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REVIEW ARTICLE

# Artificial intelligence-driven wearable technologies for neonatal cardiorespiratory monitoring. Part 2: artificial intelligence

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**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 performed a review of papers published in IEEE Xplore, Scopus, and PubMed from the year 2000 onwards, to understand the use of AI for neonatal cardiorespiratory monitoring with wearable technologies. We reviewed the advances in AI development for this application and potential future directions. For this review, we assimilated machine learning (ML) algorithms developed for neonatal cardiorespiratory monitoring, designed a taxonomy, and categorised the methods based on their learning capabilities and performance.
**RESULTS:** For AI related to wearable technologies for neonatal cardio-respiratory monitoring, 63% of studies utilised traditional ML techniques and 35% utilised deep learning techniques, including 6% that applied transfer learning on pre-trained models.
**CONCLUSIONS:** A detailed review of AI methods for neonatal cardiorespiratory wearable sensors is presented along with their advantages and disadvantages. Hierarchical models and suggestions for future developments are highlighted to translate these AI technologies into patient benefit.

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**IMPACT:**

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

## INTRODUCTION

The United Nations 3.2.2 Sustainable Development Goal aims 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.[4] According to the World Health Organisation, effective care could reduce deaths by 75%.[3] A key factor to essential care is monitoring and assessment for signs of serious health problems, particularly for sick, low birth weight and preterm babies. 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 the 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. 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. 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.

In this study, AI refers to the techniques used to detect or predict a cardiorespiratory condition or process signals to obtain cardiorespiratory information. These techniques have ranged from traditional ML 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]

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 data sets extracted from wearable technologies in 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.

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The search methodology used in this study is presented in "Review methodology". We describe the various AI technologies used with wearable sensors for neonatal cardiorespiratory monitoring ("AI techniques"). 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 being employed in the literature and identify appropriate AI techniques that could be useful in clinical practice. For example, the traditional ML methods are, in most cases, interpretable and explainable, and require less data for training and hence are preferred by clinicians. 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 clinical needs. 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 ("Discussion" and "Conclusions").

## REVIEW METHODOLOGY

A search was proposed for wearable technology and AI for neonatal cardiorespiratory monitoring. In part 1 of our review article, we found 107 articles related to wearable technology for neonatal cardiorespiratory monitoring. Of these 107 articles, 14 were included as they were related to AI.

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", and "Breathing"

This resulted in a total of 1680 articles. 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 (C.S. and E.G.) independently searched for additional articles. Five further papers were obtained using a snowballing technique. In total, 56 articles were obtained to review in this paper. The PRISMA flow diagram is presented in Fig. 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 created a stacked plot to show the popularity of AI methods in this study.

## AI TECHNIQUES

For neonatal health monitoring, AI techniques have been used on data obtained from both wearable and non-wearable devices.[8,9] To implement AI techniques in general, there are four major steps: (i) data extraction, (ii) pre-processing, (iii) training, and (iv) testing steps.[10] For example, the continuous data obtained from wearable technologies such as textile electrodes (e.g., electrocardiogram (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[11] and band-pass filtered. Audio signals are also band-pass filtered.[12] The AI techniques identified for this application are categorised into supervised learning,[6] unsupervised learning,[13] and reinforcement learning (RL).[14] In the next subsection, we focus on the evolution, taxonomy and comparative study of AI techniques used for cardiorespiratory monitoring of wearable data.

### Evolution of AI

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

*Wearable cardiorespiratory monitoring for infants.* The initial AI work using wearable cardiorespiratory monitoring was conducted

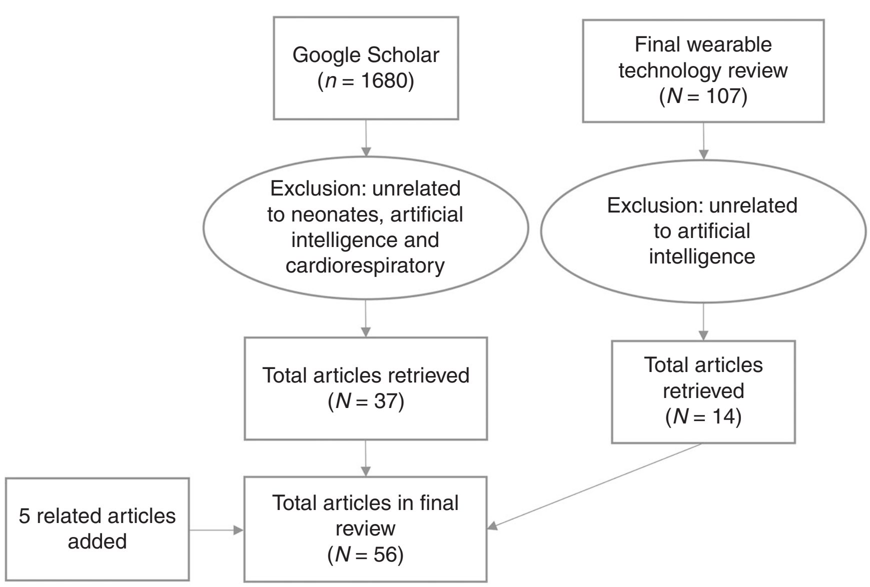


**Fig. 1** PRISMA flow diagram if included studies.

in 2012, which employed the support vector machine (SVM) algorithm with radial basis function on pulse oximetry data acquired from neonates.[6] SVM is a popular traditional ML algorithm, that classifies data based on hyperplanes, which can be linear, polynomial, and radial basis functions. Patron et al.[15] and Mongan et al.[16] 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 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.[11] employed different combinations of popular traditional ML algorithms such as Decision tree, SVM, *k*-nearest neighbours (K-NN), and deep learning algorithm (ANN) as a two-stage classifier on ECG data. First, they selected the combination of the classifiers giving the optimal performance. Second, they used the optimal classifier for the final classification. The decision tree algorithm is based on the rules, which splits data into roots and nodes during classification.

De Greef et al.[17] employed the traditional ML algorithm, called the 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[18] realised the importance of the deep learning approach and proposed to use of the ANN algorithm for the classification of infant breathing patterns on data obtained from the breathing sensor. Furthermore, Acharya et al.[8] utilised three classifiers (naive Bayes (NB), logistic regression (LR), and decision trees) for respiratory monitoring on data obtained from the abdomen and shoulder. In the meantime, considering the efficacy of LR for the classification, Raknim et al.[19] employed multiple LR models for neonatal sepsis monitoring on the data achieved from the wearable ballistocardiography sensor.

Using traditional ML algorithms, Urdal et al.[20] implemented the Vu classifier for newborn resuscitation detection on ECG data. They also used accelerometer data to observe the heart rate (HR) during different activities. These activities included chest compressions, back stimulation, tactile stimulation, drying thoroughly, moving the baby and uncategorised movements. Furthermore, Ostojic et al.[21] proposed to use of four traditional ML 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.[22] proposed deep learning 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.[23] employed both deep learning (ANN) and traditional ML 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 ML methods, Hansen et al.[24] 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 respiratory monitoring.

More recently, Vahabi et al.[25] proposed to use of deep learning (ResNet-50) and traditional ML 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 normalisation.

*Electrical-based cardiorespiratory monitoring*. Four studies reported using electrical-based sensors for cardiorespiratory monitoring. Khodadad et al.[26] devised a breath detector classifier, which is based on the traditional ML 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.[27] used several traditional ML algorithms such as RF, LR, and K-NN to detect the HR variability 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.[28] employed the XGBoost algorithm, a traditional ML algorithm, on the ECG data of neonates. The XGBoost algorithm is a decision tree ensemble algorithm, using gradient boosting. More recently, Macfarlane et al.[29] recommended a deep learning method (CNN model) for the ECG interpretation during the 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 several levels of convolution operation across the input image.

*Optical-based cardiorespiratory monitoring*. Three studies report optical sensors for data extraction during cardiorespiratory monitoring. Villarroel et al.[30] employed the deep learning 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.[31] employed the traditional ML 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 ensemble algorithm, using gradient boosting. Recently, Huang et al.[32] employed both video and PPG data obtained from pulse oximeter data to train the deep learning model (LSTM model) for neonatal HR monitoring.

*Mechanical-based cardiorespiratory monitoring*. The first AI work for cardiorespiratory monitoring using mechanical sensors for newborns was carried out in 2001. The researchers implemented the deep learning method (ANN algorithm) on data captured from a digital stethoscope attached to the infant After 14 years, there was a gradual increase in mechanical sensors for neonatal cardiorespiratory monitoring. Amiri et al.[33] proposed the use of an RF algorithm, a traditional ML method, for heart murmur detection on phonocardiogram (PCG) data achieved from a digital stethoscope that was connected to a mobile phone. Bokov et al.[34] employed the SVM algorithm for wheeze detection on the audio data recorded using smartphones in the paediatric population. In 2016, Sola et al.[35] proposed to use traditional ML 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 sensors. Shelevytsky et al.[36] proposed to use of the traditional ML method (SVM) for the classification of PCG data during the heart condition classification of the newborn. Bardou et al.[13] 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 ML algorithms (K-NN, SVM, and GMM), the handcrafted features for audio data were used, whereas, for the deep learning method (CNN), the spectrogram, which 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.[37]

underscored the application of the deep learning 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.[38] a applied SVM, Decision trees, K-NN, and dynamic classifiers 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 was an increasing number of studies using AI for cardiorespiratory monitoring. Gomez-Quintana et al.[39] employed the XGBoost algorithm, for the classification of neonatal PCG signals that were obtained from a digital stethoscope. Apart from traditional ML methods in the same year, Jani et al.[40] suggested using a deep learning 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.[41] highlighted the application of heart murmur detection using ANN and logistic regression, from a paediatric and neonatal population on PCG data. Grooby et al.[42,43] proposed to use deep learning algorithms (e.g., YAMNet), and traditional ML 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. Lastly, Gomez-Quintana et al.[12] employed the XGBoost algorithm for the classification of neonatal PCG signals. The XGBoost algorithm was responsible for detecting patent ductus arteriosus in neonates.

*Multi-sensor-based cardiorespiratory monitoring*. Research using multi-sensor-based cardiorespiratory monitoring began in 2013. The purpose of their AI method is to predict the mortality of infants. Furthermore, Rinta-Koski et al.[44] used a Gaussian process classifier on standard clinical features, which includes HR 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 ML algorithms, Pais et al.[45] employed the LDA algorithm for the classification of ECG and pulse oximetry data to determine HR 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 apnoea in neonates.

Similarly, Jalali et al.[46] proposed to use of the SVM classifier for the classification of periventricular leukomalacia after cardiac surgery. Their method utilises vital signs of neonates, including HR data achieved from pulse oximetry. In their method, SVM is used to predict periventricular leukomalacia based on vital signs data. Moreover, Joshi et al.[47] proposed to use the XGBoost algorithm trained on HR, respiratory rate (RR), and pulse oximetry data obtained from neonates to predict critical cardiorespiratory conditions. Hassan et al.[48] employed the ANN to detect sleep apnoea on temperature and pulse oximeter data from neonates. Similarly, Pini[49] utilised the random forest and K-NN algorithms for the maternal, foetal, and neonatal profiling of the physiological signals with qualitative data such as maternal lifestyle factors.

Recently in 2021, Zuzarte et al.[50] 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.[51] 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 the Rocchio classifier, classifies the data to the nearest mean of the training data belonging to the class.

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

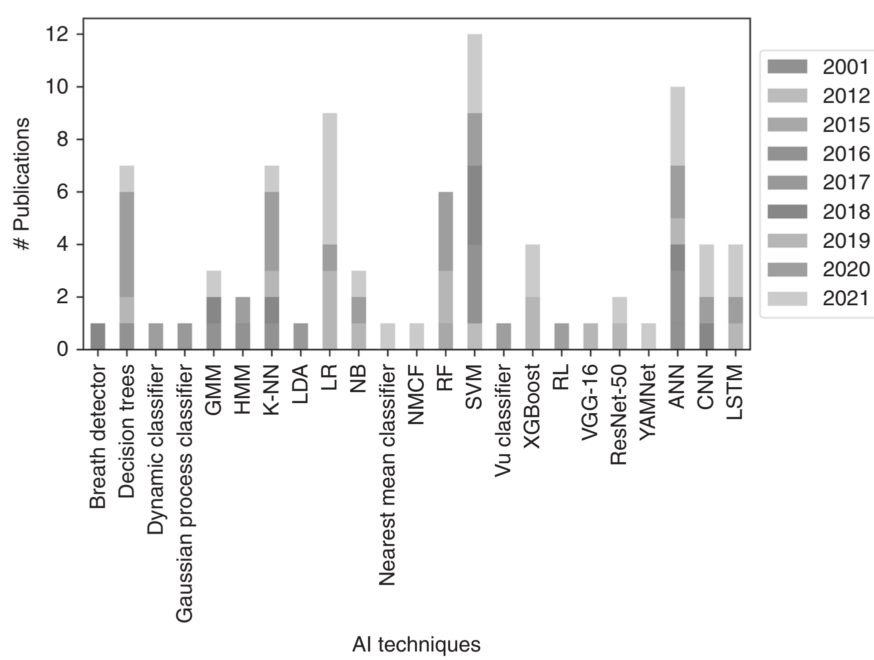


**Fig. 2 Comparison of artificial intelligence (AI) techniques by year for neonatal cardiorespiratory monitoring.** AI techniques are grouped from left to right as traditional machine learning-based, reward/punishment-based, pre-trained deep learning models, and non-pre-trained deep learning models. ANN artificial neural network, CNN convolutional neural network, GMM Gaussian mixture model, HMM hidden Markov model, K-NN *k*-nearest neighbour, LDA linear discriminant analysis, LR logistic regression, LSTM long short-term model, NB naive Bayes, NMCF non-negative matrix co-factorisation, RL reinforcement learning, RF random forest, SVM support vector machine, XGBoost extreme graduate boosting.

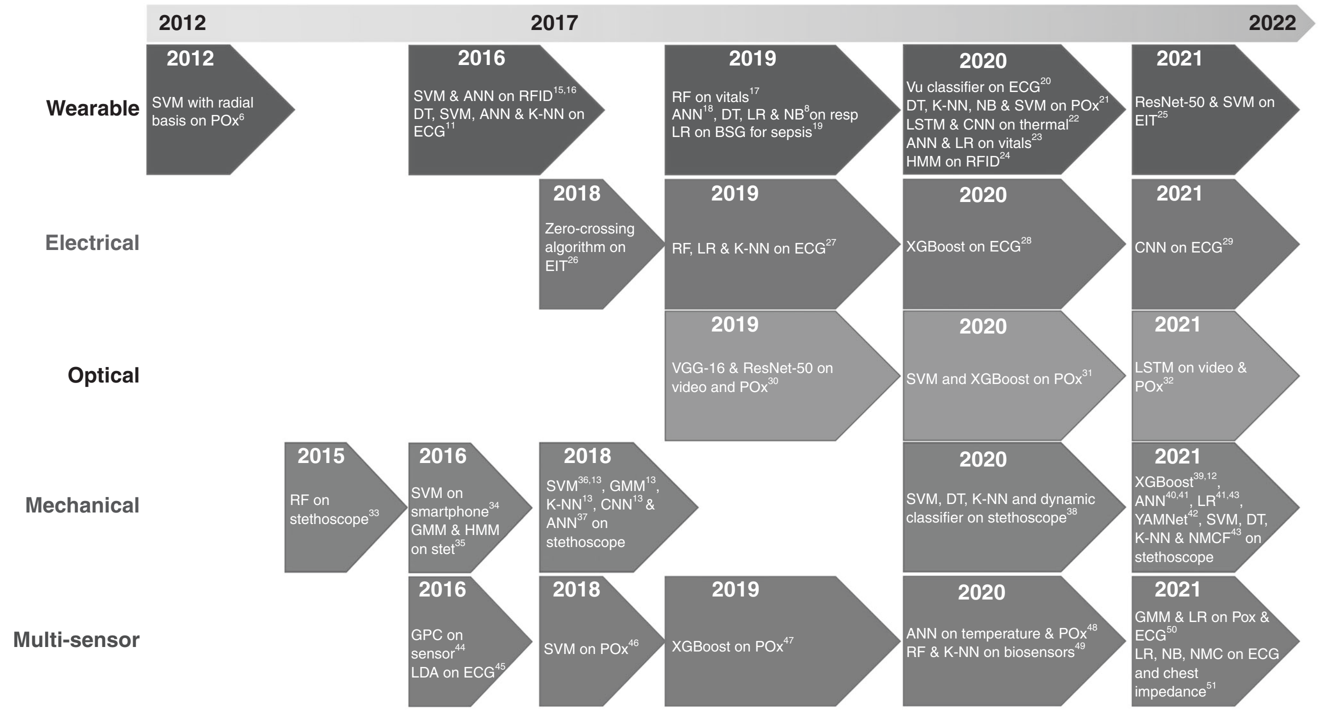


**Fig. 3 Timeline depicting the evolution of artificial intelligence (AI) techniques on wearable, electrical, optical, mechanical, and multi-sensor-based cardiorespiratory monitoring.** ANN artificial neural network, BSG ballistocardiograph, CNN convolutional neural network, DT decision tree, ECG electrocardiogram, GMM Gaussian mixture model, GPC Gaussian process classification, HMM hidden Markov model, K-NN *k*-nearest neighbour, LDA linear discriminant analysis, LR logistic regression, LSTM long short-term model, NB naive Bayes, NMC nearest mean classifier, NMCF non-negative matrix co-factorisation, POx pulse oximeter, RL reinforcement learning, RF random forest, RFID radio frequency identification, Stet stethoscope, SVM support vector machine, XGBoost extreme graduate boosting.

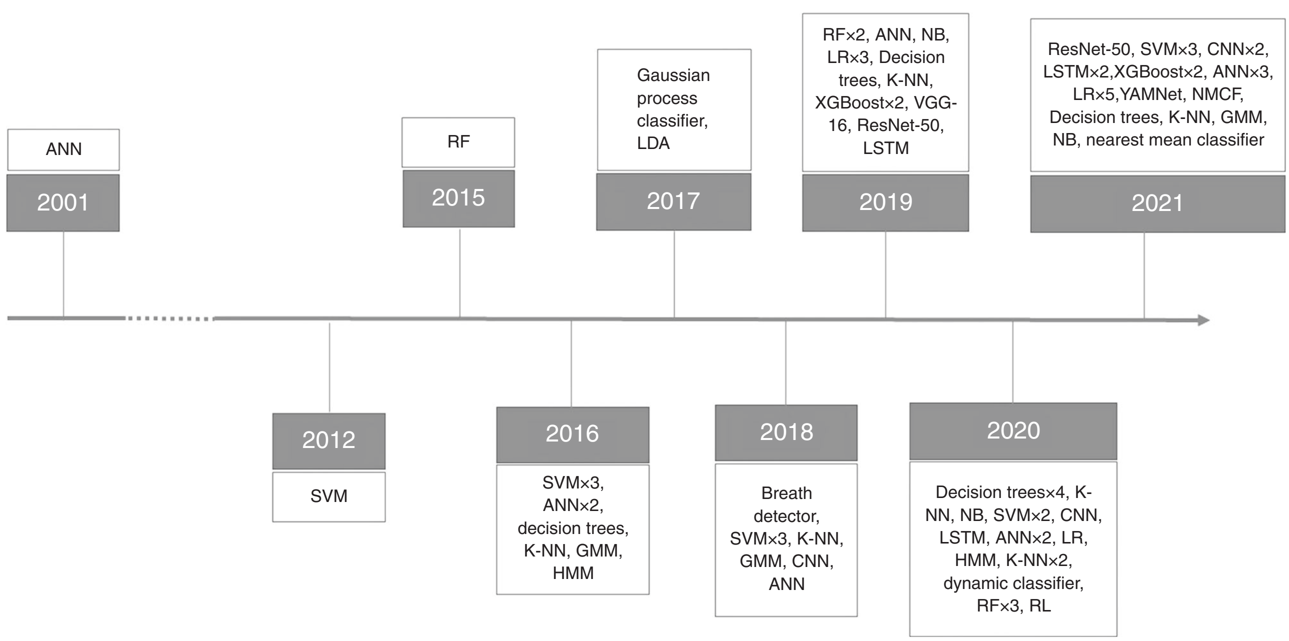


**Fig. 4** AI timeline showing the methods with "×": indicating how many times they have been used in the literature.

In 2019, Chisi et al.[52] suggested using AI for overall health monitoring of clinical data obtained from wearable sensors such as ECG and pulse oximeter data in the paediatric population. Tandon et al.[53] also highlighted the efficacy of ML algorithms for the detection of paediatric cardiovascular disease on continuous physiological data (CPD) obtained from wearable biosensors.

Ranjit and Kissoon[14] discussed different applications of AI, particularly RL for early detection of sepsis and septic shock in the paediatric population on different data such as RR, HR, and $SpO_2$. During the same year, Chong et al.[54] highlighted the use of decision trees and RF for the health monitoring of HR, RR, and oxygen saturation in the paediatric population. Goulooze et al.[55] explained algorithms such as RF and decision trees for paediatric and neonatal health monitoring such as sepsis detection on the early results of laboratory tests and nursing observations. Johnson et al.[56] underscored the importance of ML algorithms for health monitoring, including neonatal population on clinical features such as HR, RR 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 ML algorithms on the data extracted from the RFID-based abdominal band sensors capturing the RR of neonates. Hasan et al.[58] also discussed the ML algorithms for neonatal health monitoring using vital signs data (e.g., HR, oxygen level, etc.) achieved from the wearable sensors.

Sobhan et al.[59] elaborated on 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 populations. 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 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 (Fig. 2) and a timeline (Fig. 3). From Fig. 4, we observed that the SVM algorithms are the most popular (12 publications), whereas the ANNs (10 publications) are the second most used algorithms in the literature. This data shows that the traditional ML algorithm (e.g., SVM) is still dominant for neonatal cardiorespiratory monitoring despite the great promise of the deep learning algorithm (ANN) in this domain.

### 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 ML (e.g., SVM,[38] Decision trees,[11] etc.), deep learning-based (e.g., CNN,[22] LSTM,[22] etc.) and reward/punishment-based AI methods (e.g., RL method[14]). Deep learning-based methods[22] extract the higher-order information from the input data to improve performance. The higher-order information is achieved by using different operations such as convolution and activation; however, traditional ML AI techniques do not produce such types of information during their learning process. The reward/punishment AI techniques (e.g., RL algorithm)

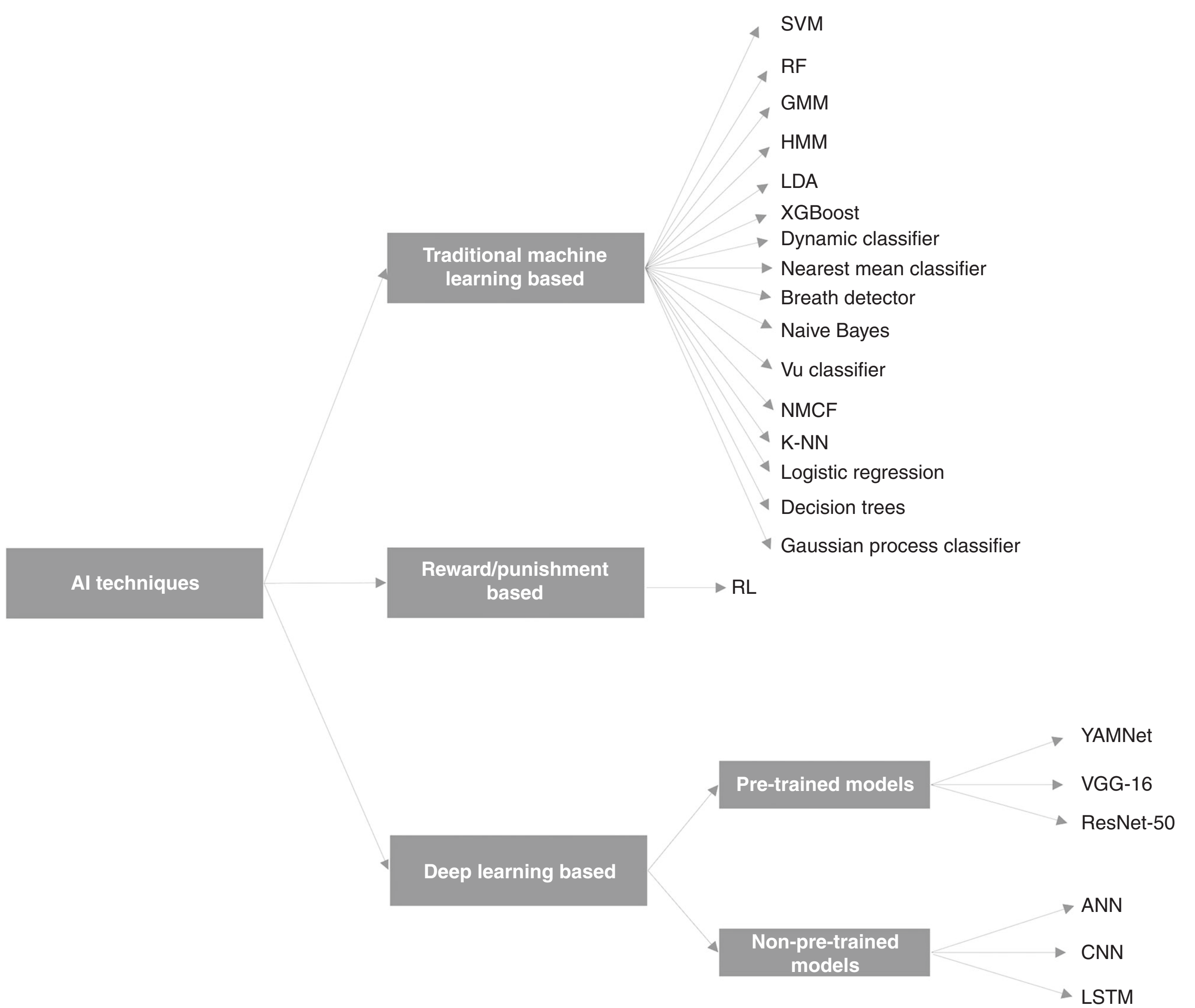


**Fig. 5 Taxonomy of artificial intelligence (AI) techniques used in neonatal cardiorespiratory monitoring.** ANN artificial neural network, CNN convolutional neural network, GMM Gaussian mixture model, HMM hidden Markov model, K-NN *k*-nearest neighbour, LDA linear discriminant analysis, LR logistic regression, LSTM long short-term model, NB naive Bayes, NMCF non-negative matrix co-factorisation, RF random forest, RL reinforcement learning, SVM support vector machine, XGBoost extreme graduate boosting.

**Table 1.** Comparison between different artificial intelligence (AI) techniques with wearables for neonatal cardiorespiratory monitoring.

| AI techniques | Advantages | Disadvantages |
|---|---|---|
| Artificial neural network | • Ability to extract complex non-linear relationship<br>• Model trained in one domain can be used for other domains, also called transferable. | • Black box<br>• Extensive empirical testing is required to tune the hyper-parameters |
| Support vector machine | • Efficient for high-dimension feature vector<br>• Relatively memory-efficient | • Not good for big data<br>• Performance degrades if more outliers are present<br>• Non-transferable |
| Random forest | • Ensemble learning and performance improvement<br>• Can be used for both classification and regression | • Higher complexity<br>• Longer computation time |
| Gaussian mixture model | • Works for overlapped clusters, which might not be possible from K-NN and DBSCAN<br>• Easy to implement<br>• Fast algorithm | • Sensitive to noise and outliers<br>• Requires a large number of parameters<br>• Requires more data to get good results |
| Hidden Markov model | • Interpretable<br>• Simple and easy to understand | • Uses the Viterbi algorithm, which is expensive computationally<br>• Slower |
| Linear discriminant analysis | • Simple and fast algorithm<br>• Interpretable and explainable | • Requires normal distribution of data |
| Decision tree | • Interpretable and explainable<br>• Can work on a limited data | • Requires a higher time for the higher-dimensional data<br>• Higher computational complexity |
| Gaussian process classifier | • Easy to implement<br>• Flexible<br>• Faster | • More hyper-parameter tuning<br>• Lose efficiency in higher dimension space |
| Breath detector | • Easy to implement as it uses a simple decision approach<br>• Easy to understand as it uses threshold in the algorithm | • Higher computational complexity because of zero-crossing algorithm<br>• The selection of appropriate threshold requires extensive study |
| Logistic regression | • Simple to interpret the output<br>• Less complex | • Difficultly in modelling complex relationship |
| Convolutional neural network | • Capture the spatial information<br>• High order semantic information<br>• Transferable | • Prone to overfitting<br>• Huge data set required<br>• Black box |
| eXtreme gradient boosting | • Parallelisation<br>• Can learn the non-linear pattern<br>• Uses different regularisation to avoid overfitting | • Ineffective for sparse and unstructured data<br>• Sensitive to outliers |
| ResNet-50 | • Comparatively lower-sized weight file for fine-tuning and transfer learning<br>• Transferable<br>• The higher number of intermediate layers to produce more semantic information than VGG-16 | • Lack of interpretability and explainability if used alone<br>• Increased complexity of model architecture |
| *k*-nearest neighbour | • Easy to implement<br>• Can work for classification and regression<br>• Interpretable and explainable | • Slow<br>• Not useful with the higher-dimensional feature vector<br>• Outliers' sensitivity |
| Vu classifier | • Easy to implement<br>• Ensemble approach | • No approach for class imbalance problem<br>• Requires more data for good accuracy<br>• Prone to over-fitting<br>• Computational issues |
| Dynamic classifier | • Easy to use ensemble learning<br>• Performance improvement than normal standalone classifier | • Computationally complex<br>• Limited algorithms available for the experiment to this date |
| Naive Bayes | • Fast<br>• Can work on a limited data set<br>• Interpretable and explainable | • Assumes all variables as an independent<br>• Provides zero frequency if the testing data are not in the training |
| Reinforcement learning | • Can solve complex problems<br>• Correct error during training<br>• In absence of training data, it learns from experience | • Not useful for solving simple problems<br>• Data-hungry<br>• Curse of dimensionality limits the performance |
| Non-negative matrix factorisation | • Low storage<br>• Work on a limited data<br>• Interpretability | • Sensitive with respect to initialisation<br>• Might not be useful for big data |
| Long short-term memory | • Capture the temporal sequence information<br>• Transferable<br>• Provides a higher-order semantic information | • Black box<br>• Prone to overfitting<br>• Needs extensive works for hyper-parameter tuning<br>• Produce a lower performance |
| YAMNet | • Transferable<br>• Imparts several high-order information from several layers for the input audio | • Black box<br>• Prone to overfitting if we re-train from scratch |
| VGG-16 | • Few layers to extract useful information, so easy to experiment<br>• Transferable | • Black box<br>• Big weight file during transfer learning, so not good for edge computing |
| Nearest mean classifier | Efficient and easy to implement<br>Interpretable | May not work properly if data is not linearly separable<br>May not work properly for data having semantically similar information |
| Rule-based | Easy to implement<br>Interpretable | Unable to work in a complex case with multiple conditions<br>Problem in generalisability |

**Table 2.** Comparative study of different artificial intelligence (AI) techniques for neonatal cardiorespiratory monitoring using performance and explainability.

| AI techniques | Representative performance | Representative data set | Subjects | Explainability and interpretability |
|---|---|---|---|---|
| Artificial neural network[40] | Sensitivity of 87.00% and specificity of 100.00% for the identification of a murmur as innocent or pathologic | Phonocardiogram data | 106 subjects | Difficult in explainability and interpretability |
| Support vector machine[16] | Accuracy of 77.00% for the breathing cessation classification | Data from RFID tags | Not available | Difficult in explainability and interpretability |
| Random forest[33] | Accuracy of 97.60%, sensitivity of 96.80% and specificity of 98.40% to classify between innocent and pathological murmurs | Phonocardiogram data | 120 subjects | Difficult in explainability and interpretability |
| Gaussian mixture model[13] | Accuracy of 86.68% for lung sound. And accuracy of 82.85% for non-lung sound detection | Mel-frequency filter bank from audio signals | Over 50 subjects of all age groups | Interpretable and explainable |
| Hidden Markov model[35] | Not available | Mel-frequency filter bank from audio signals | Not available | Interpretable and explainable |
| Linear discriminant analysis[45] | Accuracy of 95.23% for apnoea detection | Pulse oximetry data | Not available | Interpretable and explainable |
| Decision tree[8] | Accuracy of 85.50% for breathing vs non-breathing classification | Data from RFID tags | Not available | Interpretable and explainable |
| Gaussian process classifier[44] | Highest AUC of 0.94 for the detection of mortality | Pulse oximetry data | 2059 subjects | Difficult in explainability and interpretability |
| Breath detector[26] | Optimal false positive rate of 0.06, and true positive rate of 0.84 for breath detection | Data from EIT | Not available | Explainable and interpretable |
| Logistic regression[8] | Accuracy of 73.60% for the breathing vs non-breathing classification | Data from RFID tags | Not available | Explainable and interpretable |
| Convolutional neural network[13] | Accuracy of 95.56% to classify different lung sounds | Mel-frequency cepstrum features | 50 subjects of all age groups | Difficult in explainability and interpretability |
| eXtreme gradient boosting[31] | AUC of 0.79 and precision of 0.63 for flash capillary refill time.<br>AUC of 0.77 and precision of 0.50 for prolonged capillary refill time | Pulse oximeter data | 99 subjects | Difficult in interpretability and explainability |
| ResNet-50[25] | Used for feature extraction to classify with others, so not performance reported | Data from EIT | 15 subjects | Difficult in interpretability and explainability |
| *k*-nearest neighbour[21] | Accuracy of 98.55%, sensitivity of 81.68%, and specificity of 99.46% specificity for the false alarm rate detection | Pulse oximeter data | 25 subjects | Interpretable and explainable |
| Vu classifier[11] | Accuracy of 78.70% (3-class performance for chest compression, stimulation, and others) and accuracy of 79.80% (2-class performance for chest compression and stimulation or other) | ECG and accelerometer data | 30 subjects | Difficult in explainability and interpretability |
| Dynamic classifier[38] | Accuracy of 93.00% for heart sounds and accuracy of 82.00% for lung sounds classification | Chest sound data | 76 subjects | Difficult in explainability and interpretability |
| Naive Bayes[8] | Accuracy of 72.70% for breathing vs non-breathing classification | Data from RFID tags | Not available | Interpretable and explainable |
| Reinforcement learning[14] | Not reported | Not reported | Not available | Difficult in explainability and interpretability |
| Non-negative matrix co-factorisation[43] | Accuracy of 3.6 b.p.m. and 1.2 b.p.m. in heart and breathing rate estimation, respectively | Chest sound data | 60 subjects | Interpretable and explainable |
| Long short-term memory[22] | Accuracy of 99.88% for the detection of apnoea | Pulse oximetry data | | Difficult in explainability and interpretability |

**Table 2.** continued

| AI techniques | Representative performance | Representative data set | Subjects | Explainability and interpretability |
|---|---|---|---|---|
| YAMNet[42] | Balanced accuracy of 59.30% and 46.60% for heart and lung qualities, respectively | Chest sound data | 119 subjects | Difficult in explainability and interpretability |
| VGG-16[30] | Accuracy of 92.40% for patient detection for heart rate detection from skin | Video data with pulse oximeter data | 30 subjects | Difficult in explainability and interpretability |
| Nearest mean classifier[51] | Maximum mean accuracy of 72.00% for sepsis detection | Electrocardiogram-based data | 325 subjects | Interpretable and explainable |

*AUC* area under the receiver operating characteristic curve, *EIT* electrical impedance tomography, *MFCC* Mel-frequency cepstrum coefficients, *RFID* radio frequency identification.

learn the data based on rewards and punishment strategy as discussed in "Evolution of AI". Under the traditional AI techniques, there are several algorithms, for example, SVM, RF, Logistic regression, etc. The deep learning 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 data sets (e.g., image data sets), 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 Fig. 5.

### 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 small data sets common in biomedical research. Also, they have a higher level of interpretability, which helps establish trust and acceptability among clinicians and healthcare professionals. Tables 1 and 2 summarise the comparison of different AI techniques used in cardiorespiratory monitoring alongside their advantages and disadvantages. We compare the AI methods based on several factors such as model complexity, performance, and interpretability.

## DISCUSSION

AI techniques, sensor technologies and their evolution being adopted in neonatal cardiorespiratory monitoring are discussed in this section.

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 "Wearable cardiorespiratory monitoring for infants" and Supplementary Table 1, there have been few studies that evaluate the use of wearable sensor collected data. While many of the existing AI techniques presented for neonatal cardiorespiratory monitoring in this paper seem 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.

According to Figs. 2–4, more AI techniques, including both traditional ML and deep learning, 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 ML methods outnumbers the number of deep learning and reward/punishment methods (Fig. 2). In addition, some classifiers such as Gaussian process classifiers that were published before 2019 are less popular in recent years, whereas methods such as XGBoost and LR are on the rise along with deep learning methods such as LSTM and ResNet-50.

The taxonomy diagram in Fig. 5 illustrates that AI techniques for cardiorespiratory monitoring of wearable data are moving towards more traditional ML 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 ML 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 methods and traditional ML 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 methods[30] such as ResNet-50 and VGG-16, might be more useful with big data, but less so with limited data.

Furthermore, we compared AI methods in terms of explainability and performance. 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.

While AI offers great promise in the home and hospital environment, further studies are required in two areas. First, 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. Second, 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 to see the translation of these AI techniques from research into clinical practice.

## CONCLUSIONS

We reviewed several AI techniques for neonatal cardiorespiratory monitoring on wearable data and designed a hierarchical taxonomy and AI timeline based on them. We found the rising popularity of traditional AI methods (e.g., SVM, XGBoost) compared to deep learning 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

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

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## AUTHOR CONTRIBUTIONS

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The authors declare no competing interests.

## ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Patient consent was not required.

## ADDITIONAL INFORMATION

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