IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received December 29, 2020, accepted January 23, 2021, date of publication February 2, 2021, date of current version February 12, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3056558

Deep Analysis of EIT Dataset to Classify Apnea and Non-Apnea Cases in Neonatal Patients

NAFISEH VAHABI[1], (Member, IEEE), REBECCA YERWORTH[2], MARTIJN MIEDEMA[3], ANTON VAN KAAM[3], RICHARD BAYFORD[4], (Life Senior Member, IEEE), AND ANDREAS DEMOSTHENOUS[1], (Fellow, IEEE)

[1]Department of Electronic and Electrical Engineering, University College London, London WC1E 6BT, U.K.
[2]Department of Medical Physics and Biomedical Engineering, University College London, London WC1E 6BT, U.K.
[3]Emma Children's Hospital, Amsterdam UMC, University of Amsterdam, 1012 WX Amsterdam, The Netherlands
[4]Department of Natural Sciences, Middlesex University, London NW4 4BT, U.K.

Corresponding author: Nafiseh Vahabi (n.vahabi@ucl.ac.uk)

This work was supported by the Engineering and Physical Sciences Research Council (EPSRC) under Grant EP/R513143/1.

ABSTRACT Electrical impedance tomography (EIT) is a non-invasive imaging modality that can provide information about dynamic volume changes in the lung. This type of image does not represent structural lung information but provides changes in regions over time. EIT raw datasets or boundary voltages are comprised of two components, termed real and imaginary parts, due to the nature of cell membranes of the lung tissue. In this paper, we present the first use of EIT boundary voltage data obtained from infants for the automatic detection of apnea using machine learning, and investigate which components contain the main features of apnea events. We selected 15 premature neonates with an episode of apnea in their breathing pattern and applied a hybrid classification model that combines two established methods; a pre-trained transfer learning method with a convolutional neural network with 50 layers deep (ResNet50) architecture, and a support vector machine (SVM) classifier. ResNet50 training was undertaken using an ImageNet dataset. The learnt parameters were fed into the SVM classifier to identify apnea and non-apnea cases from neonates' EIT datasets. The performance of our classification approach on the real part, the imaginary part and the absolute value of EIT boundary voltage datasets were investigated. We discovered that the imaginary component contained a larger proportion of apnea features.

INDEX TERMS Apnea classification algorithm, EIT data analysis, electrical impedance tomography, pre-trained ResNet50, transfer learning algorithm.

I. INTRODUCTION

Apnea in adults is a breathing disorder event that occurs as a result of the absence of inspiratory airflow for at least 10 s [1]. During the apneic episodes, the soft tissue in the rear of the throat collapses and causes a blockage in the airway, decreasing the respiratory rate. This can cause an increase in the CO_2 level in the blood and cause choking during sleep. It also decreases the amount of oxygen delivered from the lungs to the heart, brain and rest of the body [2], [3]. Several studies have supported the association of apnea with heart failure, hypertension and arrhythmia in adults which makes apnea detection techniques a vital indicator for clinicians [4]–[7]. However, the cause of neonatal apnea is mainly due to the prematurity of the brain and spinal cord that controls the breathing. Apnea due to prematurity can cause babies to take larger gasps of air when breathing, followed by periods of shallow breathing or stopped breathing [8].

EIT is a non-invasive, radiation-free technique that images an object by injecting small ac currents through electrodes on its boundary, and measures the resulting potentials developed on the same or other electrodes. This process permits the estimation of the distribution of the inner conductance (impedance) of the object. When applied to the thorax, this allows both global and regional changes in aeration and ventilation, and ventilation/perfusion mismatch, to be ascertained in real-time. The images do not provide static structural equivalents to magnetic resonance imaging (MRI) or computed tomography (CT) scans of the lung but represent the air volume change in the lung with a high temporal

The associate editor coordinating the review of this manuscript and approving it for publication was Gianmaria Silvello.

resolution (typically about 49 images per second [9]). EIT offers several advantages; it utilises a wearable electrode belt for continuous monitoring application, it does not use ionizing radiation and is capable of high temporal resolution. However, EIT has lower spatial resolution than CT and can be prone to artefacts from electrodes. The measured voltages at the electrodes on the body surface consist of two voltage components, the real part which is mainly due to the applied low frequency current and the imaginary part which is the phase component and increases as the frequency increases [10].

The rest of this paper is organized as follows. Section II reviews the algorithms for EIT interpretation and different methods to detect apnea cases, particularly those using reconstructed images from EIT datasets. Section III gives a summary of the clinical EIT datasets used, and Section IV provides a detailed description of the proposed approach. Results and performance of the proposed algorithm are described in Section V. In Section VI, a discussion of the results is presented. Conclusions drawn in Section VII.

II. RELATED WORK AND OUR CONTRIBUTION

A. EIT INTERPRETATION TECHNIQUES

Despite the advantages of using EIT technology in various clinical applications, interpretation of an EIT dataset has been a challenge due to the lack of well-established methods [11], [12]. In this section, the main approaches to the reconstruction of EIT datasets are summarized. Methods based on artificial neural networks (ANNs) have been applied to EIT simulated reconstructed images for the classification of abnormalities in the lung [13]. However, the neural networks are trained and tested with only simulated image data obtained by solving the mathematical model equations governing current flow through the simulated thoracic region.

An alternative is based on a novel approach combining both linear and non-linear methods [14] and the use of an ANN as a post-processing method to enhance the quality of the image reconstruction algorithm. This method post-processes the image and is not suitable for real time detection of apnea. More recently a machine learning based approach called D-bar was proposed [15] to generate more reliable images from an EIT phantom dataset. In the latter study, low-pass filtering of non-linear Fourier data is used, and a convolutional neuron network (CNN) is applied as a post-processing method to sharpen the features of the reconstructed EIT images. This method does not address the extraction of clinical parameters but focuses on the improvement of the resolution of the reconstructed image.

A further study investigating total generalized variation regularization was implemented [16] to improve the identification of sharp edges in EIT reconstruction images. It used the GREIT algorithm [11] from the Electrical Impedance Tomography and Diffuse Optical Tomography Reconstruction Software (EIDORS) to reconstruct EIT images and reported the improvement in terms of total variation regularization. Recently, a novel reconstruction method to convert an ill-posed problem to a well-posed problem using a variety of training datasets to generate low dimensional estimated solutions has been proposed [17]. It proved the feasibility of developing auto-encoder algorithms to generate compact lung images using EIT, however, it did not use grand truth label data for training. Another method reduces the dimensionality of EIT reconstruction images using discrete cosine transformation (DCT) of thorax slides [18], but it only presents the part of the lung where conductivity changes occur. The latest study [19] demonstrates a method to improve the quality of EIT reconstructed images by applying a super-resolution technique.

In these studies, a number of issues have been frequently reported. They include: high EIT reconstruction error, losing valuable features in datasets by reconstructing the raw data, and analysis becoming computationally expensive and slow. Most importantly, EIT is an ill-posed problem which currently does not provide perfect reconstruction solutions. In addition, the reconstructed images are based on the real parts of complex numbers. This led us to investigate the possibility of using an EIT boundary voltage dataset to avoid applying any image reconstruction algorithm which filters the image and can remove useful information. In particular, we used the imaginary part of EIT boundary voltages as well as the real part. We used datasets from 15 premature neonates who exhibited a period of apneic breathing. The majority of studies on EIT data only considered the real part of its voltage component and ignored the imaginary part. However, one investigation [20] suggested the phase angle of EIT complex value could be an indicator for breathing cycle. In our study the analysis investigates which component of the EIT complex dataset contains more informative features of apnea data. Also, we compared the result with the absolute value of the complex number dataset.

B. APNEA DETECTION IN NEONATES

The automatic detection of apnea in neonates has previously been examined using several different methods. Pais and González [21] identified the apnea period based on a combination of patterns in time and frequency domain ECG signals, and pulse oximeter time-domain signals. However, these signals do not provide a direct measurement of breathing, only the effect of the heart and blood volume changes.

An alternative approach has been proposed in which a motion detection video camera is used to monitor the respiratory rate of infants using a phase based algorithm [22]. This method is similar to a motion detection approach, which is a combination of Eulerian video magnification, short-time Fourier transform and optical flow in infants using video frames [23]. It is also possible to use the electromyography (EMG) signal of the diaphragm muscle [24] which records the respiratory signals and analyses neuromuscular activity to detect an episode of apnea. However, all these methods are limited as apnea motion detection methods suffer from many non-respiration related movements which are difficult to minimise in a neonate environment. Also, the computation time required to extract a respiration signal during video monitoring in real-time is high due to the optical flow algorithm.

Other methods based on various machine learning models such as ANNs and long short-term memory (LSTM) using ECG data [25], CNN and logistic regression using oximeter data [26] and support vector machine (SVM) using ECG data [27] have been proposed. However, they all rely on indirect methods to obtain their physiological data on lung function which limits their ability to predict the apnea event.

Our approach using EIT can provide dynamic information in regional lung ventilation. It allows the assessment of lung function by continuous and real time monitoring of premature neonate lung in neonatal intensive care [9]. Other imaging modalities cannot offer the same advantages as EIT. For example, CT and MRI provide a static image of lung anatomy but cannot be used at the bedside. Also, X-ray produces a static image and is limited for infants under 5 years due to the risk of ionizing radiation causing cancer [28], [29].

The aim of this study is to investigate the potential use of EIT boundary voltage dataset for detection of apnea for premature neonates. More importantly, to identify which component of a raw EIT dataset contains the most informative features of an EIT dataset.

The contributions of this paper are as follows:

a. We present the first work undertaken on EIT boundary measurement data obtained from infants in a clinical study (cradlproject.org) for the automatic detection of apnea.
b. The EIT is formed of two parts due to the nature of the human tissue which has a real part (non-frequency dependent) and a reactive component (frequency dependent), which is due to the cell membranes acting as capacitors. This research investigates the contribution to the detection of apnea of each component of the measured boundary voltage and highlights the need to consider the reactive component, which is often discarded, as is evident in the majority of published research on EIT datasets, where only the real part of the data is considered.
c. This research provides evidence that there is valuable information in the imaginary part reactance) as well as the real part of EIT data.
d. The method employed in this paper uses EIT boundary voltage data without any pre-processing, filtering or image reconstruction, to avoid losing the information content. The image reconstruction algorithms used in EIT filter the information content and could introduce significant errors or misinterpretation of the clinical indicators as well as affect the accuracy of the classification algorithm.
e. This paper also reports the first use of a hybrid classification model (CNN and SVM) on real clinical EIT datasets to predict apnea from a non-apnea datasets.

TABLE 1. Details of neonate patients used in this study.

Neonate ID	Gender	Weight (gr)	Age (week)
N1	Male	1270	32
N2	Female	1240	29
N3	Female	1290	31
N4	Male	1840	29
N5	Female	1320	33
N6	Female	1820	31
N7	Male	2100	30
N8	Male	930	28
N9	Male	1100	28
N10	Male	1800	31
N11	Male	1900	34
N12	Male	2100	33
N13	Female	1000	28
N14	Male	2000	37
N15	Male	1000	28

III. EIT DATA DESCRIPTION

15 EIT datasets were obtained of premature neonate patients provided by the Emma Children's Hospital, Academic Medical Centre (AMC), in the Netherlands under ethics ID number NCT 02962505 in ClinicalTrials.gov. Data was acquired using a Swisstom EIT system with 32 electrodes at a rate of 49 frames per second. 32 electrodes are inserted in the belt equidistant apart and the neonate patients wore the belt around their chest as shown in Fig. 1. Details about each neonate in this study are provided in Table 1. In our datasets, we considered both male and female neonate patients. The dataset from each neonate was recorded over 72 hours and were stored in sub-folders of approximately 20 minutes length. The dataset used for training and testing of our classification model are from confirmed cases of apnea and non-apnea samples provided by an experienced clinician in the Academic Medical Centre (AMC), the Netherlands.

IV. METHODOLOGY

A. PREPARING DATASETS

No pre-processing techniques such as filtering, denoising or image reconstruction were applied on the original boundary voltage data from the EIT system. The reason was to avoid losing any valuable information or introducing significant errors to our datasets. Data was recorded from 32 sensors, however, it is possible that a few electrodes did not attach to the neonates' bodies properly during the data recording. If four or more electrodes were disconnected the measurement was discounted until the electrodes could be reattached. In addition, the output of each electrode was checked to make sure it was within a valid contact impedance threshold, otherwise the algorithm would exclude this as a false measurement. The apnea files are annotated with the time period of apnea, pre-apnea and post-apnea within 20 minutes for each neonate patient by the clinicians who looked at the visual patterns of the apnea signal based on their experience. It must be noted that the clinician used

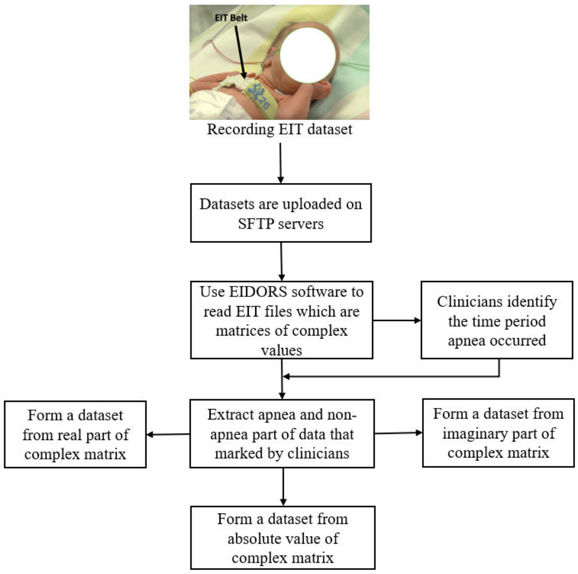


FIGURE 1. **Dataset preparation diagram. Three datasets are formed from EIT complex number matrix: real part, imaginary part and absolute value of complex numbers.**

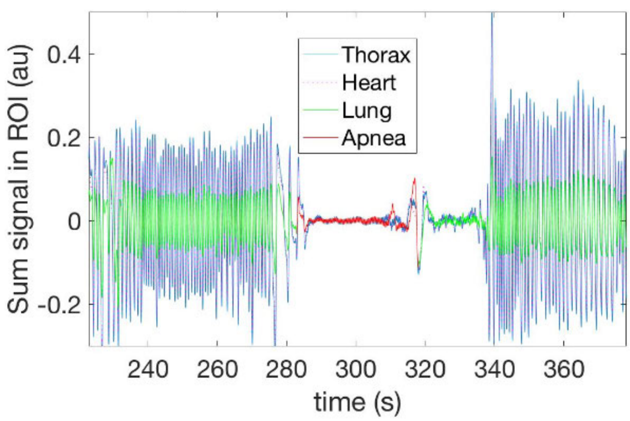


FIGURE 2. **A Period of apnea. The signal of EIT from neonate N4 shows the window of recording EIT data. The red signal is the area marked as apnea.**

the EIT reconstructed images which are produced by the EIDORS software for their annotation. An example of an apnea episode is shown in Fig. 2 where the red section of the signal between 285 s and 315 s is marked as an apnea episode. Clinicians use figures like this to annotate apnea in EIT data.

The two classes of dataset, apnea and normal (non-apnea), are then ready for further analysis. Apnea frames which are close to the pre-apnea or post-apnea episode are removed to create high-quality apnea datasets.

B. CNN AND SVM HYBRID CLASSIFICATION MODEL

SVM and CNN are both state-of-the-art methods which solve linear and non-linear classification problems [30]. In this study we employed a hybrid classification method which is a combination of CNN and SVM [30]. Pre-trained CNN with Residual Network 50 (ResNet50) architecture, as an automatic feature extractor, is used with a SVM as a classifier. A hybrid classification model was used to explore which components of the datasets contained more informative features of apnea in EIT data. The data presented is a matrix of complex numbers and we investigated the presence of apnea features in their real, imaginary and absolute values.

SVM is a binary multi-class classifier which projects data into feature space to find the optimal hyperplanes for classifying data into groups. The mathematical details of SVM algorithm can be found in [31]. CNN is one of the deep learning algorithms which is formed from a core of convolutional, max pooling and fully connected layers [32]. Many different architectures designed and reported in the literature [33] are based on CNN algorithms. The number of neurons in each layer and their order were chosen to solve a specific task. A detailed comprehensive analysis is provided in [33], which compares different types of CNN deep architecture, their performance and application to medical images. AlexNet, GoogleNet, CifarNet and ResNet50 are popular CNN architectures successfully adapted to classify medical images [34], [35]. It has been reported that ResNet50 produces notably better results, because it solves both the degradation problem and vanishing gradient problem [36], [37]. To test and evaluate the performance of each network architecture, high quality databases such as ImageNet dataset are used for training and learning processes. ImageNet is a large-scale well-annotated dataset which contains more than 1.2 million categorized natural images of over 1000 classes.

Training CNN algorithms from scratch, using feature sets from pre-trained CNN algorithms and developing unsupervised pre-trained CNN with supervised fine-tuning are three techniques which have frequently been used in medical image classification problems [33]. Transfer learning is another classification method in which the first network, trained on a high quality large dataset such as ImageNet, and the features learnt from the first training network transfer and repurposed to the second network to train on a second dataset [36]. Therefore, transfer learning can act as an automatic feature extractor which is found to be particularly useful when applied on raw medical images [33].

Transfer learning algorithms have two main properties that make them an ideal approach for our application. Firstly, transfer learning enables training of models using small annotated datasets by leveraging of popular methods that have already been trained on a very large labelled dataset. Secondly, they significantly reduce the computational resources required, and training time as we do not need to train all the layers to achieve the result [33]. Therefore, we employed pre-trained transfer learning as an automatic feature extractor using ResNet50 architecture. Fig. 3 presents samples of raw EIT 2D-frames for both apnea and non-apnea cases. ResNet50 trained on ImageNet dataset and its input layer takes 224-by-224 RGB images. The ResNet50 network is formed by a series of convolutional layers, max-pooling layers and Softmax layers with rectified linear units (ReLu). It is followed by the fully connected layer and finished by a classification layer. The details of its architecture can

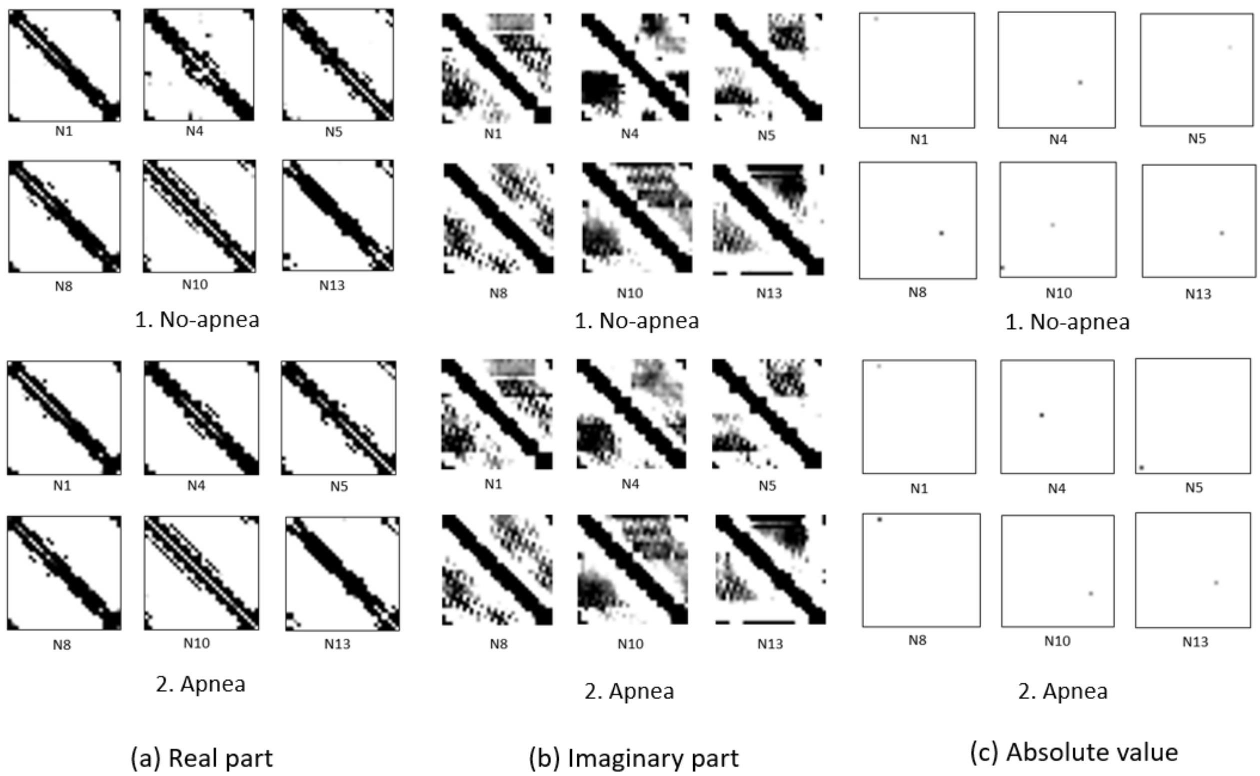


FIGURE 3. Sample of apnea and non-apnea datasets from neonates. Sample of voltage data frame from different neonates in our case study are presented across all three categories; real part (a), imaginary part (b) and absolute value (c). Complex impedance is divided into a real part (resistance) and an imaginary part (reactance). The magnitude of complex impedance shows the absolute value.

be found in [38]. The first layers of the network learnt the primary features of the dataset such as edges and colors as shown in Fig. 4. The deeper layers learnt more abstract and complex features and combined them with the primary features. Therefore, the higher-level features are more suitable for the classification task as they represent richer information of the image.

We selected the feature map from immediately before the final layer, which is the classification layer, for our application. The extracted feature map from the training set is used to train the SVM classifier with stochastic gradient descent (SGD) solver. The implementation of the hybrid classification algorithm using SVM is provided in [30] where SVM is implemented with radial basis function (RBF) kernel. Our datasets were recorded from premature neonates which is a real-world dataset and the classification problem is non-linear. RBF is a preferred kernel to solve a non-linear problem compared with linear kernel that is only used to solve linear problems. To evaluate the accuracy of the SVM classifier, the same procedure is repeated but using the feature map from the test set and calculating the mean of accuracy of predicted label by the SVM classifier.

The final step was to use our trained SVM algorithm to classify our EIT datasets. The block diagram of our model is shown in Fig. 5. The size of each image in our datasets is 32-by-32 and are grey scale images. The images were resized to 224-by-224 and converted to RGB to match the requirement of ResNet50 network. We had 15 neonate patients and for each patient three datasets containing the real, imaginary and magnitude components were prepared. In each category, there were 1000 apnea voltage frames and 1000 non-apnea voltage frames. The SVM classifier was fed with each category to investigate which one contained the

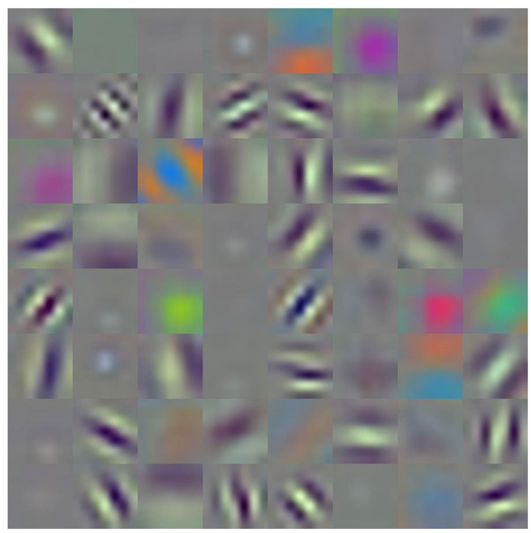


FIGURE 4. First layer feature map. The primary features of ImageNet dataset extracted from first layer of ResNet50 network. Filters on the first layer learnt information about colors and edges of the input images.

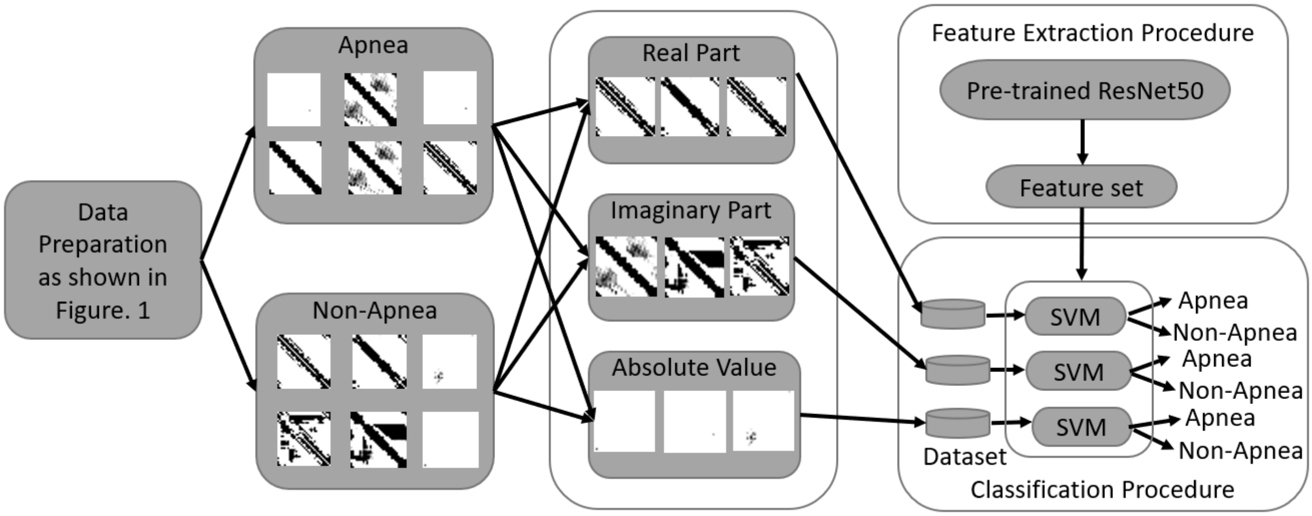


FIGURE 5. An overview diagram of our classification model. The extracted feature set from ResNet50 is used to train the SVM algorithm. Then, the SVM classifier is fed with 1000 voltage frames in each category of our datasets (real part, imaginary part and absolute value) to identify which category contains more apnea features. Complex impedance is divided into a real part (resistance) and an imaginary part (reactant). The EIT is formed of two parts due to the nature of the human tissue which has a real part and a reactive component, which is due to cell membranes. The complex impedance is dependent on the injected current frequency.

more informative apnea features. The results of our analysis are presented in Section V.

V. RESULTS

The reported performance of our classification model is based upon the proportion of the correctly classified samples. We measured the accuracy of our model on both training and testing datasets. Pre-trained ResNet50 network for feature extraction is employed as it did not require any computation overhead for training. Dataset from 10 patients (patient number 1 to 10 in Table 1) were used to train the model, 2 patients (patient 11 and 12) for validation, and the last three patients for testing. The pre-trained ResNet50 network was not modified [39]. Our EIT training data was only used to train the SVM classifier. Neural Network and Deep Learning toolbox from Matlab2020a as well as NVIDIA GeForce RTX 2080 GPU were used to implement the classification model. Each patient dataset has three categories: real part, imaginary part and absolute value. In each category, there are two classes: apnea and non-apnea with 1000 sample EIT images in each class. The average time it takes to run the classification model for real part dataset is 42 s, for imaginary part dataset is 50 s and for absolute value dataset is 35 s.

Fig. 6 illustrates the comparison between the performance of our classification model using real data, imaginary data and absolute value datasets of 10 neonate patients. The classification model achieves optimal accuracy (97%) using the imaginary part of datasets to classify apnea and non-apnea images. As is shown in Fig. 6, out of the 10 neonate patients in training datasets, the model has an accuracy between 78% and 99% for 8 cases using the imaginary part of datasets. Our model can classify apnea and non-apnea with an accuracy between 65% and 98% amongst only 5 patients using the real part of EIT datasets. The model produces the least accurate result when the SVM classifier trained by the absolute value of boundary voltage. Datasets from patients 11 and 12 (Table 1) are used to validate the model during the training process and to fine-tune hyper-parameters. The final model is evaluated by our testing set which was a completely unseen dataset and made of data from the neonates 13, 14 and 15. Fig. 7 shows the result of the classification model on testing data. The result suggests that proposed classification model produces more accurate results using the imaginary part of an EIT datasets compared to the real part.

VI. DISCUSSION AND FUTURE WORK

In this study, we particularly avoided any pre-processing techniques such as any filtering and normalization, to our datasets to find out the performance of the classification methods using EIT boundary voltage data. Apnea datasets were labelled manually by experienced clinicians and whilst this is very time consuming and labor intensive for the clinician, it provides the ground truth. The automatic apnea detection algorithm could help clinicians to identify the apnea frames faster. However, further study is required to optimize the performance of the algorithm and reduce the classification error.

All the neonates in this study were premature, between 28 and 37 weeks old (Table 1). The best classification result (99% accuracy) amongst all three datasets (real part, imaginary part and absolute value) is the neonate number 14 (N14) which is the oldest patient (37 weeks). Interestingly, the least accurate classification performance (50% accuracy) represents to one of the youngest patients (28 weeks old) who is also the lightest (930 gr) neonate.

We also analyzed the boundary voltage frames of the youngest neonates and compared it with the older patients. A consistent pattern is identified in the absolute value dataset

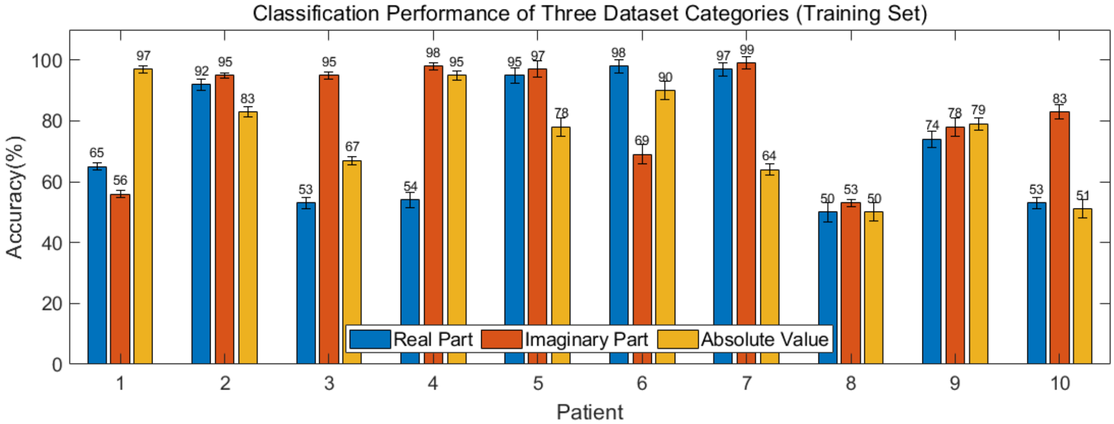


FIGURE 6. A comparison between performance of the classification model using three datasets; real part, imaginary part and absolute value.

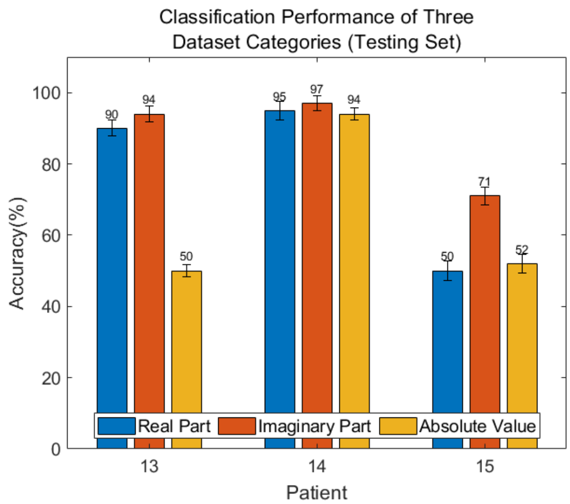


FIGURE 7. A comparison between performance of the classification model using three datasets; real part, imaginary part and absolute value.

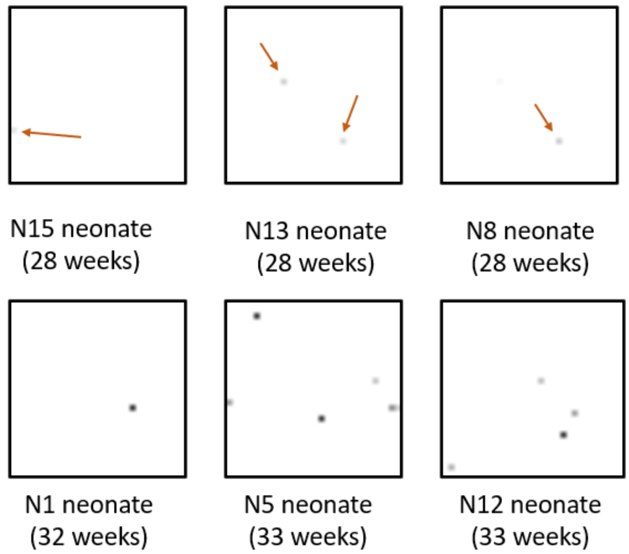


FIGURE 8. Comparison of the absolute value datasets between the youngest neonates and the older ones.

of the youngest neonate (Fig. 8). There are a few faded circles in all absolute value data frames, however, for the frames belonging to the youngest neonates the brightness of those circles is very poor and to the extent that some of the frames look plain white. Fig. 8 shows three boundary voltage frames of absolute value datasets belonging to the youngest neonates (N15, N13 and N8). This could be one the of the reasons that our classification model does not perform well using absolute value datasets for the youngest neonate where the classification accuracy for N15 is 52%, N13 and N8 are 50% (Table 1).

High quality well-labelled data in medical imaging is desirable but rarely available due to the cost and necessary workload of clinicians. Our analyses have shown that a pre-trained transfer network such as the ResNet50 algorithm can be successfully applied to EIT raw images and act as an automatic feature extractor. The results proved transfer learning is one of the efficient methods to train a smaller dataset. Furthermore, our findings emphasises the importance of the imaginary part of EIT boundary voltage and should be included in the EIT reconstruction algorithm.

VII. CONCLUSION

In this paper, a hybrid transfer learning technique has been proposed to classify apnea and non-apnea events in EIT boundary voltage datasets from neonate's patients with an accuracy of between 71% and 97% when the testing dataset is applied. For the proposed classification algorithm, the imaginary part of the complex impedance contains more unique identifiable features of apnea compared with the real part or the absolute components. The real part only measures the dc component; the body is made up of cells which have reactive components and appear to be more sensitivity to apnea. When the absolute is used the reactive component is relativity small compared to the values of the real part and this can result in increased inaccuracy. In addition, transfer learning can successfully be utilized to classify poor resolution EIT data frame without any pre-processing and reconstruction techniques which generally introduce a significant error to the outcome. Although the dataset in this study was only from 15 neonate patients, it was formed from both male and female premature neonates with a variety of weight and heigh ranges which makes the outcome more reliable. However, there is a need to have a more well-annotated patient dataset to increase the generalization and robustness of the model for possible on-line application in a clinical setting.

ACKNOWLEDGMENT

The study is registered in a clinical trials registry (ClinicalTrials.gov, NCT02962505). It was approved by the ethics committees at Emma Children's Hospital, Amsterdam, Netherlands (Ethics number: METC 2016/184).

REFERENCES

[1] S. Javaheri, F. Barbe, F. Campos-Rodriguez, J. A. Dempsey, R. Khayat, S. Javaheri, A. Malhotra, M. A. Martinez-Garcia, R. Mehra, A. I. Pack, and V. Y. Polotsky, "Sleep apnea: Types, mechanisms, and clinical cardiovascular consequences," *J. Amer. College Cardiol.*, vol. 69, no. 7, pp. 841–858, 2017.

[2] P. E. Peppard, T. Young, J. H. Barnet, M. E. W. P. Hagen, and K. M. Hla, "Increased prevalence of sleep-disordered breathing in adults," *Amer. J. Epidemiol.*, vol. 177, no. 9, pp. 1006–1014, May 2013.

[3] A. Witkowski, A. Prejbisz, E. Florczak, J. Kądziela, P. Śliwiński, P. Bieleń, I. Michałowska, M. Kabat, E. Warchoł, M. Januszewicz, K. Narkiewicz, V. K. Somers, P. A. Sobotka, and A. Januszewicz, "Effects of renal sympathetic denervation on blood pressure, sleep apnea course, and glycemic control in patients with resistant hypertension and sleep apnea," *Hypertension*, vol. 58, no. 4, pp. 559–565, Oct. 2011.

[4] R. D. McEvoy, N. Antic, E. Heeley, Y. Luo, O. Ou, O. Mediano, R. Chen, L. Drager, and Z. Liu, "CPAP for prevention of cardiovascular events in obstructive sleep apnea," *New England J. Med.*, vol. 375, no. 10, pp. 919–931, 2016.

[5] G. Ozdemir, H. Nasifoglu, and O. Erogul, "A time-series approach to predict obstructive sleep apnea (OSA) episodes," in *Proc. 2nd World Congr. Electr. Eng. Comput. Syst. Sci.*, Jul. 2016.

[6] J. Han, H.-B. Shin, D.-U. Jeong, and K. S. Park, "Detection of apneic events from single channel nasal airflow using 2nd derivative method," *Comput. Methods Programs Biomed.*, vol. 91, no. 3, pp. 199–207, Sep. 2008.

[7] Y.-Y. Lin, H.-T. Wu, C.-A. Hsu, P.-C. Huang, Y.-H. Huang, and Y.-L. Lo, "Sleep apnea detection based on thoracic and abdominal movement signals of wearable piezoelectric bands," *IEEE J. Biomed. Health Informat.*, vol. 21, no. 6, pp. 1533–1545, Nov. 2017.

[8] S. Mishra, R. Agarwal, M. Jeevasankar, R. Aggarwal, A. K. Deorari, and V. K. Paul, "Apnea in the newborn," *Indian J. Pediatrics*, vol. 68, no. 10, pp. 959–962, 2001.

[9] D. Khodadad, S. Nordebo, B. Müller, A. Waldmann, R. Yerworth, T. Becher, I. Frerichs, L. Sophocleous, A. van Kaam, M. Miedema, N. Seifnaraghi, and R. Bayford, "Optimized breath detection algorithm in electrical impedance tomography," *Physiological Meas.*, vol. 39, no. 9, Sep. 2018, Art. no. 094001.

[10] B. Brown, "Electrical impedance tomography (EIT): A review," *J. Med. Eng. Technol.*, vol. 27, no. 3, pp. 97–108, Jan. 2003.

[11] A. Adler, J. H. Arnold, R. Bayford, A. Borsic, B. Brown, P. Dixon, T. J. C. Faes, I. Frerichs, H. Gagnon, Y. Gärber, B. Grychtol, G. Hahn, W. R. B. Lionheart, A. Malik, R. P. Patterson, J. Stocks, A. Tizzard, N. Weiler, and G. K. Wolf, "GREIT: A unified approach to 2D linear EIT reconstruction of lung images," *Physiological Meas.*, vol. 30, no. 6, pp. S35–S55, Jun. 2009.

[12] I. Frerichs, "Electrical impedance tomography (EIT) in applications related to lung and ventilation: A review of experimental and clinical activities," *Physiological Meas.*, vol. 21, no. 2, pp. R1–R21, May 2000.

[13] A. S. Minhas and M. R. Reddy, "Neural network based approach for anomaly detection in the lungs region by electrical impedance tomography," *Physiological Meas.*, vol. 26, no. 4, pp. 489–502, Aug. 2005.

[14] S. Martin and C. T. M. Choi, "A post-processing method for three-dimensional electrical impedance tomography," *Sci. Rep.*, vol. 7, no. 1, pp. 1–10, Dec. 2017.

[15] S. J. Hamilton and A. Hauptmann, "Deep D-bar: Real-time electrical impedance tomography imaging with deep neural networks," *IEEE Trans. Med. Imag.*, vol. 37, no. 10, pp. 2367–2377, Oct. 2018.

[16] B. Gong, B. Schullcke, S. Krueger-Ziolek, F. Zhang, U. Mueller-Lisse, and K. Moeller, "Higher order total variation regularization for EIT reconstruction," *Med. Biol. Eng. Comput.*, vol. 56, no. 8, pp. 1367–1378, Aug. 2018.

[17] J. K. Seo, K. C. Kim, A. Jargal, K. Lee, and B. Harrach, "A learning-based method for solving ill-posed nonlinear inverse problems: A simulation study of lung EIT," *SIAM J. Imag. Sci.*, vol. 12, no. 3, pp. 1275–1295, Jan. 2019.

[18] B. Schullcke, B. Gong, S. Krueger-Ziolek, M. Soleimani, U. Mueller-Lisse, and K. Moeller, "Structural-functional lung imaging using a combined CT-EIT and a discrete cosine transformation reconstruction method," *Sci. Rep.*, vol. 6, no. 1, p. 25951, Sep. 2016.

[19] M. Zamani, R. Bayford, and A. Demosthenous, "Adaptive electrical impedance tomography resolution enhancement using statistically quantized projected image sub-bands," *IEEE Access*, vol. 8, pp. 99797–99805, 2020.

[20] D. Khodadad, S. Nordebo, N. Seifnaraghi, R. Yerworth, A. D. Waldmann, B. Muller, I. Frerichs, A. van Kaam, M. Miedema, and R. Bayford, "The value of phase angle in electrical impedance tomography breath detection," in *Proc. Prog. Electromagn. Res. Symp. (PIERS-Toyama)*, Aug. 2018, pp. 1040–1043.

[21] C. M. Pais and S. A. González, "A new method to detect apneas in neonates," in *Proc. Workshop Eng. Appl.*, 2017, pp. 667–678.

[22] D. M. Tveit, K. Engan, I. Austvoll, and O. Meinich-Bache, "Motion based detection of respiration rate in infants using video," in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Sep. 2016, pp. 1225–1229.

[23] N. Koolen, O. Decroupet, A. Dereymaeker, K. Jansen, J. Vervisch, V. Matic, B. Vanrumste, G. Naulaers, S. Van Huffel, and M. De Vos, "Automated respiration detection from neonatal video data," in *Proc. Int. Conf. Pattern Recognit. Appl. Methods*, 2015, pp. 164–169.

[24] J. Mauricio Ochoa, J. S. Osorio, R. Torres, and C. N. McLeod, "Development of an apnea detector for neonates using diaphragmatic surface electromyography," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Sep. 2009, pp. 7095–7098.

[25] D. Novak, K. Mucha, and T. Al-Ani, "Long short-term memory for apnea detection based on heart rate variability," in *Proc. 30th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug. 2008, pp. 5234–5237.

[26] J. V. Marcos, R. Hornero, D. Álvarez, F. del Campo, and C. Zamarrón, "Assessment of four statistical pattern recognition techniques to assist in obstructive sleep apnoea diagnosis from nocturnal oximetry," *Med. Eng. Phys.*, vol. 31, no. 8, pp. 971–978, Oct. 2009.

[27] B. Yılmaz, M. H. Asyalı, E. Arıkan, S. Yetkin, and F. Özgen, "Sleep stage and obstructive apneaic epoch classification using single-lead ECG," *Biomed. Eng.*, vol. 9, no. 1, pp. 1–14, 2010.

[28] S. Dunlop, J. Hough, T. Riedel, J. F. Fraser, K. Dunster, and A. Schibler, "Electrical impedance tomography in extremely prematurely born infants and during high frequency oscillatory ventilation analyzed in the frequency domain," *Physiological Meas.*, vol. 27, no. 11, p. 1151, 2006.

[29] I. Frerichs, M. B. P. Amato, A. H. van Kaam, D. G. Tingay, Z. Zhao, B. Grychtol, M. Bodenstein, H. Gagnon, S. H. Böhm, E. Teschner, O. Stenqvist, T. Mauri, V. Torsani, L. Camporota, A. Schibler, G. K. Wolf, D. Gommers, S. Leonhardt, A. Adler, and T. study group, "Chest electrical impedance tomography examination, data analysis, terminology, clinical use and recommendations: Consensus statement of the TRanslational EIT developmeNt stuDy group," *Thorax*, vol. 72, no. 1, pp. 83–93, Jan. 2017.

[30] X. X. Niu and C. Y. Suen, "A novel hybrid CNN–SVM classifier for recognizing handwritten digits," *Pattern Recognit.*, vol. 45, no. 4, pp. 1318–1329, 2012.

[31] G. M. Fung, O. L. Mangasarian, and J. W. Shavlik, "Knowledge-based support vector machine classifiers," in *Proc. Adv. Neural Inf. Process. Syst.*, 2003, pp. 537–544.

[32] L. C. Yan, Y. S. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 251, no. 7553, pp. 436–444, 2015.

[33] H. C. Shin, H. R. Roth, M. Gao, L. Lu, Z. Xu, I. Nogues, J. Yao, D. Mollura, and R. M. Summers, "Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning," *IEEE Trans. Med. Imag.*, vol. 35, no. 5, pp. 1285–1298, Feb. 2016.

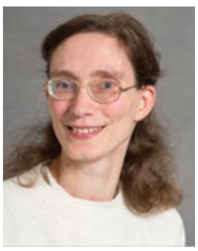
[34] X. Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri, and R. M. Summers, "ChestX-ray8: Hospital-scale chest X-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jul. 2017, pp. 2097–2106.

[35] I. M. Baltruschat, H. Nickisch, M. Grass, T. Knopp, and A. Saalbach, ''Comparison of deep learning approaches for multi-label chest X-ray classification,'' *Sci. Rep.*, vol. 9, no. 1, pp. 1–10, Dec. 2019.
[36] P. Khojasteh, L. A. Passos, Jr., T. Carvalho, E. Rezende, B. Aliahmad, J. P. Papa, and D. K. Kumar, ''Exudate detection in fundus images using deeply-learnable features,'' *Comput. Biol. Med.*, vol. 104, pp. 62–69, Jan. 2019.
[37] A. S. B. Reddy and D. S. Juliet, ''Transfer learning with ResNet-50 for malaria cell-image classification,'' in *Proc. Int. Conf. Commun. Signal Process. (ICCSP)*, Apr. 2019, pp. 945–949.
[38] A. Krizhevsky, I. Sutskever, and G. E. Hinton, ''Imagenet classification with deep convolutional neural networks,'' in *Proc. Adv. Neural Inf. Process. Syst.*, 2012, pp. 1097–1105.
[39] K. Nguyen, C. Fookes, A. Ross, and S. Sridharan, ''Iris recognition with off-the-shelf CNN features: A deep learning perspective,'' *IEEE Access*, vol. 6, pp. 18848–18855, 2018.

NAFISEH VAHABI (Member, IEEE) received the M.Eng. degree in computer science with artificial intelligence from the Department of Electronics and Computer Engineering, University of Southampton, U.K., in 2013, the master's degree (MRes) in medical robotics and image guided intervention from Imperial College London, U.K., in 2014, and the Ph.D. degree from the Department of Electronic and Electrical Engineering, University College London (UCL), in 2019.

She is currently a Research Fellow with the Sensors, Systems, and Circuit Group, Department of Electronic and Electrical Engineering, UCL. She is also an Associate Fellow of the Higher Education Academy. Her research interests include machine learning, deep learning, image processing, and signal processing.

She is a member of the Institute of Engineering and Technology and the IEEE Woman in Engineering. She was awarded the scholarship from the Engineering and Physical Sciences Research Council (EPSRC) to pursue the Ph.D. degree and was awarded a EPSRC Doctoral Prize Fellowship to develop deep learning algorithms to analyze electrical impedance tomography datasets from premature neonatal lungs.



REBECCA YERWORTH received the MRes degree in advanced instrumentation studies and the Ph.D. degree in fluid flow in incontinence pads from the University College London, in 1996 and 2000, respectively, and the PGCE (post compulsory education) from the Institute of Education, London, in 2008. She is currently a Senior Teaching Fellow with the Department of Medical Physics and Biomedical Engineering, University College London. Her research interest includes electrical impedance tomography.

MARTIJN MIEDEMA received the M.D. and Ph.D. degrees. He is currently working with the Emma Children's Hospital, Amsterdam UMC, University of Amsterdam, The Netherlands.

ANTON VAN KAAM is currently a Professor of Neonatology with the Faculty of Medicine, University of Amsterdam (AMC-UvA). He is also a Paediatrician-Neonatologist with the Emma Children's Hospital (EKZ), Academic Medical Center (AMC), Amsterdam. Since 2010, he has been the Head of the AMC's Neonatology Intensive Care Unit. He also studies the effects of clinical interventions on the lung function and the risk of long-term damage to the lungs (bronchopulmonary dysplasia). He has a special interest in mechanical intervention and the use of adrenal gland hormones (steroids).

Prof. Van Kaam is a member of the Netherlands Neonatal Research Network (NNRN), the Chairman of the Neonatal Pulmonology Section of the Dutch Society of Neonatology, a member of the Neonatal Pulmonology Section of the European Society of Pediatric Research, and the Chairman of the Board of Dutch Neonatal Intensive Care Unit directors.

RICHARD BAYFORD (Life Senior Member, IEEE) received the Ph.D. degree. He is currently the Director of Biophysics with the Centre for Investigative Oncology, the Head of Biophysics, an Engineering group, and a Professor of Biophysics and Engineering with Middlesex University, and a Visiting Professor with the UCL Department of Electronic and Electrical Engineering. His research interests include biomedical imaging, bio-modeling, nanotechnology, deep brain stimulation, tele-medical systems, instrumentation, and biosensors. He has worked as PI on many EPSRC, EU, and industrial sponsored research projects and attracted over£12M funding. He has published more than 300 articles in the above research fields. He has recently coordinator on a €5.5M H2020 Grant (CRADL). He is a Fellow of the Institute of Physics, FInstIPEM, Fellow of the Royal Society of Biology, and a Senior Member of IEE. He was awarded EPSRC Bright ideas project and recently EPSRC PNEUMACRIT (£1.8M). He has chaired the journal committee for IPEM. From 2008 to 2013, he served as the Editor-in-Chief for *Physiological Measurement* and as the Vice Chair Publications and Communications of the European Federation of Organisations for Medical Physics.

ANDREAS DEMOSTHENOUS (Fellow, IEEE) received the B.Eng. degree in electrical and electronic engineering from the University of Leicester, Leicester, U.K., the M.Sc. degree in telecommunications technology from Aston University, Birmingham, U.K., and the Ph.D. degree in electronic and electrical engineering from University College London (UCL), London, U.K., in 1992, 1994, and 1998, respectively.

He is currently a Professor with the Department of Electronic and Electrical Engineering, UCL, and leads the Analogue and Biomedical Electronics Group. He has made outstanding contributions to improving safety and performance in integrated circuit design for active medical devices, such as spinal cord and brain stimulator. He has numerous collaborations for cross-disciplinary research, both within the U.K. and internationally. He has authored more than 300 papers in journals and international conference proceedings, several book chapters, and holds several patents. His research interests include analogue and mixed-signal integrated circuits for biomedical, sensor, and signal processing applications. He is a Fellow of the Institution of Engineering and Technology and a Chartered Engineer. He was a co-recipient of a number of best paper awards and has graduated many Ph.D. students. From 2006 to 2007 and from 2008 to 2009, he was an Associate Editor. From 2014 to 2015, he was the Deputy Editor-in-Chief of the IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS—II: EXPRESS BRIEFS. From 2016 to 2019, he was the Editor-in-Chief of the IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS—I: REGULAR PAPERS. He is an Associate Editor of the IEEE TRANSACTIONS ON BIOMEDICAL CIRCUITS AND SYSTEMS. He serves for the International Advisory Board of Physiological Measurement. He has served on the technical committees for a number of international conferences, including the European Solid-State Circuits Conference (ESSCIRC) and the International Symposium on Circuits and Systems (ISCAS).