Intelligent system development to monitor the neonatal behaviour: A review

Syed Adil Hussain Shah[1,*,†], Angelo di Terlizzi[1,†] and Marco Agostino Deriu[2,†]

[1]Department of Research and Development (R&D), GPI SpA, Trento, Italy
[2]PolitoBIOMed Lab, Department of Mechanical and Aerospace Engineering, Politecnico di Torino, Turin, Italy

Abstract

The early birth of children can be associated with neurodevelopmental disease onset. In such cases, the lack of early diagnosis and early medical treatment negatively affects the rest of the child's life. In this context, recent developments in artificial intelligence (AI) in the medical field suggest a possible key role also in the cases of preterm birth through the integration of various sources of neurodiagnostic data in order to extract clinical information. In this manuscript, we have addressed the importance of the development of intelligent systems merging with the Internet of Medical Things (IoMT) for the analysis of the baby's movement. More in detail, we here consider a general prototype of an incubator for neonatal intensive care unit (NICU) and related tools capable of detecting/measuring vital signs and patient characteristics for newborns with particular attention to preterm infants. In this context, we will also provide a brief explanation of available datasets, such as BabyPose Dataset, MINI-RGBD, and MIA dataset. Furthermore, we will explore data mining techniques and the role of IoMT in the context of preterm infants and children. Finally, emphasis will be placed on technology communication, combination, and multidisciplinary research pursuing more accurate and improved self-guided techniques and systems.

Keywords

Preterm birth, Incubator system, Intensive care unit, Data mining, Baby motion analysis, Internet of medical things

1. Introduction

According to World Health Organization (WHO) observations, the first month of life is a very dangerous period for child survival, with 2.4 million newborns dying in 2020 [1, 2]. The highest neonatal mortality rate was recorded in sub-Saharan Africa and Central and South Asia, with about 25 deaths per 1000 births [3, 4].

The main causes of death from preterm birth are lack of breathing at birth, low birth weight, illness, and other infection factors. In general, preterm birth is divided into three categories according to the gestational age of delivery: moderate preterm (MP: 32-37 weeks), very preterm

DETERMINED 2022: Neurodevelopmental Impairments in Preterm Children — Computational Advancements, August 26, 2022, Ljubljana, Slovenia

*Corresponding author.
†These authors contributed equally.
syedadilhussain.shah@gpi.it (S. A. H. Shah); angelo.diterlizzi@gpi.it (A. d. Terlizzi); marco.deriu@polito.it (M. A. Deriu)
https://www.dimeas.polito.it/en/personale/scheda/(nominativo)/marco.deriu (M. A. Deriu)
0000-0003-1918-1772 (M. A. Deriu)

(VP - 28-32 weeks), and extremely preterm (EP - less than 28 weeks) [5].

The normal and stable duration of delivery is considered completed when the pregnancy cycle exceeds 37 weeks of gestation. The earlier the birth, the higher the risk of death, and the need to monitor the preterm infant in the neonatal intensive care unit (NICU) for a long-time increase. Because of this critical condition, artificial intelligence systems for example coupled with incubator sensor systems can play an important role in overcoming the preterm mortality rate and improving the quality of care.

In recent years, many researchers have been working on the development of intelligence systems to improve the performance of neonatal behavior monitoring and analysis. In this area, contact and noncontact clinical data sources are being used to design automated intelligent systems. In addition, computer systems that were previously inadequate at the home of traditional and handcrafted features are now performing very well mainly due to the integration of machine learning and deep learning algorithms. In this regard, a general software architecture for neonatal sensing and monitoring is shown in Figure 1, which includes various IoMT-related concepts and technologies such as artificial intelligence, devices, sensors, big data, mobile devices, and what is considered for the design of state-of-the-art NICU incubators.

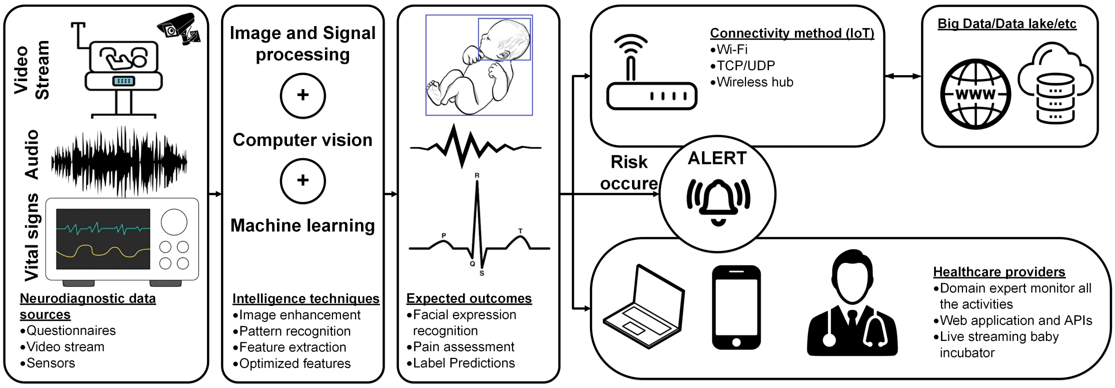

Figure 1: The general flow of an automated system to monitor neonatal behaviour.

As said, monitoring neonatal behaviors is a key clinical activity for early diagnosis of possible abnormalities or diseases. In this context, the AI and computer vision fields have given a lot of attention to the automated identification and classification of newborn behaviors [6, 7, 8]. The manual process to monitor the behaviour of newborn babies was complex and too much costly. Moreover, it is dangerous for neonatals to survive in low-resource environments. Therefore, an automated AI system with the implementation of hardware can be useful for neurologists and domain experts to monitor the baby's condition in a single incubator in a NICU. For the development of AI systems, the researchers believe that such applications will be helpful for doctors to analyze the behaviour of preterm birth.

Based on the above-mentioned premises in the present review work we will discuss issues related to the role of AI systems and IoT that may help in designing automated systems to obtain accurate results and reduce the complexity rate in the field of NICU incubator implementation. More specifically, the article focuses on issues concerning: i) the knowledge base on the

Neonatal Intensive Care Unit and related conditions; ii) data collection issues and publicly available reference datasets; iii) the role of data mining techniques for monitoring neurological disorders; iv) the role of IoT in the medical environment and the potential of the mentioned technologies in the field of incubator design and development.

2. General features of NICU Incubators

An incubator is a device used to monitor clinical parameters and maintain environmental conditions suitable for the life of a newborn baby. It is generally used in preterm birth or in cases of specific pathologies at birth. The device is equipped with sensors that are capable of monitoring/supporting the patient's condition through the detection of behavioural and physiological parameters (e.g. blood pressure, oxygenation, temperature, cardiac function, etc.) of newborns that help doctors to prevent any morbidity leading to the critical phase [9, 10]. The real-time analysis gives the advantage of early detection of any type of complication, which can help protect the infant and increase its survival rate [11, 12]. The single incubator in the NICU is a separate, self-contained area for each individual infant under the supervision of an expert. A NICU incubator usually requires multidisciplinary skills and highly qualified specialists, being built for those environments that manage the critical phase of preterm infants [13].

2.1. Main pathological conditions requiring the use of NICU incubators

In the following list, the main conditions requiring the use of incubators are detailed:
• Intraventricular hemorrhage (IVH)
Intraventricular hemorrhage (IVHs) causes the illness or disease and death of newborn infants. Infants whose birth weight is about 1500g usually develop an IVH. Mostly it occurs during the third day of birth and in some cases, it occurred before delivery. Important risk factors for IVHs are: increase atrial blood pressure, pneumothorax, and birth asphyxia [14, 15]. The potential of ML techniques to improve early detection of IVH has been highlighted in recent literature.
• Periventricular leukomalacia (PVL)
In this disease, the white matter near the cerebral ventricles dies. PVL is usually developed by premature infants, whose birthweight 1500g or 3lb 5oz. PVL affects infants (birth week < 25) when they are suffering from the deprivation of oxygen during delivery and at the time of birth [16]. The variation of oxygen and CO2 in the blood cause PVL while the surgeons predict this disease by applying standard psychological parameters to infants [17]. In the aspect of intelligent system development, many researchers have proposed several techniques to predict the PVL disease in neonates [18, 19].
• Nosocomial Infection
Infections are the most common cause of mortality and illness for infants [20]. Around 45% of infants born before 25-28 weeks of gestation and kept alive in NICU incubators face critical infections. This infection, mainly caused by pathogens present in the hospital, is difficult to be identified at an early stage given that symptoms appear at the advanced pathological stage. Clinical checkups are mainly responsible for the infection spread [21]. Few examples of intelligent system for recognition of the above-mentioned neonatal infection are reported in literature [22, 23].

• Pneumothorax
Pneumothorax occurs when air or gas accumulated in the process of inhaling and exhaling. In the body, the pleural cavity is a fluid-filled space that surrounds the lungs. Usually, 1-2% of infants face gas and air in their pleural cavities. There are two layers that surround the lungs. One is attached to the chest wall and the other is attached to the lungs. These layers move when we inhale or exhale, and in this process, fluid is emitted from the membrane for the lubrication of the lung's smooth movement [14]. In pneumothorax, researchers have also used machine learning techniques to improve the detection as details are presented in [24, 25].

2.2. Principles for design and implementation of NICU incubators

The implementation of a single intensive care unit is divided into two main types: real and simulated prototypes, where real prototype means the testing phase in a real environment while simulated prototypes are just computer-implemented and analyzed systems. In this regard, Figure 2 has shown the general prototype of the neonatal incubator.

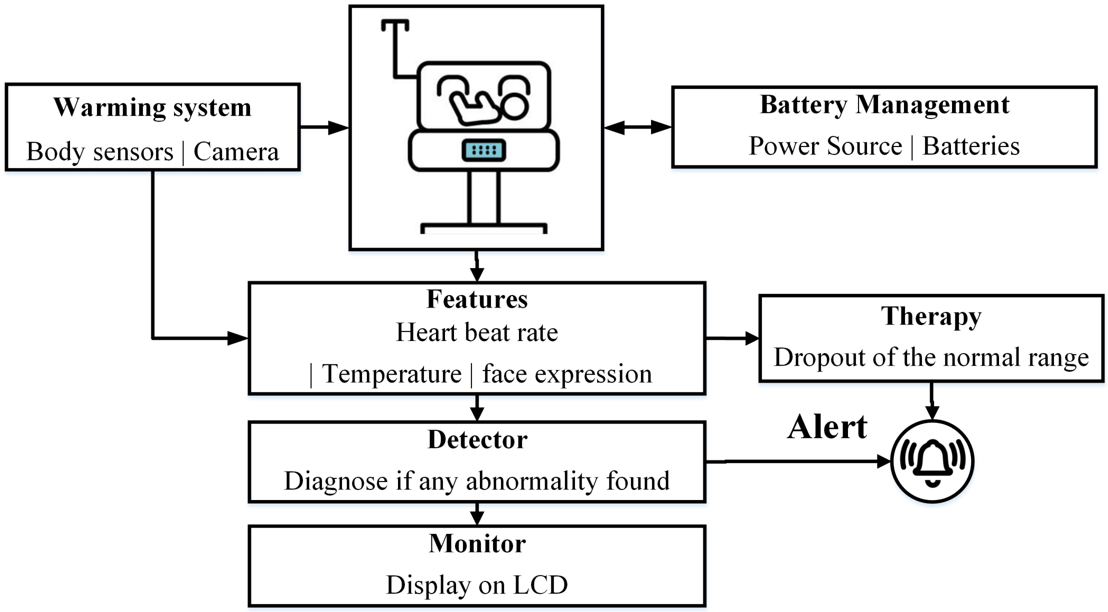

Figure 2: General prototype of neonatal Single intensive care unit [11].

There are several tools and systems which are usually connected with an incubator to monitor the condition of the baby at every moment. Due to these components, surgeons can easily analyze a number of vital signs and features like the warming system (body temperature, heart beat rate (HBR), and SpO2) and body behaviour systems (cameras). All these features of the neonatal are basically displayed on the incubator's LCD. Moreover, the power supply systems are also connected to the incubator to manage the battery system. In any condition, the behaviour, oxygen level, or temperature is sensed as a bad outcome by the machine, it generates an alert buzzer which means the patient is in a critical stage. There are several parameters related to incubators that interact with IoT and further explanations are shown in table 1.

A. F. Symon et. al. [26] developed a system that detects the movement and crying sound of a newborn baby. The objective of this study was to analyze the contactless data modality to find the state of babies and also monitor their physical behaviour. It was suggested that previous systems were just controlling the temperature and humidity of the incubator without controlling the sound pollution which they found that it is a very mandatory parameter that can provide a comfortable environment to the baby. In another research [27], they designed a hardware system in combination with IoT's based model to monitor the preterm incubator environment. The hardware components used microcontroller along with the other body temperature sensors. The performance of the proposed system was better as compared to the other related measuring systems. In this way, N. A. Zakaria et. al. [28] addressed another device to detect the infant body temperature in an incubator system. The device was a wearable sensor that measures the vital signs of baby and also sends the information to their parents through a wireless network. Furthermore, the portable device is utilized to visualize the information and any alert related to the baby health.

All the above-mentioned studies have shown contactless systems in detail but are not physically installed in any hospital. In recent research implemented at the John Radcliffe Hospital in Oxford [22]. This work has been designed similarly to previously discussed methods. They have adapted the video-based technique to monitor neonatals' respiratory rate, heart rate, and oxygen saturation. By using these features, they have developed an algorithm that efficiently detects bradycardia events in the early stages.

Table 1
Incubator parameters interacting with IoT

References	*PARAMETERS*	*SYSTEM MONITORING WITH THE PARAMETERS*
[11]	Neonatal body temperature	This is a monitoring and risk management system, through cloud services, for neonates and it manages the critical stage alarm to domain experts for personal assistance.
[29]	Incubator heat	This parameter maintains the incubator heat which is sufficient for the development of the preterm baby.
[30]	Incubator Humidity	This parameter controls the humidity level in the incubator and it helps in maintaining the temperature of the incubator.
[29, 31]	Neonatal body weight	By the help of this measure, surgeons came to know about the weight of neonate. In this way, they can analyze the growth of neonate based on his/her weight.

3. Information Technology in biomedicine and potential for data collection and treatment at NICU

IT has cardinal importance in every aspect of our lives [32, 33, 34]. It has also proved itself as an important part of the medical field as well. Health IT is processing the information of different kinds of diseases using computer knowledge and its advancements. The capability of decision-making in health IT is a lot more than that of an individual human. As we know, computers can work more efficiently than humans. Health IT can assist all over the world's medical community in diagnosing different diseases. Due to advancements in IT, the medical field is also considering IT as an important part of it. The most tremendous thing in this IT domain is the amount of required data, that is available on the internet and anyone can access that information at any time [35].

However, this is not always the case with clinical data. Although there is a huge amount of clinical data that is collected by each hospital, this collection is usually very irregular and rough, both from one field to another but also in the same field in different countries and even in the same country from hospital to hospital. In fact, even today in many hospitals, data collection is done by hand by doctors or with the help of computer tools but often in a disorganized manner. This creates a huge problem in the pre- and post-processing of clinical data whose sets are often unusable. Added to this are the various problems of ethics and data privacy, which often require lengthy approval processes for their use. The case of the study of neurodevelopmental disorders presents a further degree of difficulty, given a large number of patients, which is certainly much smaller than in studies of cardiac diseases.

In this context, it is therefore crucial to develop systems that are able to automatically collect data in a standardized manner, but also to pre- and post-process collected data in order to boost the ability to extract useful clinical information from them. This is the context for all the IT technologies, IoMT that have been introduced above and that have the potential to drastically increase the quantity and quality of clinical data that could be available to data mining and ML-driven knowledge extraction algorithms. In this vision, a single NICU incubator becomes also a data collector for infant disease investigation based on real-world data. Nevertheless, some data for the analysis of the preterm's behaviour have already been collected and made available to the community. Those datasets are listed in Table 2.

3.1. Internet of medical things (IoMT) and potential for neonatal data sharing

Internet of Things (IoT) is an emerging technology that is increasing the data in various sectors daily. Big data analysis is a technique used to handle and evaluate enormous amounts of data using various methods. The IoT is a general paradigm. It changes its shape according to the environment, when we deal with the medical environment it is known as the IoMT. The objective of IoTs is to provide remote access to different physical devices and machines on service providers that cover location-based services, smart cities, smart streets, and homes. The IoT applications use invariably cloud storage combined with fog computing. Ubiquitous systems are increasing day by day and it reaches 50 billion in 2020 [31]. Nowadays, researchers have included many components in IoMT which have started to make the medical staff's life very easy like web portals, WSN (Wireless Sensor Nodes), RFID (Radio Frequency Identification),

Table 2
The publicly available dataset of infants, newborns, and toddlers

Dataset	*Modalities*	*Short Description*
Baby-Pose[36]	videos	The dataset contains 16 videos of 640 x 480 per frame size with 8–16-bit depth including 12 newborn cases with landmarks
MINI-RGBD[37]	videos	The dataset contains 12 videos having 640 x 480 per frame size with RGB Channels. This dataset is labeled on 25 infant babies
3D-AD[38]	videos	The dataset contains 100 videos with 512 x 424 frame size. In this dataset, the behaviour of toddlers is labeled
InfantsData[39]	videos	The dataset contains 85 videos with variant frame size and RGB channels. The dataset is labeled on 18 infant cases' landmarks
SyRIP[40]	images	The dataset contains the RGB channel images of 17 infant patients
SSBD[41]	videos	75 Youtube video, (m x n) frame size of RGB channels with benchmark dataset of behaviours of the preterm babies.

LCDs, detection sensors, etc [21, 42, 43]. In this scenario, L. Nachabe et. al. [44] designed a Distributed Neonatal Incubator Monitoring System (DNIMS) for neonates in which distributed software agents were used to connect different end-users like medical staff, parents, etc. This kind of system is the need of the current time because it is not just generating and storing the data in the servers but also in parallel, reformatting the data for the medical staff and caretakers [45].

3.2. Big Data Management tools and their potential application for future big data collection by novel generation of incubators

In the near future, we hope to have a massive amount of data coming from the next generation of incubators in NICUs. Several technologies for managing big data have already been developed and successfully employed in other medical fields. In this context, it is worth mentioning that five main strategies are recognized as successful in big data management: (1) create structured big data, (2) data sharing culture to develop information, (3) training to use big data analytics, (4) big data analytics with the combination of cloud computing, and (5) using big data analytics techniques to generate new business ideas. The need of analytics is linked with improvement in patient-centric services, detection of disease before it spreads, and -monitoring of the quality of services and methods of treatment. Some tools like Apache Hadoop is highly scalable storage platform. It provides cost-effective storage for large data. Apache Spark [46] is an open-source, in-memory processing machine. Its performance is much faster than Hadoop [47]. Another renowned platform namely MapReduce is used for interactive data mining. There are other large numbers of big data analytics tools/platforms which are publicly available and can be found at [48].

3.3. Data Mining techniques for extracting knowledge from collected data

Modern IT has radically amplified the capacity and power of data mining and information extraction from data. Classical or ML/DL driven data mining concern the analysis of observational datasets to extract knowledge from them unraveled unknown relationships and rationalize data in useful ways for the end-user. In the context of data coming from NICU incubators, Figure 3 can be helpful in the development of an efficient automated health care system.

Following the flow described in Figure 3, we may identify the main techniques/steps characterizing data mining technology. Those are general steps that can be specified depending on the chosen application. For example, preprocessing applied to data concerning studies in Table 3 will be principally used to upgrade the nature of an image with diminishing varieties. This is done to eradicate any infringements that cause entanglements in the preparing stage which cause broad utilization of reality assets [49]. Several key destinations can be accomplished with preprocessing which incorporates commotion evacuation, differentiate improvement, brightening, and recoloring revision. For evacuation, channels are broadly utilized, for example, mean and middle channels, Gaussian low-pass sifting, etc. Morphological strategies are additionally utilized for image sharpness upgrade purposes [50]. For differentiating improvement, differentiate extending strategies and histogram adjustment procedures have been generally used to enhance the contrast in the images. For brightening adjustment and recoloring varieties, shading standardization procedures have been mostly utilized [51].

Classification, data rationalization, knowledge extraction, and statistical formulation usually follow the preprocessing and can be combined or not. There are a high number of application examples of data mining techniques applied to the medical field. In Table 3 we report the most important application related to neonatal behavioral investigation. Again, all these approaches can be considered for further application in concert with the novel generation of NICU incubators for data analysis and knowledge extraction to support clinical decisions and precision medicine.

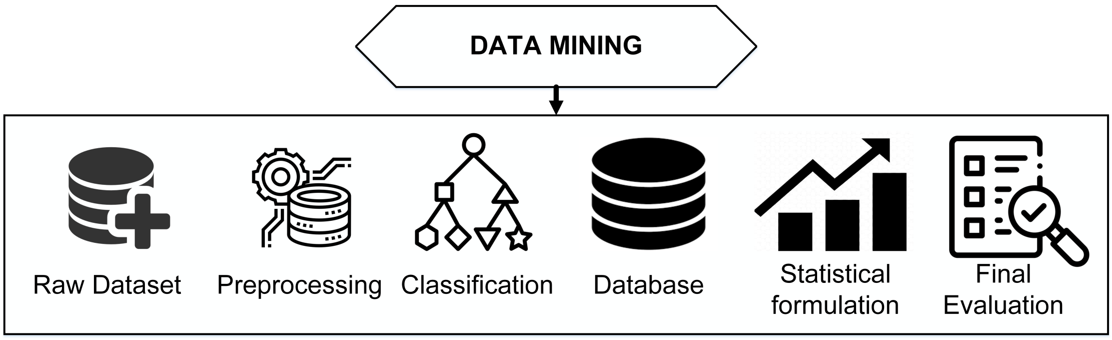

Figure 3: The block diagram of the data mining techniques for intelligent system development.

Table 3
Preprocessing and data mining research work

Study	***Environment***	***Data detail***	***Technique***	***Objectives***
[52]	Hospital	3D images	Key points recognition	Overall behaviour analysis
[53]	NICU	3D images	Convolutional neural networks (CNN's)	Overall behaviour analysis
[54]	Hospital	Multidimensional	Logistic regression algorithm	Classify normal/abnormal
[55]	Hospital	RGB images	supervised machine learning and handcrafting algorithm	Detect the Writhing movement
[56]	N/A	Synthetic	Convolutional neural network (CNN)	Classify abnormal Infant Movements
[57]	Hospital	RGB Images	Gaussian mixture model	Classify 4 type of movements
[58]	Hospital	RGB Images	Motion features, Decision Tree algorithm	Analysis CP risk
[59]	Hospital	RGB Images	Neural network	Detect the nervous condition of baby
[60]	Home/Hospital	RGB Images	Pre-trained CNN + LSTN	Detect Fidgety Movement

4. Conclusion

In the context of neonatal care, software architectures for storing data, to be then analyzed by data mining techniques, should consider innovative tools for heterogeneous (structured and unstructured) data collection as data that may be collected through hardware diagnostic devices, custom sensors, and software solutions installed in a NICU incubator (or a set of NICU incubators). Those data either the raw data or the processed data – should thus be handled as sensitive data, considering the appropriate ethical and privacy procedures, amongst which compliance to the General Data Protection Regulation (GDPR). Examples of data sources are (a) clinical data and Electronic health records (EHRs); (b) imaging data; (c) IoT device data streams. It is worth noticing that developing data collectors and management systems for neonatal care may take advantage of existent tools already applied to manage data in other fields of medicine and explicitly developed to manage patient health data with all the protection systems that need to be used for this type of sensitive data.

Acknowledgment

The present research work has been developed as part of the PARENT project, funded by the European Union's Horizon 2020 research and innovation program under the Marie Sklodowska-Curie-Innovative Training Network 2020, Grant Agreement N° 956394 (https://parenth2020.com/).

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Newborn mortality, 2021. URL: https://www.who.int/news-room/fact-sheets/detail/levels-and-trends-in-child-mortality-report-2021, accessed Mar. 15, 2022).

[2] Newborn mortality, 2020. URL: https://www.who.int/news-room/fact-sheets/detail/newborns-reducing-mortality, accessed Mar. 15, 2022).

[3] T. Tekelab, C. Chojenta, R. Smith, D. Loxton, The impact of antenatal care on neonatal mortality in sub-saharan africa: A systematic review and meta-analysis, PLOS ONE 14 (2019) 0222566,. doi:10.1371/JOURNAL.PONE.0222566.

[4] Towards maternal and newborn survival in the WHO South-East Asia Region i Implementation experience of the WHO SEARO model of point-of-care quality improvement (POCQI) Towards maternal and newborn survival in the WHO South-East Asia Region Implementation experience of the WHO SEARO model of point-of-care quality improvement, POCQI), 2020.

[5] B. Koullali, The association between parity and spontaneous preterm birth: A population based study, BMC Pregnancy and Childbirth 20 (2020) 1–8,. doi:10.1186/S12884-020-02940-W/TABLES/3.

[6] S. M. Mathews, Explainable artificial intelligence applications in nlp, biomedical, and malware classification: a literature review, in: Intelligent computing-proceedings of the computing conference, Springer, 2019, pp. 1269–1292.

[7] M. S. Salekin, P. R. Mouton, G. Zamzmi, R. Patel, D. Goldgof, M. Kneusel, S. L. Elkins, E. Murray, M. E. Coughlin, D. Maguire, et al., Future roles of artificial intelligence in early pain management of newborns, Paediatric and Neonatal Pain 3 (2021) 134–145.

[8] P. K. D. Pramanik, S. Pal, P. Choudhury, Beyond automation: the cognitive iot. artificial intelligence brings sense to the internet of things, in: Cognitive computing for big data systems over IoT, Springer, 2018, pp. 1–37.

[9] J. Nates, Icu admission, discharge, and triage guidelines: A framework to enhance clinical operations, development of institutional policies, and further research, Critical Care Medicine 44 (2016) 1553–1602,. doi:10.1097/CCM.0000000000001856.

[10] A. Ehteshami, F. Sadoughi, M. Ahmadi, P. Kashefi, Intensive care information system impacts, Acta Informatica Medica 21 (2013) 185,. doi:10.5455/AIM.2013.21.185-191.

[11] A. Zaylaa, M. Rashid, M. Shaib, I. Majzoub, A handy preterm infant incubator for providing

intensive care: Simulation, 3d printed prototype, and evaluation, Journal of Healthcare Engineering 2018 (2018). doi:10.1155/2018/8937985.
[12] E. Küng, L. Aichhorn, A. Berger, T. Werther, Mirrored ribs: A sign for pneumothorax in neonates, Pediatric Critical Care Medicine (2020) 944– 947,. doi:10.1097/PCC.0000000000002381.
[13] C. Bassford, Decisions regarding admission to the icu and international initiatives to improve the decision-making process, Critical Care 21 (2017) 1–3,. doi:10.1186/S13054-017-1749-3/METRICS.
[14] D. Szpecht, M. Szymankiewicz, I. Nowak, J. Gadzinowski, Intraventricular hemorrhage in neonates born before 32 weeks of gestation—retrospective analysis of risk factors, Child's Nervous System 32 (2016) 1399–1404,. doi:10.1007/S00381-016-3127-X/TABLES/1.
[15] N. Shah, C. Wusthoff, Intracranial hemorrhage in the neonate, Neonatal Network 35 (2016) 67–72,. doi:10.1891/0730-0832.35.2.67.
[16] M. Deshmukh, S. Patole, Antenatal corticosteroids in impending preterm deliveries before 25 weeks' gestation, Archives of Disease in Childhood - Fetal and Neonatal Edition 103 (2018) 173– 176,. doi:10.1136/ARCHDISCHILD-2017-313840.
[17] N. Zaghloul, H. Patel, M. Ahmed, A model of periventricular leukomalacia (pvl) in neonate mice with histopathological and neurodevelopmental outcomes mimicking human pvl in neonates, PLOS ONE 12 (2017) 0175438,. doi:10.1371/JOURNAL.PONE.0175438.
[18] A. Jalali, A. F. Simpao, J. A. Gálvez, D. J. Licht, C. Nataraj, Prediction of periventricular leukomalacia in neonates after cardiac surgery using machine learning algorithms, Journal of medical systems 42 (2018) 1–11.
[19] D. Bender, D. J. Licht, C. Nataraj, A novel embedded feature selection and dimensionality reduction method for an svm type classifier to predict periventricular leukomalacia (pvl) in neonates, Applied Sciences 11 (2021) 11156.
[20] S. Edwardson, C. Cairns, Nosocomial infections in the icu, Anaesthesia Intensive Care Medicine 20 (2019) 14–18,. doi:10.1016/J.MPAIC.2018.11.004.
[21] H. Khan, F. Baig, R. Mehboob, Nosocomial infections: Epidemiology, prevention, control and surveillance, Asian Pacific Journal of Tropical Biomedicine 7 (2017) 478–482,. doi:10.1016/J.APJTB.2017.01.019.
[22] J.-F. Hsu, Y.-F. Chang, H.-J. Cheng, C. Yang, C.-Y. Lin, S.-M. Chu, H.-R. Huang, M.-C. Chiang, H.-C. Wang, M.-H. Tsai, Machine learning approaches to predict in-hospital mortality among neonates with clinically suspected sepsis in the neonatal intensive care unit, Journal of Personalized Medicine 11 (2021) 695.
[23] M. Beltempo, G. Bresson, G. Lacroix, Using machine learning to predict nosocomial infections and medical accidents in a nicu (2020).
[24] C. Mehanian, S. Kulhare, R. Millin, X. Zheng, C. Gregory, M. Zhu, H. Xie, J. Jones, J. Lazar, A. Halse, et al., Deep learning-based pneumothorax detection in ultrasound videos, in: Smart Ultrasound Imaging and Perinatal, Preterm and Paediatric Image Analysis, Springer, 2019, pp. 74–82.
[25] S. Röhrich, T. Schlegl, C. Bardach, H. Prosch, G. Langs, Deep learning detection and quantification of pneumothorax in heterogeneous routine chest computed tomography, European radiology experimental 4 (2020) 1–11.
[26] A. Symon, N. Hassan, H. Rashid, I. Ahmed, S. Reza, Design and development of a smart

baby monitoring system based on raspberry pi and pi camera, in: 4th International Conference on Advances in Electrical Engineering, ICAEE 2017, volume 2018-January, 2017, pp. 117–122,. doi:10.1109/ICAEE.2017.8255338.

[27] W. Shalannanda, I. Zakia, E. Sutanto, F. Fahmi, Design of hardware module of iot-based infant incubator monitoring system, in: Proceedings - 2020 6th International Conference on Wireless and Telematics, ICWT, 2020. doi:10.1109/ICWT50448.2020.9243665.

[28] N. Zakaria, F. Saleh, M. Razak, Iot (internet of things) based infant body temperature monitoring, in: 2nd International Conference on BioSignal Analysis, Processing and Systems, ICBAPS, 2018, pp. 148–153,. doi:10.1109/ICBAPS.2018.8527408.

[29] L. Lamidi, A. Kholiq, M. Ali, A low cost baby incubator design equipped with vital sign parameters, Indonesian Journal of Electronics, Electromedical Engineering, and Medical Informatics 3 (2021) 53–58,. doi:10.35882/IJEEEMI.V3I2.3.

[30] S. Alduwaish, Automated humidity control system for neonatal incubator, Journal of Physics: Conference Series 2071 (2021) 012029,. doi:10.1088/1742-6596/2071/1/012029.

[31] M. Nampira, A. Kholiq, Lamidi, A modification of infant warmer with monitoring of oxygen saturation, heart rate and skin temperature, Journal of Electronics, Electromedical Engineering, and Medical Informatics 3 (2021) 19–25,. doi:10.35882/JEEEMI.V3I1.4.

[32] C. Kruse, A. Beane, Health information technology continues to show positive effect on medical outcomes: Systematic review, J Med Internet Res 2018;20(2):e41 (2018) 8793,. URL: https://www.jmir.org/2018/2/e41,. doi:10.2196/JMIR.8793.

[33] M. Javaid, A. Haleem, Industry 4.0 applications in medical field: A brief review, Current Medicine Research and Practice 9 (2019) 102–109,. doi:10.1016/J.CMRP.2019.04.001.

[34] M. Yamin, It applications in healthcare management: a survey, International Journal of Information Technology (Singapore 10 (2018) 503–509,. doi:10.1007/S41870-018-0203-3/FIGURES/3.

[35] H. Ke, Cloud-aided online eeg classification system for brain healthcare: A case study of depression evaluation with a lightweight cnn, Software: Practice and Experience 50 (2020) 596–610,. doi:10.1002/SPE.2668.

[36] L. Migliorelli, S. Moccia, R. Pietrini, V. Carnielli, E. Frontoni, The babypose dataset, Data in Brief 33 (2020) 106329,. doi:10.1016/J.DIB.2020.106329.

[37] N. Hesse, C. Bodensteiner, M. Arens, U. G. Hofmann, R. Weinberger, A. Sebastian Schroeder, Computer vision for medical infant motion analysis: State of the art and rgb-d data set, in: Proceedings of the European Conference on Computer Vision (ECCV) Workshops, 2018, pp. 0–0.

[38] O. Rihawi, D. Merad, J. Damoiseaux, 3d-ad: 3d-autism dataset for repetitive behaviours with kinect sensor, in: 2017 14th IEEE International Conference on Advanced Video and Signal Based Surveillance, AVSS 2017, 2017. doi:10.1109/AVSS.2017.8078544.

[39] C. Chambers, Computer vision to automatically assess infant neuromotor risk, IEEE Transactions on Neural Systems and Rehabilitation Engineering 28 (2020) 2431–2442,. doi:10.1109/TNSRE.2020.3029121.

[40] X. Huang, N. Fu, S. Liu, S. Ostadabbas, Invariant representation learning for infant pose estimation with small data, in: Proceedings - 2021 16th IEEE International Conference on Automatic Face and Gesture Recognition, FG 2021, 2021. doi:10.1109/FG52635.2021.

9666956.
[41] S. Rajagopalan, A. Dhall, R. Goecke, Self-stimulatory behaviours in the wild for autism diagnosis, 2013. doi:10.1109/ICCVW.2013.103.
[42] B. Priya, S. Rajendran, R. Bala, R. Gobbi, Remote wireless health monitoring systems, in: 2009 Innovative Technologies in Intelligent Systems and Industrial Applications, CITISIA 2009, 2009, pp. 383–388,. doi:10.1109/CITISIA.2009.5224177.
[43] Microcontroller based baby incubator using sensors | semantic scholar, 2022. URL: https://www.semanticscholar.org/paper/Microcontroller-Based-Baby-Incubator-Using-Sensors-Suruthi-Suma/d9ba98adde1adcfe0fff3970b58cf516efa8968e.
[44] L. Nachabe, M. Girod-Genet, B. ElHassan, J. Jammas, M-health application for neonatal incubator signals monitoring through a coap-based multi-agent system, in: 2015 International Conference on Advances in Biomedical Engineering, ICABME 2015, 2015, pp. 170–173,. doi:10.1109/ICABME.2015.7323279.
[45] A. Vyas, S. Abimannan, R. Hwang, Sensitive healthcare data: Privacy and security issues and proposed solutions, Emerging Technologies for Healthcare (2021) 93–127,. doi:10.1002/9781119792345.CH4.
[46] S. Salloum, R. Dautov, X. Chen, P. Peng, J. Huang, Big data analytics on apache spark, International Journal of Data Science and Analytics 1 (2016) 145–164,. doi:10.1007/S41060-016-0027-9/FIGURES/6.
[47] P. Merla, Y. Liang, Data analysis using hadoop mapreduce environment, in: Proceedings - 2017 IEEE International Conference on Big Data, Big Data, volume 2018-January, 2017, pp. 4783–4785,. doi:10.1109/BIGDATA.2017.8258541.
[48] Top 30 big data tools for data analysis in 2022 | octoparse, 2022. URL: https://www.octoparse.com/blog/top-30-big-data-tools-for-data-analysis-in-2021#, accessed Jul. 20, 2022).
[49] S. Tripathy, T. Swarnkar, A comparative analysis on filtering techniques used in preprocessing of mammogram image, in: Advances in Intelligent Systems and Computing, volume 1082, 2020, pp. 455–464,. doi:10.1007/978-981-15-1081-6_39.
[50] L. Courtenay, D. Herranz-Rodrigo, R. Huguet, M. Maté-González, D. González-Aguilera, J. Yravedra, Obtaining new resolutions in carnivore tooth pit morphological analyses: A methodological update for digital taphonomy 15 (2020) 0240328,.
[51] E. Gastal, M. Oliveiray, Adaptive manifolds for real-time high-dimensional filtering, ACM Transactions on Graphics (TOG 31 (2012). doi:10.1145/2185520.2185529.
[52] N. Hesse, A. Schroder, W. Muller-Felber, C. Bodensteiner, M. Arens, U. Hofmann, Body pose estimation in depth images for infant motion analysis, in: Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, 2017, pp. 1909–1912,. doi:10.1109/EMBC.2017.8037221.
[53] S. Moccia, L. Migliorelli, V. Carnielli, E. Frontoni, Preterm infants' pose estimation with spatio-temporal features, IEEE Transactions on Biomedical Engineering 67 (2020) 2370–2380,. doi:10.1109/TBME.2019.2961448.
[54] P. Marschik, A novel way to measure and predict development: A heuristic approach to facilitate the early detection of neurodevelopmental disorders, Current Neurology and Neuroscience Reports 17 (2017) 1–15,. doi:10.1007/S11910-017-0748-8/FIGURES/4.
[55] I. Doroniewicz, Writhing movement detection in newborns on the second and third day

of life using pose-based feature machine learning classification, Sensors 20 (2020) 5986,. doi:10.3390/S20215986.
[56] K. McCay, E. Ho, H. Shum, G. Fehringer, C. Marcroft, N. Embleton, Abnormal infant movements classification with deep learning on pose-based features, IEEE Access 8 (2020) 51582–51592,. doi:10.1109/ACCESS.2020.2980269.
[57] T. Tsuji, Markerless measurement and evaluation of general movements in infants, Scientific Reports 10 (2020) 1–13,. doi:10.1038/s41598-020-57580-z.
[58] E. Ihlen, Machine learning of infant spontaneous movements for the early prediction of cerebral palsy: A multi-site cohort study, Journal of Clinical Medicine 9 (2020) 5,. doi:10.3390/JCM9010005.
[59] S. Reich, Novel ai driven approach to classify infant motor functions, Scientific Reports 11 (2021) 1–13,. doi:10.1038/s41598-021-89347-5.
[60] W. Schmidt, M. Regan, M. Fahey, A. Paplinski, General movement assessment by machine learning: why is it so difficult?, Journal of Medical Artificial Intelligence 2 (2019). doi:10.21037/JMAI.2019.06.02.