Review Article

Artificial Intelligence-Driven Wearable Technologies for Neonatal Cardiorespiratory Monitoring: Part 2 Artificial Intelligence

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Artificial Intelligence, Cardiorespiratory, Health Monitoring, Heart, Lung, Machine learning, Neonatal, Newborn, Infant, Wearable.

Impact Statement

- State-of-the-art review in artificial intelligence used for wearable neonatal cardiorespiratory monitoring
- Taxonomy design for artificial intelligence (AI) methods
- Comparative study of AI methods based on their advantages and disadvantages

Abstract

Background
With the development of Artificial Intelligence (AI) techniques, smart health monitoring, particularly neonatal cardiorespiratory monitoring with wearable devices is becoming more popular. To this end, it is crucial to investigate the trend of AI and wearable sensors being developed in this domain.

Methods
We perform a systematic review of papers published in IEEE Xplore, Scopus, and PubMed from the year 2000 onwards, to understand the use of AI techniques for neonatal cardiorespiratory monitoring with wearable technologies. We reviewed the advances in AI development for this application and potential future directions. To review the advances in AI for this application, we assimilated machine learning algorithms developed for neonatal cardiorespiratory monitoring, designed a taxonomy, and categorised the methods based on their learning capabilities and performance.

Results
For the AI approach, 63% of studies utilised traditional machine learning techniques and 35% of papers utilised deep learning techniques, including 6% that applied transfer learning on pre-trained models.

Conclusion
A detailed review of AI methods for neonatal cardiorespiratory wearable sensors is presented along with their advantages and disadvantages. Hierarchical models are presented and suggestions for future developments are highlighted to translate these AI technologies into patient benefit.

1. Introduction

The United Nations created the 3.2.2. Sustainable Development Goal to reduce neonatal mortality to 1.2% of live births by 2030 (1). Virtually all (99%) of neonatal deaths occur in the developing world, in low and middle-income countries (2, 3). These deaths are associated with conditions and diseases due to lack of skilled care in the critical early stages of life (4). According to the World Health Organization, effective care could reduce deaths by 75% (3). A key factor to essential care is monitoring and assessment for signs of serious health problems, in particular for sick, low birth weight and preterm babies in the hospital and home environments. The major causes of mortality relate to cardiorespiratory conditions such as pneumonia, underdeveloped lungs due to preterm birth and birth asphyxia (2-5). Hence, cardiorespiratory monitoring is essential, as it enables detection, monitoring and prognosis of diseases, allowing timely and specific care to be provided (3, 4).

Wearable technology enables continuous cardiorespiratory monitoring in both hospital and home environments. When used in conjunction with AI, it offers the possibility of early detection of diseases, reducing the workload for clinicians, and providing the best possible outcomes for newborns. This review investigates the usage of AI and wearable technology for neonatal cardiorespiratory monitoring. Wearable technologies were reviewed in detail in part 1 of our review article. We now focus on AI techniques for neonatal cardiorespiratory monitoring in part 2.

For the purposes of this study, AI refers to machine learning techniques used to detect or predict a cardiorespiratory condition or process signals to obtain cardiorespiratory information. These techniques have ranged from traditional machine learning-based classifiers to deep learning models. AI-driven wearable technologies have shown promise in continuous health monitoring for paediatric clinical practice (6). These applications have included disease diagnosis, individualised treatment guidance, and prognostic evaluation (7). For example, Goulooze et al. (8) discussed how AI methods such as linear models, tree-based models, and deep learning-based models can be applied to datasets achieved from wearable sensors using analytes (e.g., sweat) in infants. Furthermore, Hunter et al. proposed the application of supervised AI methods such as Support Vector Machine (SVM) and eXtreme Gradient Boosting (XGBoost) algorithms on the waveforms achieved from pulse oximeters for the clinical judgement of capillary refill time in children (9).

Although the use of AI for neonatal monitoring has great potential, it has not been widely studied. It is crucial to identify the feasibility and potential of AI methods on the datasets extracted from wearable technologies in neonatal cardiorespiratory monitoring. This review offers a detailed study of wearable technologies and how they could be driven by AI methods for neonatal cardiorespiratory monitoring. This review will help inform the future direction of the best AI techniques to accompany the most promising wearable technologies in this domain.

The search methodology used in this study is presented in **Section 2**. We describe the various AI technologies used with wearable sensors for neonatal cardiorespiratory monitoring (**Section 3**). Under this section, we present the evolution of AI technologies, followed by a novel taxonomy design and analysis of each technique. The proposed taxonomy helps the understanding of the types of AI technologies (e.g., traditional machine learning and deep learning) being employed in the literature. It helps identify an appropriate AI technique that could be useful according to the clinical requirements. For example, the traditional machine learning methods are, in most cases, interpretable and explainable, and require less data for training. For this reason, these methods have been preferred by clinicians. For example, the traditional machine learning methods are, in most cases, interpretable and explainable, and require less data for training. For these reasons, these methods have been preferred by clinicians as discussed in the literature. Furthermore, the documentation of the evolution and progress of AI technologies, and analysis of the benefits and drawbacks of each technique, enables us to select the best AI technique based on the needs of the health practitioners. Lastly, we recommend the most popular wearable sensors and AI methods to be used in the future, based on their advantages and disadvantages, evolution, and taxonomy (**Sections 4 and 5**).

2. Systematic Review Methodology

A systematic search was proposed for wearable technology and AI for neonatal cardiorespiratory monitoring. In part 1 of our review article, we found 117 articles related to wearable technology for neonatal cardiorespiratory monitoring. Of these 117 articles, 14 were included as they were related to artificial intelligence.

An additional search in google scholar was also performed with the below query string on 05 January 2022:

1. Restrict to neonatal population
    a. Search terms: "Neonatal", "Pediatric" and "Paediatric"
2. Restrict to wearable technology
    a. Search terms: "Wearables"
3. AI
    a. Search terms: "Artificial Intelligence", "Machine Learning" and "Deep Learning"
4. Restrict to cardiorespiratory monitoring
    a. Search terms: "Cardiac", "Heart", "Respiratory", "Lung", "Breathing"

This resulted in a total of 1,680 articles. Those articles that were unrelated (i.e., not neonatal, AI, nor cardiorespiratory monitoring focused) and missing full-text and/or minimal information provided were removed. Two authors (CS and EG) independently searched for any additional articles. Six further papers were obtained using a snowballing technique. In total 56 articles were obtained to review in this paper. The detailed PRISMA flow diagram is presented in **Figure 1**. Based on the literature review in the neonatal cardiorespiratory monitoring-related articles, we designed a new taxonomy to provide more insights into AI techniques under the study domain. Similarly, we plotted the stacked plot to show the popularity of AI methods in this study.

3. AI Techniques

For neonatal health monitoring, AI techniques have been used on data obtained from both wearable and non-wearable devices (10, 11). To implement the AI techniques in general, there are four major steps: i) data extraction, ii) pre-processing, iii) training and iv) testing steps (12). For example, the continuous data obtained from wearable technologies such as textile electrodes (e.g., ECG), or non-wearable devices such as digital stethoscopes (e.g., heart and lung sound) are pre-processed to remove artefacts and noises, which are used for training the AI models. Furthermore, the pre-processing task depends on the nature of extracted data. As an example, ECG signals are notch filtered at 50 Hz (13) and band-pass filtered. Audio signals are also band-pass filtered (14). The AI techniques identified for this application are classified into three broad groups: supervised learning (6), unsupervised learning (15), and reinforcement learning (RL) (16). Here, our focus is on AI techniques for cardiorespiratory monitoring with wearable technology. Thus, in the next subsection, we focus on the evolution, taxonomy and comparative study of AI techniques being used for cardiorespiratory monitoring on wearable data. Then in the following subsections, we present AI techniques that have been used for neonatal cardiorespiratory monitoring and are suitable for data collected from wearable sensors.

3.1. Evolution of AI

In this section, the evolution of AI techniques is presented using six different perspectives.

3.1.1. Wearable Cardiorespiratory Monitoring for Infants

The initial AI work using wearable cardiorespiratory monitoring was conducted in 2012, which employed the SVM algorithm with radial basis function on pulse oximetry data acquired from neonates (6). The SVM, which is a popular traditional machine learning algorithm, classifies data based on the hyperplanes, which can be linear, polynomial, and radial basis functions. Patron et al. (17) and Mongan et al. (18) employed the SVM algorithm and artificial neural network (ANN) respectively, on data collected from radio-frequency identification (RFID) tags in a wearable belt. The ANN is a deep learning-based algorithm, which contains different intermediate layers for the semantic information, and requires one-dimensional feature vector representation to train the model during classification. Furthermore, Vu et al. (13) employed different combinations of popular traditional machine learning algorithms such as Decision tree, SVM, k-nearest neighbours (K-NN), and deep learning-based algorithm (ANN) as a 2-stage classifier on ECG data. First, they selected the combination of the classifiers giving the optimal performance. Second, they used the optimal classifier to perform the final classification procedure. The decision tree algorithm is based on the rules, which splits data into roots and nodes during classification.

De Greef et al. (19) employed the traditional machine learning algorithm, called random forest (RF) algorithm, to classify the vital signs data obtained from the clothing wearable sensors for newborn heart diseases detection. At the same time, Munz and Wolf (20) realised the importance of deep learning-based approach and proposed to use the ANN algorithm for the classification of infant breathing patterns on data obtained from the breathing sensor. Furthermore, Acharya et al. (10) utilised three multiple classifiers (naive bayes (NB), logistic regression (LR), and decision trees) for neonatal respiratory monitoring on data obtained from the abdomen and shoulder. In the meantime, considering the efficacy of LR for the classification, Raknim et al. (21) employed multiple LR models for neonatal sepsis monitoring on the data achieved from the wearable ballistocardiography sensor.

Using traditional machine learning algorithms, Urdal et al. (22) implemented the Vu classifier for newborn resuscitation detection on ECG data. They also used accelerometer data to observe the heart rate during different activities. These activities included chest compressions, back stimulation, tactile stimulation, drying thoroughly, moving the baby and uncategorised movements. Furthermore, Ostojic et al. (23) proposed to use four traditional machine learning algorithms (decision tree, K-NN, NB, and SVM) on pulse oximetry data for reducing the false alarm rate. Here, the NB algorithm considers the prior and posterior probabilities to predict the class labels in the data. Similarly, Shamsir et al. (24) proposed deep learning-based methods (convolutional neural network (CNN) and long short-term memory (LSTM)) for the classification of neonatal breathing and blood oxygen level data obtained from thermal sensors to detect respiratory failure. The LSTM model captures the sequential information of data during classification. Xu et al. (25) employed both deep learning-based (ANN) and traditional machine learning-based methods (LR) on the vital signs data extracted from two patches stuck on the neonate's body. LR is based on the statistical model that employs the logistic function to learn the data. Following the efficacy of traditional machine learning methods, Hansen et al. (26) employed the hidden Markov Model (HMM) coupling with the higher-order features obtained from the Minkowski and Mahalanobis distances on multi-tag RFID measurements from abdominal belts for neonatal respiratory monitoring.

More recently, Vahabi et al. (27) proposed to use deep learning-based (ResNet-50) and traditional machine learning-based methods (SVM) on wearable electrical impedance tomography (EIT) data for neonatal sleep apnoea detection. Here, the ResNet-50, a 50-layer deep learning model, extracts the semantic information of the input image using the residual connection (the output of a layer is a convolution of its input plus input) and batch normalization.

3.1.2. Electrical-Based Cardiorespiratory Monitoring

Four studies reported using electrical-based sensors for cardiorespiratory monitoring. Khodadad et al. (28) devised a breath detector classifier, which is based on traditional machine learning-based method, on the EIT data for lung function. This classifier relies on zero-crossing, which utilises the optimised threshold parameters above and below the zero value of the data for the classification. Gomez et al. (29) used several traditional machine learning algorithms such as RF, LR, and K-NN to detect the heart rate variability (HRV) for neonatal sepsis on ECG data. The RF algorithm is an ensemble learning algorithm that creates multiple decision trees during training and ensembles the output from multiple trees. The K-NN algorithm classifies the ECG data based on similarity matching. Their results show that the proposed model can assist physicians in remote monitoring. Also, Mahmud et al. (30) employed the XGBoost algorithm, a traditional machine learning algorithm, on ECG data of neonates. The XGBoost algorithm is a decision tree-based ensemble algorithm, using gradient boosting. More recently, Macfarlane et al. (31) recommended the deep learning-based method (CNN model) for the ECG interpretation during monitoring of both neonates and adults as ANN was not found to be superior. The CNN algorithm employs the visual input and extracts the semantic information after the several levels of convolution operation across the input image.

3.1.3. Optical-Based Cardiorespiratory Monitoring

Three studies report optical-based sensors for data extraction during cardiorespiratory monitoring. Villarroel et al. (32) employed the deep learning-based models (VGG-16 and ResNet-50) to monitor the vital signs on video and pulse oximeter data collected from preterm infants. The original VGG-16 model comprises 16 deep layers to extract the semantic information of the input image (e.g., video frame) during its analysis. Hunter et al. (9) employed the traditional machine learning based methods (SVM and XGBoost algorithms) on pulse oximeter data for the clinical judgement of capillary refill time in children aged 1 to 12. The XGBoost algorithm is a decision tree-based ensemble algorithm, using gradient boosting. Recently, Huang et al. (33) employed both video and PPG data obtained from pulse oximeter data to train the deep learning-based model (LSTM model) for neonatal heart rate monitoring.

3.1.4. Mechanical-Based Cardiorespiratory Monitoring

The first AI work for cardiorespiratory monitoring using mechanical-based sensors for newborns was carried out in 2001. The researchers implemented the deep learning-based method (ANN algorithm) on data captured from a digital stethoscope attached to the infant (12). After 14 years, there was a gradual increase in mechanical-based sensors for neonatal cardiorespiratory monitoring. Amiri et al. (34) proposed the use of an RF algorithm, a traditional machine learning-based method, for heart murmur detection on phonocardiogram (PCG) data achieved from a digital stethoscope that was connected to a mobile phone. Bokov et al. (35) employed the SVM algorithm for wheeze detection on the audio data recorded using smartphones in the paediatric population. In 2016, Sola et al. (36) proposed to use traditional machine learning-based algorithms (Gaussian mixture model (GMM) and HMM) on the Mel-frequency filter bank from audio signals obtained from the digital stethoscope to detect childhood pneumonia. The GMM helps learn the unsupervised pattern of data, whereas the HMM helps find the sequential pattern of data.

In 2018, three groups reported cardiorespiratory monitoring using mechanical-based sensors. Shelevytsky et al. (37) proposed to use the traditional machine learning-based method (SVM) for the classification of PCG data during the heart condition classification of the newborn. Bardou et al. (15) employed different algorithms such as K-NN, SVM, GMM, and CNN algorithms on the audio data extracted by digital stethoscopes from the heart of different age groups, including newborns and adults. To train the traditional machine learning-based algorithms (K-NN, SVM, and GMM), the handcrafted features for audio data were used, whereas, for the deep learning-based method (CNN), the spectrogram that is the visual representation of audio data was used. In their work, handcrafted features include the Mel frequency cepstral coefficients and texture features. Ramanathan et al. (38) underscored the application of the deep learning-based method (ANN) being used in a digital stethoscope used for extracting audio signals from the human body, including children and newborns.

In 2020, Grooby et al. (39) applied SVM, Decision trees, K-NN, and dynamic classifier for the classification during the quality assessment of chest sounds obtained from a digital stethoscope. Here, the dynamic classifier is based on the ensemble approach, which selects the optimal base classifiers or their combination to improve the performance. Their result shows that the dynamic classifier outperforms the individual classifiers.

By 2021, there are an increasing number of studies using AI reported in the literature for cardiorespiratory monitoring. Gomez-Quintana et al. (40) employed the XGBoost algorithm, for the classification of neonatal PCG signals that were obtained from a digital stethoscope. Apart from traditional machine learning-based methods in the same year, Jani et al. (41) suggested using a deep learning-based method (ANN) on the PCG data obtained from the digital stethoscope for heart murmur detection from neonatal to adult health monitoring. Similarly, Oliveira et al. (42) highlighted the application of heart murmur detection using ANN and logistic regression, from a paediatric and neonatal population on PCG data. Grooby et al. (43, 44) proposed to use deep learning-based algorithms (e.g., YAMNet), and traditional machine learning-based algorithms (e.g., non-negative matrix co-factorisation (NMCF), SVM, decision trees, K-NN, and LR) for neonatal chest sound separation, which contains both noisy and mixed samples as well as heart/lung quality assessment problems on digital stethoscope data. Last but not the least, Gomez-Quintana et al. (14) employed the XGBoost algorithm for the classification of neonatal PCG signals. In their work, the XGBoost algorithm is responsible for detecting patent ductus arteriosus in neonates.

3.1.5. Multi Sensor-Based Cardiorespiratory Monitoring

Research using multi sensor-based cardiorespiratory monitoring began in 2013. The purpose of their AI method is to predict mortality of infants. Furthermore, Rinta-Koski et al. (45) used Gaussian process classifier on standard clinical features, which includes heart rate and blood pressure, to predict mortality. Gaussian process classifier is based on Laplace approximation, which focuses on the posterior probabilities of the variables. Following the similar trend of using traditional machine learning-based algorithms, Pais et al. (46) employed the LDA algorithm for the classification of ECG and pulse oximetry data to determine the heart rate variability. The LDA algorithm expresses the data as the linear combination of features that discriminate between two or more classes. Here, the LDA algorithm is responsible for detecting the apnoea in neonates.

Similarly, Jalali et al. (47) also proposed to use the SVM classifier for the classification of periventricular leukomalacia after cardiac surgery. Their method utilises vital signs of neonates, including heart rate data achieved from pulse oximetry. In their method, SVM is used to predict periventricular leukomalacia based on vital signs data. Moreover, Joshi et al. (48) proposed to use the XGBoost algorithm trained on heart rate, breathing rate and pulse oximetry data obtained from neonates to predict critical cardiorespiratory conditions. Hassan et al. (49) employed the ANN to detect sleep apnoea on temperature and pulse oximeter data from neonates. Similarly, Pini (50) utilised the random forest and K-NN algorithms for the maternal, foetal, and neonatal profiling of the physiological signals with the qualitative data such as maternal lifestyle factors.

Recently in 2021, Zuzarte et al. (51) employed GMM and LR methods for the classification of cardiorespiratory and movement features achieved from the pulse oximeter and ECG electrodes. The GMM and LR methods are used to detect neonatal apnoeic events. Their results suggest that the use of such technologies helps reduce morbidity and mortality. Cabrera-Quiros et al. (52) utilised LR, NB, and nearest mean classifiers for the detection of late onset sepsis on continuous high resolution ECG and chest impedance data in neonates. The nearest mean classifier, also called rocchio classifier, classifies the data to the nearest mean of the training data belonging to the class.

3.1.6. Review Papers

Here, we discuss review papers providing information related to neonatal, paediatric, and/or adult health monitoring, including cardiorespiratory, using AI techniques on either wearable or non-wearable-based data.

In 2019, Chisi et al. (53) suggested using AI techniques for overall health monitoring on clinical data obtained from wearable sensors such as ECG and pulse oximeter data in the paediatric population. Tandon et al. (54) also highlighted the efficacy of machine learning algorithms for the detection of paediatric cardiovascular disease on continuous physiological data (CPD) obtained from wearable biosensors.

Ranjit and Kissoon (16) discussed different applications of AI technique, particularly reinforcement learning for early detection of sepsis and septic shock in the paediatric population on different data such as respiratory rate, heart rate and SpO2. During the same year, Chong et al. (55) highlighted the use of decision trees and RF for the health monitoring of heart rate, breathing rate, and oxygen saturation in the paediatric population. Goulooze et al. (8) explained algorithms such as RF and decision trees for the paediatric and neonatal health monitoring such as neonatal sepsis detection on the early results of laboratory tests and nursing observations. Johnson et al. (56) underscored the importance of machine learning algorithms for health monitoring, including neonatal population on clinical features such as heart rate, breathing rate and oxygen level. They highlighted these data could be extracted using mobile devices and body-worn wearable sensors. Memon et al. (57) underscored the application of machine learning algorithms on the data extracted from the RFID-based abdominal band sensors capturing the breathing rate of neonates. Hasan et al. (58) also discussed the machine learning algorithms for neonatal health monitoring using vital signs data (e.g., heart rate, oxygen level, etc.) achieved from the wearable sensors.

Sobhan et al. (59) elaborated the popular AI techniques (e.g., LR and SVM) for the heart and respiration functions on the health data (e.g., ECG and SCG) collected using wearable or non-wearable sensors for both adult and non-adult population. Lin et al. (60) discussed using deep learning methods for the classification of heart sound signals on wearable data, including ECG and PCG for both neonatal and adult health monitoring. Furthermore, Lyu et al. (61) also underscored the use of deep learning-based algorithms (e.g., ANN, CNN and LSTM) on the wearable data (e.g., ECG and blood pressure,) for both neonatal and adult health monitoring in 2021.

The overall evolution of AI techniques ranging from 2001 to 2021 is summarised using a stacked bar plot, which is presented in **Figure 2** and a timeline in **Figure 3**. From **Figure 2**, we observed that the SVM algorithms are the most popular (12 publications), whereas the ANN (10 publications) is the second most used algorithms in the literature. This data shows that the traditional machine learning-based algorithm (e.g., SVM) is still dominant for neonatal cardiorespiratory monitoring despite the great promise of the deep learning-based algorithm (ANN) in this domain.

3.2. Taxonomy of AI Techniques used with Wearable Technology for Neonatal Cardiorespiratory Monitoring Purpose

Based on the research works using several AI methods for cardiorespiratory monitoring in the literature, we categorise them into three broad categories: traditional machine learning-based (e.g., SVM (39), Decision trees (13), etc.), deep learning-based (e.g., CNN (24), LSTM (24), etc.) and reward/punishment-based AI methods (e.g., RL method (16)). Deep learning-based methods (24) extract the higher-order information from the input data to improve the performance. The higher-order information is achieved by using different operations such as convolution and activation; however, traditional machine learning-based AI techniques do not produce such types of information during their learning process. The reward/punishment-based AI techniques (e.g., RL algorithm) learn the data based on rewards and punishment strategy as discussed in the previous **Section 3.1**. Under the traditional AI techniques, there are several algorithms, for example, SVM, RF, Logistic regression, etc. The deep learning-based AI techniques are further divided into two groups: pre-trained and non-pre-trained AI techniques. Pre-trained AI techniques (e.g., ResNet-50, VGG-16, etc.) have been already pre-trained with large datasets (e.g., image datasets), which help produce features based on them, whereas non-pre-trained AI techniques (e.g., LSTM) need to be trained from scratch. The taxonomy is presented in **Figure 4**.

3.3. Comparison of AI Techniques used with Wearable Technology for Neonatal Cardiorespiratory Monitoring

The AI technologies used for neonatal cardiorespiratory monitoring have their own peculiarities and importance in terms of applicability and viability. For example, most of the traditional AI techniques are more appropriate for a limited number of samples that are prevalent in biomedical research. Also, they have a higher level of interpretability, which helps establish trust and acceptability among clinicians and healthcare professionals. **Table 1 and 2** summarises the comparison of different AI techniques used in cardiorespiratory monitoring alongside their advantanges and disadvantages. We compare the AI methods based on several factors such as model complexity, performance, and interpretability.

4. Discussion

Here, we discuss the overall AI techniques and sensor technologies being adopted in neonatal cardiorespiratory monitoring. Specifically, the evolving trends of AI techniques and sensor technologies being studied.

For data collected from wearable sensors, AI has been used mainly for apnoea detection, along with sepsis and general critical health detection. However, as presented in **Section 3.1.1.** and **Supplementary Table 1**, there have been few studies that evaluate the use of wearable sensor collected data. Whilst many of the existing AI techniques presented for neonatal cardiorespiratory monitoring in this paper should be suitable, further research and clinical validation would be required. This is especially important as wearable sensor data is typically more prone to noise such as motion artefact and typically provides weaker physiological signals. Therefore, it would be expected these AI techniques would either not work off-the-shelf or provide lower accuracy than reported. In future, the use of AI to improve the signal quality of wearable sensor collected data would be of interest to resolve this limitation. Furthermore, wearable sensors typically offer the opportunity of multiple physiological signals and vitals which has yet to be fully utilised in AI techniques.

From **Figures 2, 3**, **and 4** we saw that more AI techniques, including both traditional machine learning and deep learning-based, have been used for neonatal cardiorespiratory monitoring. Also, we noted that the SVM algorithm is the most popular AI technique to date, particularly prior to 2019. After 2019, there are several emerging AI techniques, including K-NN, ANN, SVM, RF, LR, and XGBoost. Furthermore, the number of traditional machine learning-based methods outnumber the number of deep learning-based and reward/punishment-based methods (**Figure 2**). In addition, some of the classifiers such as Gaussian process classifiers that published before 2019 are less popular in recent years, whereas methods such as XGBoost and LR are on the rise along with the deep learning-based methods such as LSTM and ResNet-50.

The taxonomy diagram in **Figure 4** illustrates that AI techniques for cardiorespiratory monitoring on wearable data are moving towards more traditional machine learning-based methods. As an example, the SVM classifier, one of the most popular algorithms, is being used mostly for classification problems. The reasons for their popularity could be explained twofold. First, traditional machine learning models (59) are easy to implement and have fewer hyperparameters, thereby reducing the time for the optimal model deployment. Second, health practitioners/clinicians prefer interpretable and explainable AI models. The traditional AI methods are mostly interpretable and explainable and could work on limited data.

We observe that both deep learning-based methods and traditional machine learning-based methods have both advantages and disadvantages in their application (**Table 1**). For instance, SVM may work for higher dimensional data, but it fails to produce the expected result using big data. However, deep learning-based methods (32) such as ResNet-50 and VGG-16, might be more useful with big data, but less so limited data.

Furthermore, we compared AI methods in terms of explainability and performance (**Table 2**). From **Table 2**, we observed that the highest-performing algorithms are ANN and K-NN, which provide the highest specificity of 100% and 99.46%, respectively. Regarding explainability and interpretability features, the ANN algorithm is difficult to explain and interpret, whereas K-NN is interpretable and explainable.

Whilst AI offers great promise in the home and hospital environment, further studies are required in two areas. Firstly, the impact of the AI algorithms needs to be investigated to demonstrate the benefit of these algorithms to improve health (reduction in mortality and morbidity) and financial (reduction in clinician workload and health interventions) outcomes. Secondly, studies determining the acceptability and key concerns of these AI algorithms from clinicians in the hospital environment and parents in the home environment are required. These two areas are important in order to see the translation of these AI techniques from research into clinical practice.

5. Conclusions

We reviewed several AI techniques for neonatal cardiorespiratory monitoring on wearable data and designed a heirachical taxonomy and AI timeline based on them. We found the rising popularity of traditional AI methods (e.g., SVM, XGBoost) compared to deep learning-based methods (e.g., ANN, CNN). Our study also found that the application of AI methods in this domain is still in its infancy. As more sensor technology develops and produces more data, we need to identify the best AI methods in this domain.

Data Availability Statement

Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

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- Substantial contributions to conception and design, acquisition of data, or analysis and interpretation of data- Chiranjibi Sitaula, Ethan Grooby, T'ng Chang Kwok, Don Sharkey, Faezeh Marzbanrad, Atul Malhotra
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