TIPTEKNO'24 MEDICAL TECHNOLOGIES CONGRESS
10-12 October 2024
Yasmin Bodrum Resort, Muğla, Türkiye

Detection of Asphyxia and Apnea of Newborns Under Incubator Treatment Using Respiration Signals and Machine learning

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***Abstract*— Premature infants may have several health problems, breathing problems are the most common form of these problems. Detection of breathing problems in newborns accurately is a very important issue. Premature infants generally are taken in neonatal intensive care under incubator treatment. This study aimed to propose a machine learning-based algorithm using respiration signals of infants to detect abnormal respiration events. 9 Time domain features were extracted from respiration signals and used as inputs of classifiers. The neighborhood component analysis method was applied to detect the most important features. 4 Features were selected as important features and were given as inputs of classifiers. The K-Nearest Neighbors KNN (K=9) algorithm reached the best performance when 2 different feature sets were given as inputs. The accuracy of KNN (K=9) with 9 features was 92.05%±8.02% while with 4 features was 90.68%±2.11%.**

Keywords—Premature; Respiration; machine learning; asphyxia; apnea

I. INTRODUCTION

A preterm newborn is defined as a sudden birth occurring before the 37th week of pregnancy. The last 3 months of pregnancy are the era in which the major fetal development stage occurs. The infant can breathe for the first time in this trimester. The World Health Organization (WHO) claims that in every 10 newborns, 1 infant is recognized as a preterm newborn, and it is estimated that approximately 15 million premature infants are born each year. Approximately one million premature babies die in the first days of life each year from complications during or related to birth; prematurity is the leading cause of death in children under five [1].

Infants that were born prematurely may have several health problems, so they are taken to the neonatal intensive care unit (NICU). The major health problems that occur in premature newborns are 1) difficulty keeping warm and 2) breathing problems. For the handling with these problems, it is necessary to provide an environment to control and boost the thermoregulation of newborns. Newborn incubators are used to provide a more suitable environment for the development of babies' health, to stabilize and maintain thermal balance in premature babies and newborns. In 1907 Pierre Budin described the link between mortality and temperature and found that only 10% of babies survived when they maintained low temperatures compared to those who maintained high temperatures. [2].

Birth asphyxia is defined as the inability of breathing to begin and continue automatically in the first era of birth, also it is the major risk of neonatal adaptation situation to after birth is the initiation of adequate respiratory effort. Approximately 10-15% of infants need support for respiration and ventilation. Birth asphyxia leads to a blood-gas exchange deficit. In the long period, birth asphyxia results in metabolic acidosis, apnea, and progressive hypoxemia [3].

Another breathing problem in newborns is apnea of prematurity (AOP). AOP is defined as the abruption of breathing for at least 20 seconds, accompanied by both bradycardia and oxygen desaturation in an infant with a gestational age < 37 weeks. AOP is among the most common diagnoses in (NICU) [4].

Lee et al. propose an algorithm to detect AOP using neonates' Electrocardiography (ECG) signals [5]. Hassan et al. also proposed an algorithm based on respiration signals to detect AOP [6]. Vergales et al. tried to automate apnea analysis in preterm infants. They used waveform, vital signs, and alarm data from very-low-birth-weight infants for this purpose. They

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reported 74% accuracy rate [7]. Lorato et al. also used a thermal camera to monitor the respiration movement of infants.

There are several studies This study aimed to propose a machine learning-based algorithm to detect asphyxia and apnea of prematurity under incubator treatment using respiration signals [8].

II. MATERIALS & METHODS

A. Database

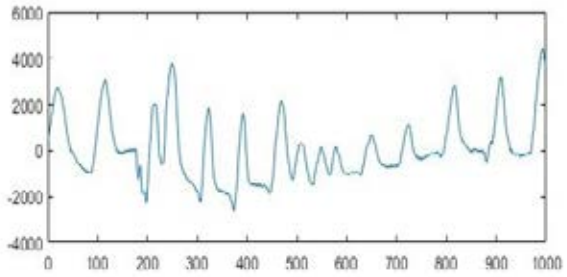
In this study, the open source Preterm Infant Cardio-respiratory Signals (PICS) database was used. This database includes simultaneous respiration recordings and ECG of 10 preterm collected from the Neonatal Intensive Care Unit (NICU) of the University of Massachusetts Memorial Healthcare. Ten preterm infants with post-gestational ages of 29 3/7 to 34 2/7 weeks (mean: 31 1/7 weeks) and working weights of 843 to 2100 grams (mean: 1468 grams) were studied. Newborns included in this study did not have any comorbid illness. A single channel of a 3-lead electrocardiogram (ECG) signal was recorded at 500 Hz from bedside patient monitors for ~20-70 hours per infant. Using external inductance bands placed around the chest wall and abdomen, respiratory signals were also recorded (50 Hz) [9-10].

B. Data Augmentation & Simulating Abnormal Respiration Event

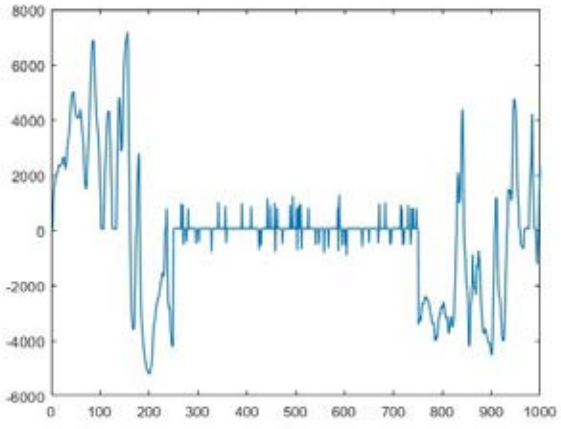
Lack of data numbers in machine learning problems is the most common challenging problem. The data slicing approach is applied to the database to boost the number of data. This method is a common 1-D data augmentation technique that is usually used in physiological signals research [11]. Every respiration signal is divided into small parts with a 30-second duration. We selected parts of 3 different patients as a healthy event. We generated abnormal respiration events from slices of 3 different records than 3 patients that were selected as healthy events. To generate abnormal respiratory events, we used down-sampling and applied the amplitude thresholding method according to the physiological definition of asphyxia and AOP.

C. Preprocessing

An Infinite Impulse Response (IIR) 4th order Butterworth band stop filter was applied on signals to 50 Hz notch noise. Also, a 4th order IIR Butterworth band pass filter with 0.5-64 Hz cut-off frequencies was applied. To surpass the abnormal amplitude spike we applied a moving average filter.



(a) Healthy event



(b) Abnormal event

Fig 1. (a) Healthy respiration event. (b) Abnormal respiration event

D. Feature Extraction

As a feature extraction part, 9 different time domain features were extracted from the respiration signal for both groups. The mean of the signal was calculated because the simulated AOP signal has smaller amplitude than the healthy part of respiration, also the maximum and minimum values of signals were calculated. Standard deviation and median values of amplitudes were calculated. Zero crossing rate of signals for each group. The average peak-to-peak value for successive peaks was calculated. This feature also represents the tidal volume of patients. The power of signals is also used as a feature.

All extracted features were selected following the morphological differences shown in Figure 1. Table 1. Summarize the list of features.

TABLE 1. LIST OF FEATURES

1) Mean of amplitudes	2) Maximum of amplitudes	3) Minimum of amplitudes
4)Median of amplitudes	5) Standard deviation of amplitudes	6) Zero-crossing
7) Peak-to-peak value	8) Root mean square (RMS)	9) RMS/peak-to-peak

E. Machine Learning

To detect asphyxia or AOP events, we used a support vector machine (SVM), adaptive boosting (Adaboost) classifier as an ensemble learning algorithm, K-nearest neighbor (KNN) and artificial neural networks (ANN). Extracted features of all parts were split to train and test subsets by using the 10-fold cross-validation (k=10) method. For the SVM method, we used linear kernel and for K-NN k=9 and 11 values, for the Adaboost classifier learner rate was chosen as 0.1, and two fully connected layers with the size of 20 and 10, and the sigmoid activation function was used for the ANN architecture. Accuracy, sensitivity, and specificity values were calculated to evaluate the performance of algorithms.

F. Evaluate The Importance of Features

Neighborhood Component Analysis (NCA) is used as feature selection method. NCA used distance metrics to calculate the weights of the features. It is a supervised feature selection method and is a non-parametric method. The NCA is developed using KNN. The advantage of the NCA is that it generates positive weights for each feature and feature ranking is calculated using NCA.

III. RESULTS

Table 2. represents the accuracies, sensitivities, and specificities values of all classifiers.

TABLE 2. CLASSIFICATION RESULTS FOR ALL FEATURES

Parameters / Algorithms	Accuracy (mean%±std%)	Sensitivity (mean%±std%)	Specificity (mean%±std%)
SVM	88.07±7.85	94.33±7.77	87.88±8.02
KNN(k=9)	92.05±8.02	95.54±1.33	91.32±11.02
KNN(k=11)	89.18±6.04	93.26±6.52	89.99±3.68
Adaboost	90.88±9.78	91.33±8.02	86.54±5.48
ANN	91.45±5.55	96.84±3.13	90.54±2.15

According to Table 2, the KNN (K = 9) classifier shows the best performance in classifying healthy and abnormal events (asphyxia or AOP).

Fig 2. shows the importance of each feature in classification results calculated by NCA. As shown in this figure, mean, maximum, minimum, and peak-to-peak values of respiration signals have a more significant role in the accuracy of classification.

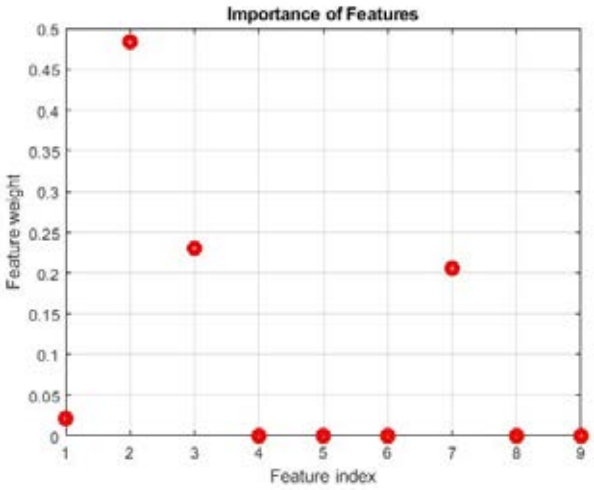


Fig 2. Importance of extracted features

Table 3. represents the accuracies, sensitivities, and specificities values of all classifiers when only mean, maximum, minimum, and peak-to-peak values of respiration signals were used as inputs of classifiers.

TABLE 3. CLASSIFICATION RESULTS FOR SELECTED FEATURES

Parameters / Algorithms	Accuracy (mean%±std%)	Sensitivity (mean%±std%)	Specificity (mean%±std%)
SVM	85.17±0.78	89.45±0.8	83.07±3.45
KNN(k=9)	90.68±2.11	92.07±4.12	88.66±5.22
KNN(k=11)	85.11±2.14	91.18±2.22	84.13±6.68
Adaboost	82.11±1.31	83.02±1.11	78.04±4.28
ANN	84.05±3.38	89.04±0.31	75.45±4.65

According to Table 3, the KNN (K = 9) classifier shows the best performance in classifying healthy and abnormal events (asphyxia or AOP).

IV. DISCUSSION & CONCLUSION

This study aimed to detect abnormal respiration events such as asphyxia or AOP of neonatal under incubator treatment using respiration signals and machine learning algorithms. For this purpose, we used respiration recordings of infants and simulated abnormal events (asphyxia or AOP). We used 9 time domain features as inputs of classifiers. KNN (K=9) classifier shows the best performance to detect normal and abnormal respiration events. Also applied the NCA method to select the most important features. 4 Features were selected as important features and used as inputs of classifiers. KNN (K=9) also reached. However, the number of features was reduced to half, performances of classifiers did not change seriously. It is important for us because we decided to run this algorithm on a microcontroller unit (MCU).

Hassan et al. reported 85% percent accuracy in detecting apnea in infants in the NICU. They proposed an IoT-based framework. Vahabi et al. also tried apnea and non-apnea events in neonatal patients. They used electrical impedance tomography (EIT) of 15 premature neonates and used RestNet50 architecture as a classification algorithm. They reported optimal accuracy as 97% [12].

V. FEATURE WORKS

As mentioned previously the abnormal events in this study were generated synthetically. As a feature work, we decided to validate our algorithm with real abnormal data and then use this algorithm as an embedded form in OKM 862- Infant Incubator that is produced by OKUMAN MEDİKAL SİSTEMLER A.Ş.



Fig 3. OKM 862-Infant Incubator

ACKNOWLEDGMENT

The Scientific and Technological Research Council of Turkey (TÜBİTAK) supports this research financially with the TEYDEB 1501 foundation program under grant no. 3220964 is gratefully acknowledged.

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