97	92

3.2. FHR

In the case of the FHR, the DWS once again yielded a high figure of 94 % for the KNN, but this time the LSDL-DWS produced a higher accuracy, as seen in Table 2. This implies that the pre-processing of the FHR signal with the LSDL has shown signs towards maximizing the prediction prowess of the signal.

Table 2. Results of the FHR signals.

Model	DWS	LSDL-DWS
DT	68	99
LDA	64	99
LR	64	99
QDA	70	99
LSVM	65	99
QSVM	83	99
CSVM	92	99
FGSVM	92	99
KNN	94	99

3.3. MHR

For the case of the MHR, although a high accuracy was obtained once again for the KNN model, the combination of the LSDL-DWS result was seen to surpass that of the DWS only, as seen in Table 3. This result goes to show the compatibility of the LSDL-DWS towards predicting and differentiating between preterm births using either the FHR and MHR signals, ahead of the EHG signals, as indicated by the results in the various tables.

Table 3. Results of the MHR signals.

Model	DWS	LSDL-DWS
DT	75	98
LDA	64	98
LR	64	97
QDA	75	n/a
LSVM	64	98
QSVM	86	98
CSVM	93	98
FGSVM	93	92
KNN	98	96

4. Conclusions and Future Work

Preterm births are a global scale epidemic which have been seen to carry lifelong health and financial implications to society at large. This work has focused on the predictions of preterm births in patients in active labor using a range of physiological signals. As part of this, this work primarily investigated the use of the DWS method, which has been seen to allow for unsupervised feature extraction towards the differentiation of preterm and term pregnancies while using physiological signals. The method was seen to provide high prediction accuracies depending on the machine learning models used, where the heartbeat-based signals provided the higher prediction accuracies. The DWS was also used in tandem with the LSDL, which offered a further boost in the prediction accuracies of the various models, with particular emphasis on the heartbeat-based signals once again. However, the potential downside of this is a more intense computational load if the model is to be deployed for online use.

Further work in this area would subsequently involve the use of the unsupervised learning algorithms alongside the unsupervised feature extraction prowess of the DWS towards potentially forming a fully automated pipeline for the prediction of preterm births from acquired physiological signals.

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