UNIVERSITAT POLITÈCNICA DE VALÈNCIA

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UNIVERSITAT POLITÈCNICA DE VALÈNCIA

Escuela Técnica Superior de Ingeniería de Telecomunicación

Desarrollo e implementación de un sistema de Monitoreo Neonatal Inteligente mediante el uso de Big Data e Inteligencia Artificial

Trabajo Fin de Grado

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Development and implementation of an Intelligent Neonatal Monitoring system through the use of Big Data and Artificial Intelligence

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Abstract

In recent years, artificial intelligence has seen promising applications in healthcare. From medical image processing to electronic health record analysis, the proliferation of multiple approaches to AI may help improve healthcare. This is particularly important in neonatal intensive care units (NICUs), where timely interventions are critical to the health status of newborns and the amount of real-time information is immense. This project provides a systematic review of 41 papers on ai, big data, and the NICU, highlighting the transformative potential of AI in the NICU and its critical role in shaping the future of neonatal care, while pointing out that challenges such as data privacy, algorithmic interpretability, and ethical considerations must be addressed to responsibly deploy AI in neonatal care. Meanwhile, this project retrospectively analyzed the physiological data of 114 preterm infants from La Fe University and Polytechnic Hospital de Valencia using the Kmeans clustering algorithm for unsupervised learning. After preprocessing and bivariate analysis, five features were selected for clustering in three groups, which resulted in an optimal profile coefficient of 0.86. Clustering results demonstrate the feasibility of predictive analysis of preterm infant physiologic data to aid physicians in making medical judgments, laying the groundwork for further clinical validation in a controlled operational environment.

Keywords

Premature Infants, NICU, Blood Gases Analysis, Machine learning, Unsupervised learning, Clustering, K-Means

摘要

近年来，人工智能在医疗保健领域的应用前景广阔。从医学图像处理到电子健康记录分析，多种人工智能方法的涌现可能有助于改善医疗保健。这一点在新生儿重症监护室（NICU）尤为重要，因为及时干预对新生儿的健康状况至关重要，而且实时信息量巨大。本项目对 41 篇有关人工智能、大数据和新生儿重症监护室的论文进行了系统综述，强调了人工智能在新生儿重症监护室中的变革潜力及其在塑造新生儿护理未来中的关键作用，同时指出要在新生儿护理中负责任地部署人工智能，必须应对数据隐私、算法可解释性和伦理考虑等挑战。与此同时，该项目采用无监督学习的 Kmeans 聚类算法，对来自拉费大学-瓦伦西亚理工医院的 114 名早产儿的生理数据进行了回顾性分析。经过预处理和双变量分析，选择了五个特征进行聚类，分为三组，得出最佳剖面系数为 0.86。聚类结果证明了对早产儿生理数据进行预测分析以帮助医生做出医疗判断的可行性，为在受控操作环境中进一步进行临床验证奠定了基础。

关键词

早产儿、新生儿重症监护室、血气分析、机器学习、无监督学习、聚类、K-Means

Chapter 1: Introduction

1.1 Background Information

1.1.1 AI in Neonatal Care: Transforming NICUs

Artificial intelligence (AI) stands out as one of the most revolutionary technologies since the industrial revolution. Its impact extends across various sectors, reshaping personal and professional interactions and facilitating significant advancements. One area where AI is particularly significant is healthcare, especially in pediatrics and the neonatal intensive care unit (NICU), which stands as a critical service for newborn infants facing life-threatening conditions.

As a specialized unit within hospitals, NICUs provide comprehensive medical care and support to newborns who require intensive monitoring, treatment, and nurturing during the fragile early stages of life. One of the primary roles of the NICU is to cater to the needs of premature infants, who are born before completing a full term of gestation, usually a gestational age between 25-26 weeks and birth weights under 2.5 Kg. Premature birth, a significant global health issue, exposes infants to a myriad of health risks and complications, ranging from respiratory distress syndrome to neurological disorders. The NICU serves as a lifeline these patients, offering trans-specialty advanced medical interventions, respiratory support, and real-time physiological monitoring to optimize their chances of survival and promote a safe development.

The NICU serves as a hub of expertise, where skilled healthcare professionals collaborate to provide tailored treatment plans, rehabilitation services, and family-centered support to ensure the best possible outcomes for every patient. In this context AI expands traditional NICU healthcare allowing to extract information to support real-time decision-making and clinical intervention.

AI has been implemented in healthcare over a wide typology of clinical applications, for example, from molecular and genetic testing to medical images of different modalities, diagnostic codes and social media. The ultimate goal of AI is to learn and identify associations between data and outcomes of interest. AI needs data generated from healthcare activities such as diagnosis, treatments and follow-up to develop, test and validate algorithms. Digitalized data in healthcare is available in a wide range of formats, including structured and non-structured schemas. AI involves a wide variety of methods that excel traditional statistical techniques and can find patterns that support the process of decision making as well as the formulation of hypotheses. AI can provide powerful tools to automate tasks and to support and inform pediatricians, nurses and other specialists.

1.1.2 Oxygenation in the Neurological Development of the Neonate

Oxygenation is a vital physiological process that refers to the transfer of oxygen from the respiratory system to the bloodstream and ultimately to the individual cells of the body. This process is fundamental and necessary for all oxygen-dependent life forms. In the human body, oxygenation occurs primarily through the lungs, where oxygen passes through the alveoli and binds to haemoglobin in the red blood cells of the bloodstream, which subsequently transports the oxygen to all parts of the body to support metabolic activity and energy production in the cells. Proper oxygenation is essential for maintaining cellular function, organ health, and overall life activity. Inadequate or excessive oxygenation can lead to disease or health problems. For example, hypoxaemia (insufficient oxygen in the blood) may lead to organ dysfunction and cell death, while oxygen toxicity (excessive oxygen intake) may damage the lungs and central nervous system[10]

The monitoring and adjustment of oxygenation is particularly important in specific clinical situations, such as the management of premature infants in neonatal intensive care units. Healthcare professionals must precisely control the supply of oxygen to ensure that it neither leads to insufficient oxygen nor causes oxygen toxicity, thus

minimizing potential negative effects on the patient's health.[12]

Oxygenation is critical to the development of the newborn's nervous system as it directly affects the function and structure of the brain. Newborns, especially premature babies, whose nervous systems are not yet fully developed, are very sensitive to oxygen levels. Proper oxygenation promotes the growth and differentiation of brain cells and contributes to the healthy development of the nervous system. However, oxygen levels that are too high or too low can have a detrimental effect on the brain. Excessive oxygen levels may lead to oxygen toxicity, affecting brain development and even leading to permanent brain damage. Conversely, insufficient oxygen may lead to hypoxia in brain tissue, affecting the normal function and development of nerve cells. Therefore, in the care of newborns, especially preterm infants, the maintenance of appropriate oxygenation levels is essential to promote healthy maturation of the nervous system[11].

1.2 System Review of Former Studies

1.2.1 Methods

Search Strategy

A systematic literature search was conducted on clinical trials on NICU involving AI techniques using 4 electronic databases: Cochrane, PubMed, Scopus and IEEE Xplore using the following search queries (consider Appendix).

Inclusion and Exclusion Criteria

We specified 3 exclusion and 3 inclusion criteria for screening. Records were not selected if they (i) did not include trials conducted in the NICU, (ii) did not describe data modelling or (iii) did not present clinical outcomes. Besides, records in other language than English and published more than 10 years ago were excluded as well. In the final eligibility assessment, the following inclusion criteria were specified to limit the scope of the review: (i) the studies must be defined as retrospective or

prospective trials, (ii) they must define specific clinical outcomes in the NICU, and (iii) they must describe the methodology of data modelling and the sources of the data. These criteria were designed to evaluate the researching lines in NICUs in the last 10 years, which include the democratization of frameworks and tools for AI application.

Figure1_ paper funneling

Selection Process

Figure 1 shows the flow diagram of the selection process. Records from the scientific literature were identified in the 4 databases defined in Table 1. The resulting data sets were combined in an Excel spreadsheet (.xlsx), rearranged by DOI, and checked for possible erroneous entries. Duplicated records were assessed by comparing DOI names and titles of the publication. The results were manually reviewed to correct minor errors due to misspellings of DOI or the title in the record database. The eligibility criteria for inclusion were then manually evaluated by title and abstract of each record, and selected records were sought for retrieval. Retrieved records were fully screened and were dismissed if they did not meet the inclusion criteria or met the exclusion criteria. Finally, data and details were extracted for included AI studies.

Data Extraction

Based on the selected records, a total of 12 categories and 40 data indicators we reported . These indicators were adapted from the CHARMS (Critical Appraisal and Data Extraction for Systematic Reviews of Prediction Modelling Studies) guideline [13]. Additionally, publication-related data such as author(s), title, journal, year of publication, and DOI were collected for analysis purposes.

The categories were designed to assess various aspects, including the objective of the clinical trial and AI, the accessibility and quality of the data development process, the methodology employed in designing and developing the AI model, the obtained results, and the discussion provided in the report. These categories not only aimed to

detail the characteristics of the AI models but also to evaluate the differences and connections between trial design, data collection, and AI implementation.

1.2.2 Data Analysis

In order to gain a deeper understanding of existing research and trends, we conducted extensive data analysis using Python scripts.Python, as a powerful programming language with rich data science libraries (such as Pandas, NumPy, and Scikit-learn) enabled us to efficiently process and analyse complex healthcare datasets, thereby identifying key trends and patterns .

Although Python is very powerful for data processing and analysis, to manage and review preliminary data we also utilised the convenience of Excel, whose intuitive interface and flexible data collation features made preliminary data cleaning and simple analysis easy and efficient.

For data visualisation, the Draw.io and SankeyMatic tools, as well as Excel's charting capabilities, were used to present the results of the study.Draw.io was used to create flowcharts and framework diagrams that clearly show the different stages and key points of the application of AI in the NICU.SankeyMatic, a dedicated Sankey diagram generation tool, was used to visualise data flows and transformation paths. This type of diagram played an important role in explaining how AI could improve the process of preterm care. Finally, Excel's charting tools were used to generate standard statistical charts such as pie charts, and bar charts, which visualise key statistical results and trends.

By using a combination of Python, Excel, Draw.io and SankeyMatic, this study not only analysed a large amount of complex data in depth, but also presented the findings in a clear and professional manner. The combined use of these tools not only enhanced the accuracy and transparency of the study, but also increased its replicability and accessibility, thus ensuring that the findings are of significant value to both academia and clinical practice.

1.2.3 Results

Articles Identified From the Database Searching:

The search identified 318 records, all published in English. Excluding 61 duplicates, 257 articles were screened by the eligibility criteria based on the title and abstract. The screening process concluded with 193 records excluded for not meeting the exclusion criteria. Thus, 64 records were assessed for eligibility. Of these, and 23 were excluded due to not being identified as a retrospective or prospective trial (n=9), lacking a complete description of methods and/or data sources (n=7), or not defining a specific clinical outcome in NICU (n=10). Therefore, a final set of 41 records were selected for further data analysis.

Clinical/AI Applications:

The main health areas covered by the selected studies included Cardiovascular conditions (n=9, 21.9%) (references), Digestive functions (n=2, 4.9%), Infections (n=6, 14.6%), Microvascular diseases (n=1, 2.4%), Neural/Brain conditions (n=8, 19.5%), and Respiratory difficulties (n=8, 19.5%). Another fraction of 6 studies were focused on clinically relevant parameters other than the aforementioned areas, such as body positioning or monitoring systems, and were thus classified under the Not Disease category. Finally, only 1 study was focused on prediction of Mortality (2.4%)

Studies were also classified according to the intended use of the AI modelling in their respective applications at NICUs (figure 2). The most common category was studies for Prognosis (n=23, 56.1%), which included studies from all previously defined health areas except for Microvascular area, followed by Classification (n=14, 34.1%), Monitoring (n=5, 12.2%), and Forecasting symptoms (n=1, 2.4%).

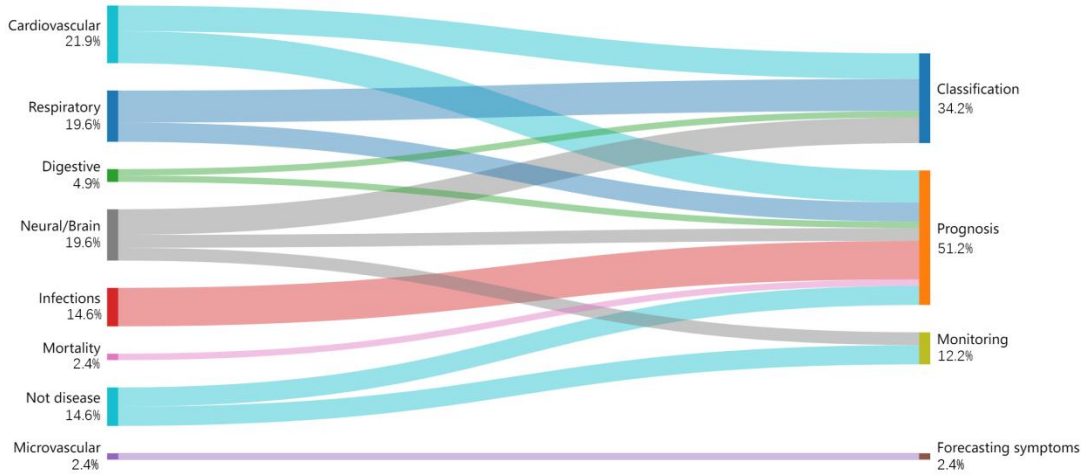


Figure2_ 2. Applications of AI in NICUs

Characteristics of the studies:

Most of the studies were performed using private data (n=37; 90.2%), while only a small fraction used publicly available data (n=4, 9.8%). The most used type of data across the selected studies (figure 3.1) consisted of physiological parameters —i.e. heart rate (HR) or oxygen saturation (SpO2), (n=37, 90.2%), followed by imaging data (n=9, 21.9%), measurement data (n=3, 7.3%) and other data (n=1, 2.4%). A great majority of the studies (n=30, 73.1%) were designed as experimental or observational trials, while the rest were designed as interventional (either two or four-arms studies). Regarding how data were treated,, more than half (n=29, n=70.7%) of the experiments used single-group data, and some used comparison vs control experiments (n=8) and cross-over arms trials (n=4, 9.8%). Finally, not all studies reported the sample size (85.3%), 15 of which consisted of 11-50 participants (36.6%), 7 of them 51-100 participants (17.1%), 7 more of them 101-500 participants (17.1%) and and 2 of them more than 500 participants (4.9%) (figure 3.5 in Multimedia Appendix).

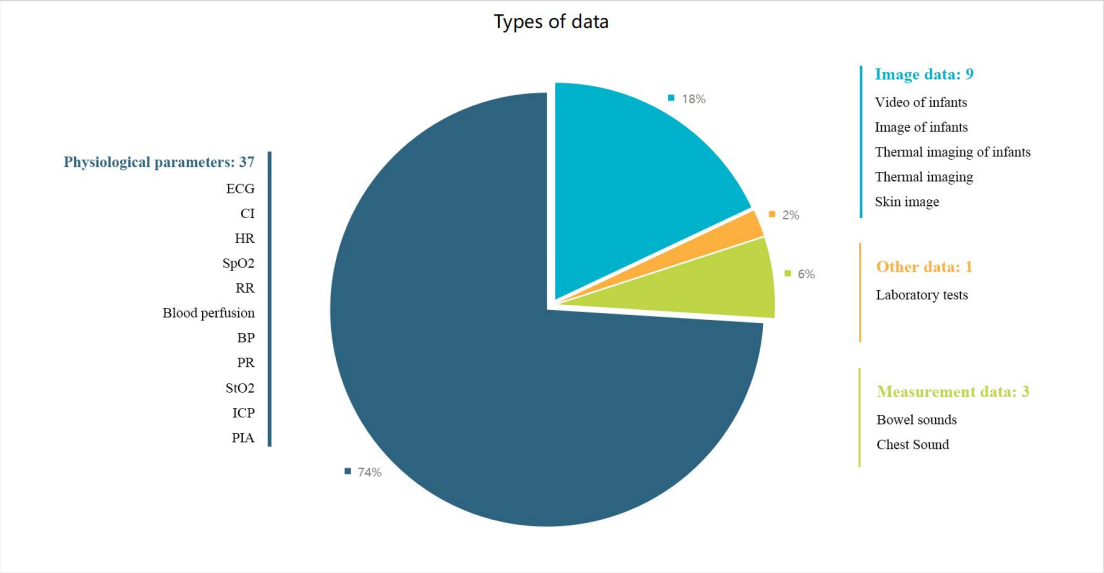


Figure3_predictors and classes

Characteristics of the AI models:

The studies contained among the selected records use a variety of AI approaches, including deep learning(n=20, 48.8%), traditional machine learning (n=13, 31.7%) and ensemble learning methods (n=2, 4.9%) (figure 4.1). The most popular family of algorithms was Convolution Neural Network (CNN) (n=14, 34.2%), followed by Random Forest (RF) model (n=7, 17.1%), Logistic Regression (LR) (n=6, 14.6%), Support Vector Machine (SVM) (n=6, 14.6%), K-Nearest Neighbors (KNN), Naive Bayes (NB) and XGBoost (XGB) (n=2, 4.9% respectively) (figure 4.1).

These models were implemented on specific predictors selected for each condition, disease or parameter of interest. In most cases they used a combination of data (n=19, 46.3%). The most common category of predictors was physiological parameters (n=37, 90.2%), which relates to medical data analysis (ie, ECG, SpO2, HR, RR, ...), and the second was Image data (n=9, 21.9%), defined as image (n=3, 7.3%) or videos (n=6, 14.6%) of infants. The rest of predictors consist of bowel sound and chest sound (n=3, 7.3%) and test records (n=1, 2.4%).

Finally, 90.2% of the studies did not mention missing data (n=37, 90.2%). The most common strategy to deal with missing data during the preprocessing steps of the data before modelling was data normalisation (n=12, 29.2%), followed by data

enhancement and data labelling and cleaning (n=7, 17.1% respectively), then feature extraction (n=5, 12.2%) and algorithm application (n=3, 7.3%). The remaining three are artefact removal, data stream synchronization and data imputation.

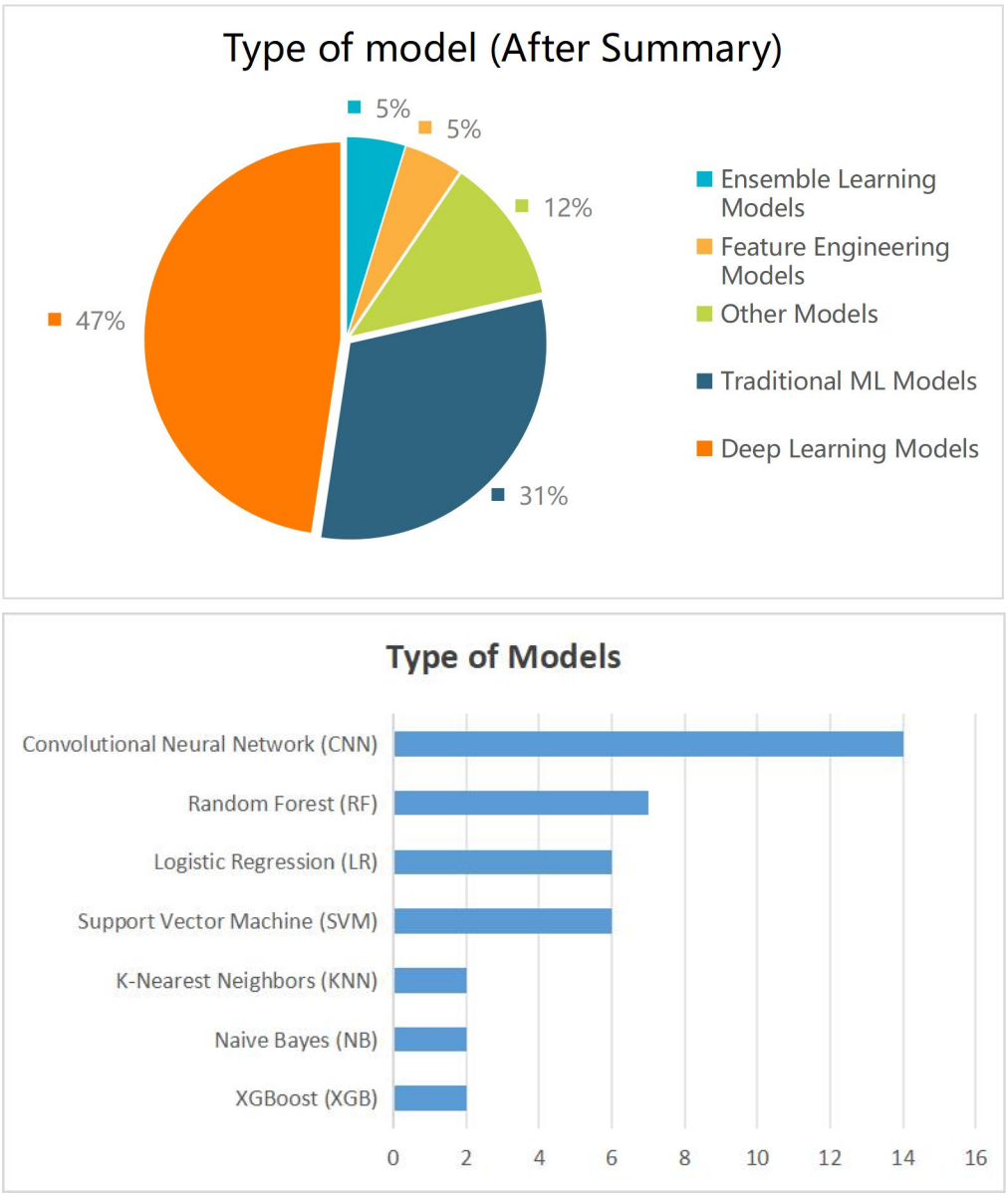


Figure 4_type of model after summary (combined)

1.2.4 **Validation**

Most of the records reported the algorithm effectiveness evaluation criteria (n=39, 95.1%). Among the most used performance evaluation metrics were Accuracy (ACC) (n=12), followed by Area Under the Curve and Area Under the Receiver Operating Characteristic Curve (AUROC) (n=6 respectively). The remaining evaluation metrics

are mean error (MEA) (n=4), F1 score (F1) (n=3), root mean square distance (RMSD), mean absolute error (n=2 respectively), Sensitivity (Se), Specificity (Sp), Intersection over Union (IoU), Root Mean Square Error (RMSE), Signal Distortion Ratio (SDR), Correlation Coefficient (CORR), Feature importance, Descriptiveness, Recommendation, Neonatal Treatment Severity Index (NTISS) and comparison between groups (n=1 respectively). between groups) (n=1 respectively).

1.2.5 Principle Findings

The models showcased in these studies performed commendably across a spectrum of tasks within neonatal intensive care, reflecting a solid performance in machine learning applications. Many studies reported high accuracy (ACC) scores, with [16] achieving an ACC of 93.8 ± 2.2% and [17] reporting an ACC of 92.52% alongside an F1 score of 95.26%. The Area Under the Curve (AUC) and Receiver Operating Characteristic (ROC) values, crucial indicators of model discrimination capacity, were also substantial, with [14] noting an AUC of 0.88 and [46] achieving an AUC of 97%.

The balance between precision and recall was captured by the F1-score, suggesting reliable model performance in identifying true cases while minimizing false positives. For example, [16] reported an F1-score of 0.93 ± 0.3. Other metrics such as sensitivity (Se) and specificity (Sp) were also mentioned, with [22] reporting 88.5% and 49% respectively, emphasizing the models' capacity to correctly identify positive instances.

Quantifying prediction errors, mean absolute error (MAE), and root mean square error (RMSE) were used, with [23] noting an MAE of 1.71 and RMSE of 1.89. These error measures are essential for understanding the magnitude of prediction deviations. Advanced metrics like the Intersect over Union (IoU) and signal-to-distortion ratio (SDR) provided insights into model precision in spatial tasks and sound quality enhancement, with [28] achieving an IoU of 0.5 and [44] reporting a median SDR improvement of 1.5 dB.

Ensemble methods and deep learning approaches, including convolutional neural networks (CNNs), highlighted the ongoing progression towards sophisticated model architectures. The study by [21] on asymmetrical convolution demonstrates the evolution of network generalization capabilities.

Lastly, the interpretability of AI models, which is crucial in clinical settings, was addressed through feature importance and explainability, as discussed by [36]. In summation, the array of studies reviewed underscore the efficacy of AI applications in enhancing neonatal care through reliable and precise monitoring and prediction tools. The array of performance metrics emphasizes the comprehensive nature of model evaluation, taking into account both predictive accuracy and clinical relevance as demonstrated in studies by authors like [16], [17], [14], and others.

1.2.6 Challenges

[14] highlighted a limitation regarding the maturity differences between the patient groups in their dataset, which could influence the LOS prediction algorithm.

[16] noted that including the surrounding environment in the detection of facial expressions could introduce confounding factors to the deep convolutional neural network (DCNN) learning process.

[19] mentioned the challenges with the size and quality of the transformed images used for early detection of late-onset neonatal sepsis, and the fact that only suspected cases were considered.

[20] faced difficulties in gathering sufficient data, especially from critically ill newborns with systemic circulatory disorders.

[22] discussed the clinical relevance of their approach but acknowledged the limitation of having a small and unevenly distributed number of positive cases,

affecting the reliability of subgroup comparisons.

[24] and [25] raised the issue that selecting a lower gestational age-based threshold for hypotensive events improves feature discriminatory power but reduces the number of subjects, impacting the confidence in observed changes.

[27] pointed out that the large set of features required for their model could be expensive to collect in an ICU setting and the need for explainable AI (XAI) to build medically acceptable clinical decision support systems.

[28] admitted that while their pressure-sensitive mat (PSM) improved model performance, it was still not sufficient for deployment in clinical environments.

[31] acknowledged the limitation of their study being conducted in a single hospital, potentially affecting the generalizability of their model.

[32] noted that they did not account for medical interventions affecting mean intracranial pressure (ICP), and the length of analyzed recordings was not standardized.

[34] discussed the challenge of dataset imbalance and the ongoing efforts to improve it for neonatal bowel sound detection.

[30] mentioned that their data was only obtained from healthy full-term infants at birth, which limits the application of their method to evaluate maturation post-birth.

[37] indicated that monitoring was limited to the lower right abdomen, and the necessity to compare bowel sounds from different abdominal quadrants.

[38] faced challenges in recruiting volunteer parents and had limitations in the

experimental setup and number of cases.

[39] pointed out the oversimplification in representing the complex EEG signal with a single parameter.

[42] aimed to tackle the limitations in future studies by exploring the role of each feature on model performance using accurate statistical analysis tests and implementing cost-effective models.

[44] and [49] dealt with the issue of overfitting in their deep learning model and sought to address it by restricting training epochs and freezing weights in the initial layers.

[45] recognized the potential for improvement by expanding their dataset, employing leave-one-subject-out testing, and exploring more robust methods for extracting the respiration signal from video.

These challenges underscore the complexities of developing AI systems for neonatal care. They range from data scarcity and quality, imbalanced datasets, and the need for model interpretability, to the particularities of clinical environments and generalizability concerns. Each study's challenges reveal the critical areas for future research and development in this field.

1.2.7 Opportunities

[14] is looking to expand their study with a larger, cross-center dataset to improve the validation and generalizability of their sepsis prediction model.

[15] aims to incorporate additional data and other pain modalities, such as body movements, into their neonatal condition monitoring system.

[16] expresses the intent to extend their work to classify more nuanced neonatal sleep states and to develop a home-based monitoring system.

[18] is planning a prospective study using the Artemis platform to classify neonatal spells, aiming to compare its sensitivity and specificity against the gold standard of polysomnography.

[20] sees the potential in combining their systemic circulation monitoring system with neural network techniques for enhanced clinical application.

[21] emphasizes the importance of developing lighter, more efficient models for sustainable, automated, and intelligent monitoring systems, especially in resource-constrained environments.

[22] suggests data sharing between institutes for external validation of algorithm performance in various settings and populations, following the promise shown by the HeRO algorithm.

[24] and [25] point out the promise shown by thermal imaging in reducing neonatal mortality and suggest that better results could be obtained with more data or advanced image enhancement techniques.

[27] anticipates that clinical parameters like RDS, jaundice, and septicaemia could show correlations when applied to larger patient cohorts, potentially yielding valuable outcomes.

[28] looks to expand their dataset to further explore the generalizability of their models for false alarm detection in NICUs.

[29] regards the preliminary results as promising and underscores the usefulness of

machine learning algorithms in developing clinical decision tools.

[30] wants to conduct a study with new patients to expand their training set for early sepsis detection and evaluate real-time monitoring adaptability in NICUs.

[31] plans to extend their monitoring and evaluation from the delivery room to the NICU, indicating an integrated patient journey approach.

[34] is set to explore additional temporal and spectral features and differentiate between normal and abnormal peristaltic bowel sounds in future work.

[36] recommends further research into NICU admission practices to understand hidden patterns contributing to increasing NICU admissions.

[37] intends to focus on whether bowel sound characteristics in neonates are age-specific and the impact of their technology in clinical settings.

[38] is committed to collecting more cases to improve the robustness of their photoplethysmography imaging system across diverse conditions.

[39] aims to perform multicenter validation studies with larger datasets for EEG monitoring in asphyxiated infants, potentially leading to a data-driven EEG background grading system.

[40] envisions obtaining optimal results from FPGA hardware systems and realizing a full on-chip system for detecting respiratory failures in neonates.

[42] plans to address the limitations mentioned in their study, likely focusing on refining their feature set and improving model accuracy and cost-effectiveness.

[44] and [49] see promise in the removal of the need for hand-crafted features by utilizing deep learning, with improvements in pre-training required for transfer learning.

[50] contemplates employing ensemble learning and advanced feature selection technologies to enhance the accuracy and robustness of decision-making systems.

[45] and [52] will extend their methodology to tasks beyond head localization, such as full pose estimation.

[53] acknowledges the need for further experimentation to develop more efficient models and to collect and annotate more data.

[54] outlines the clinical relevance of their work but calls for further investigation in larger cohorts to enable subgroup analysis.

These opportunities represent a roadmap for future innovations in neonatal care, highlighting the importance of data expansion, methodological enhancements, interdisciplinary collaboration, and the implementation of advanced computational techniques.

1.2.8 Conclusion

In conclusion, our comprehensive review of recent advances in health-related modeling highlights a diverse landscape where machine learning, including both deep learning and traditional models, alongside other computational methods, plays a pivotal role in understanding and predicting outcomes across a wide range of medical fields. Notably, cardiovascular and neural/brain health areas have seen extensive application of deep learning techniques, reflecting the complex nature of data and the necessity for sophisticated models to capture the nuances inherent in these domains. Data types utilized in these models span from traditional vital signs, such as heart rate

(HR) and blood oxygen saturation (SpO2), to more specialized forms like EEG, chest sounds, and even video of infants, underscoring the multidimensional aspect of health data.

The exploration into digestive and microvascular health areas, albeit less extensive, underscores a growing interest in applying deep learning to niche domains, utilizing specific data types such as bowel sounds and SpO2 measurements. This indicates a promising direction for future research that could unlock new understandings and therapeutic approaches in less explored areas.

Infection modeling stands out for its balanced application of deep learning and traditional machine learning models, driven by a variety of data types including ECG, HR, and RR, pointing to the critical role of predictive modeling in managing infectious diseases, especially in the context of early detection and intervention.
Mortality prediction primarily through traditional ML models based on a wide array of clinical data emphasizes the need for predictive accuracy in critical care and resource allocation. This is particularly relevant in making informed decisions regarding patient management and improving outcomes.

Finally, the review reveals an intriguing application of diverse modeling techniques to non-disease-specific data, suggesting a broader utility of predictive models in health care beyond disease diagnosis and management. The integration of ensemble learning and feature engineering models, alongside deep and traditional machine learning, illustrates a dynamic field that is rapidly evolving to adapt to the complexities of health data.

This review underscores the importance of interdisciplinary collaboration in advancing health care through technology. As computational techniques become increasingly sophisticated and health data becomes more accessible, the potential for these models to revolutionize health care, from predictive diagnostics to personalized

treatment plans, is immense. However, challenges remain, including data privacy concerns, the need for robust validation, and ensuring equitable access to the benefits of these technologies. Future research should aim to address these challenges, fostering an environment where technological advancements contribute to holistic and accessible health care solutions.

Table 1: Summary of Review

Chapter 2: Design and Implementation

2.1 Study Design

Observational and prospective study carried out in a cohort of premature babies in a regional reference Neonatology Unit (Hospital La Fe). Premature infants with bradycardic apneic syndrome with a gestational age less than 32 weeks who are stable at respiratory and metabolic levels will be included. Patients were eligible if they were <32 weeks at birth, received NICU KC with or without respiratory support. Exclusion criteria were parents who refused to participate, invasive mechanical ventilation, brain malformations, severe periventricular haemorrhage (grade 3-4), pharmacological sedation, chromosomal disorders or severe malformations. During the study time, oxygen saturation will be continuously monitored by postductal pulse oximetry (24 hours a day for 7 days). Clinical parameters will be recorded (analysis of the pulse oximetry histogram and clinical variables) and markers of oxidative stress in urine and hypoxia in plasma (metabolites and microRNAs associated with hypoxia) will be determined.

After 7 days, patients will be classified into two groups based on the time spent in the target Sat02 range (90%-95%). To do this, the SatO2 histograms will be analyzed every 24 hours and the time within said range will be determined. Those who have remained >50% of the monitored time outside the established range will be assigned to the experimental group.

The rest will be assigned to the control group. Once the study is completed, a statistical comparative study will be carried out between both groups. Finally, the neurological evolution will be analyzed using internationally validated scales (Bayley III, GMFCS, visual and hearing loss) between 18-26 postnatal months.

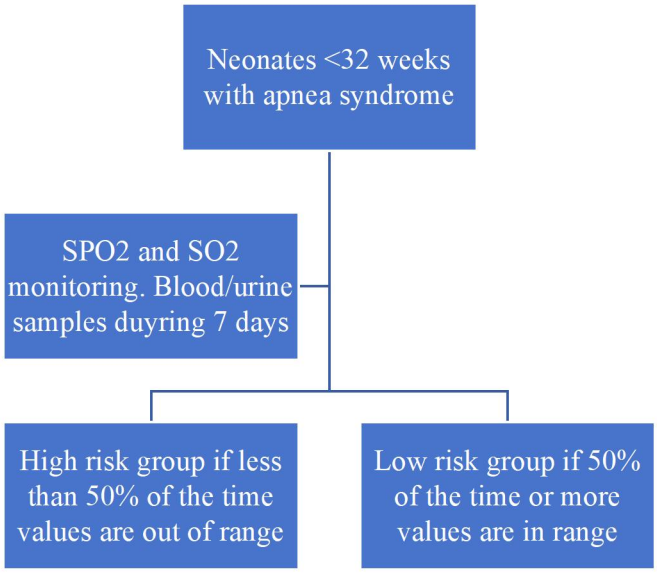


Figure 5_Candidates

2.1.1 Inclusion of Patients in Study

I.INCLUSION CRITERIA

Study population: premature neonates admitted to the Neonatal Intensive Care Unit of the La Fe University and Polytechnic Hospital in Valencia who meet the following inclusion criteria:

1. Gestational age < 32 weeks
2. Respiratory stability (No respiratory support, high flow oxygen therapy or non-invasive ventilation)
3. Complete enteral nutrition (100 ml/kg/day)
4. Gain 10 -20 g/kg/d

II.EXCLUSION CRITERIA

1. Invasive mechanical ventilation
2. Congenital heart disease
3. Persistent ductus arteriosus requiring treatment
4. Pathology requiring surgery
5. Severe congenital malformations

6. Chromosomopathies
7. Intra-periventricular hemorrhage grades III/IV
8. Seizures
9. Grade III/IV retinopathy
10. Parents' refusal to participate or sign the informed consent

III. PATIENT RECRUITMENT

The neonatologist responsible for their treatment must inform the parents about the study and give the Information Sheet to the parents and provide the Consent Sheet.
Once Consent is obtained and it has been reviewed that the patient meets all the inclusion criteria and none of the exclusion criteria, a Patient Number will be assigned. This assignment will be made from lowest to highest in order of inclusion in the study. This number will be noted in the CRD and/or medical record as soon as possible.

Two copies of the informed consent form will be made, one for the parents or legal representative and the other will be stored in the patient record.

2.1.2 Clinical Management

This study will continuously monitor and record adequate oxygen saturation using a Masimo Radical 7 monitor, centrally monitored using a different pulse oximeter than the one worn by the patient, changing position every 4 hours to conform to routine practice. Monitoring was performed 24 hours a day for 7 consecutive days.

For preterm infants, pulse oximetry alarms will be set at:

1. 990-100% for premature babies without supplemental oxygen need
2. 0-95% for premature babies with supplemental oxygen
3. 92-96% for premature babies with bronchopulmonary dysplasia and supplemental oxygen.

Patients will maintain routine monitoring during the study, including supplemental

testing and commonly used medications (e.g., caffeine, antibiotics, etc.). Participation in this study will not preclude patients from concurrently participating in other studies conducted within the unit.

2.1.3 Data Collection

The following variables will be collected and recorded in the electronic data recording sheet:

Exposure variables:

1. Gestational age
2. Birth weight and weight percentile according to Fenton charts
3. Sex
4. Multiple pregnancy
5. Prenatal corticosteroids and dose number
6. Broken bag hours
7. Chorioamnionitis
8. Low amniotic fluid
9. Birth route
10. Apgar
11. Maximum Fi02 in delivery room
12. Umbilical artery gasometry (Ph , EB, Pco2)
13. Intubation (at some point)
14. Surfactant
15. Previous mechanical ventilation, days, maximum MAP, maximum Fi02.
16. Oxygen exposure time (Fi02>0.21)
17. Systemic postnatal corticosteroids
18. Vertical or nosocomial sepsis
19. PDA without hemodynamic repercussion (ductal diameter less than 2 mm, left atrium/aorta (LA/AO) ratio < 1.5, no diastolic retrograde flow in the descending aorta)

20. ECN (Stages I-II according to Bell classification)
21. HIV I-II
22. DBP and grade
23. Postnatal age and corrected gestational age at recruitment
24. Daily weight during the control week
25. Respiratory support at recruitment
26. Medications at the time of recruitment (caffeine)

Predictor variables:

1. Time elapsed within the target range of Sat02. To do this, the saturation frequency histograms will be downloaded daily.
2. Number of isolated desaturations (minimum duration?) artifacts?
3. Number of desaturations accompanied by bradycardia and duration
4. Number of isolated bradycardias

Response variables:

1. Neurological development at 24 months postnatal:
    - Bayley III scale score
    - GMFCS
    - Visual loss, unilateral or bilateral, gradation?
    - Hearing loss
2. Biomarkers of lipid peroxidation in urine
3. Biomarkers of hypoxia (" metabolic score ") in plasma
4. Determination of circulating microRNAs

2.1.4 Obtaining and Storing Biological Samples

Determinations will be made at the beginning (time 1, first day of study) and at the

end of the study (time 2 , 7-8th day of study)

1.Blood: peripheral venous blood sample will be extracted in a tube (MiniCollect Tube K3E K3EDTA) containing ethylene - diamine -tetra-acetic acid (EDTA) as an anticoagulant. The volume to be extracted will be 0.6 mL taking advantage of routine extractions, and it will be centrifuged immediately at 1500 g for 10 minutes in a centrifuge refrigerated at 4°C. An aliquot of 30 µL of the plasma will be used for the determination of the metabolic score and an aliquot of 180 µL for the extraction of the RNA and 50 µL for the microRNAs standard using RNAseq .

Collect 0.6 ml of blood from the EDTA tube and pipette into the “T1 blood” eppendorf and centrifuge at 4 ºC and 1500 g in a refrigerated centrifuge (milk bank). Collect the supernatant plasma:
Plasma 1 -> 50 microL : metabolic score
Plasma 2 -> 180 microL : microRNA extraction
Plasma 3 -> 50 microL : microRNA pattern

Sample identification:

T1- > day 1

T2 -> last day of study (7-8th day)

The 5 eppendorfs will be deep frozen at -80ºC in the milk bank freezer, the remaining blood and plasma samples will also be preserved to carry out subsequent determinations if necessary.

2.Urine: will be collected 600 µL of urine by placing a cotton pad in the diaper, which is centrifuged to extract the urine and immediately frozen at -80°C until processed.

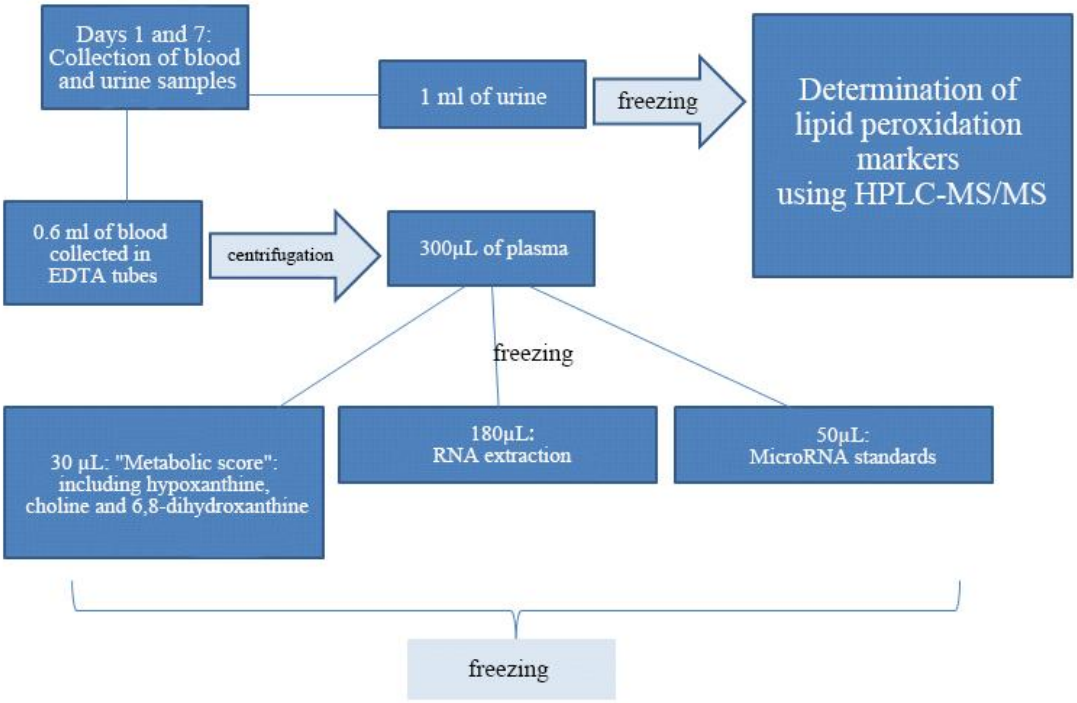


Figure 6_PROCESSING AND ANALYSIS OF BIOLOGICAL SAMPLES
Biological samples will be processed every 3 months.

2.1.5 Processing and Analysis of Biological Samples

Biomarkers of lipid peroxidation in urine

Urine samples are thawed, purified and preconcentrated by solid phase extraction. In the recovered extracts, F2-isoprostanes, isofuranes , neuroprostanes , neurofurans , dihomo-isoprostanes and dihomo-isofurans were determined using liquid chromatography coupled to tandem mass spectrometry (HPLC-MS/MS). The methods used have been developed, validated and published or are submitted for publication [55, 56, 57].

Biomarkers of hypoxia (“ metabolic score ”) in plasma

The 30 µL aliquot of plasma is thawed on ice and processed for a panel of characteristic metabolites (hypoxanthine, choline, and 6,8-dihydroxypurine) using HPLC-MS/MS. These metabolites make up the so-called metabolic score that has shown its validity in a model of prolonged hypoxia in newborn pigs [58, 59].

Determination of circulating microRNAs

180 μL of thawed plasma will be used, the RNA will be extracted, evaluating its quantity and quality, and it will be analyzed by RNA- seq . The extraction and quantification of microRNAs will be determined following the instructions of the miRNeasy kit. Serum /plasma kit (217184) from QIAGEN while the analysis of the altered expression levels of the different microRNAs will be evaluated using the Illumina-Solexa platform Sequencer . Finally, the relevant microRNAs will be quantified and validated by RT- qPCR from patients with apneic syndrome (miScript II RT kit, miScript SUBR Green PCR kit, miScript PCR Controls and miScript Primer Assays).

2.1.6 Experimental/Control Group Assignment

Every 24 hours the SatO2 histograms will be analyzed and the time within the range (90%-95%) and outside of it will be determined. In the case of patients with bronchopulmonary dysplasia, the alarm limits will be 92-96%. Depending on the time spent in the target Sat02 range, you will be assigned to one of the two groups.

Those who have remained >50% of the monitored time outside the established range will be assigned to the high-risk group. The rest will be assigned to the low-risk group (<50% of the time outside the established saturation range). Once the study is completed, a statistical comparative study will be carried out between both groups.

2.2 Hardware Introduction

Observational and prospective study carried out in a cohort of premature babies in a regional reference Neonatology Unit in Hospital Universitari i Politècnic La Fe. SpO2 and HR were continuously measured by oximetry (Radical-7® Pulse CO-Oximeter®; Masimo®, Irvine, CA, USA) with high-sensitivity settings, neonatal profile, and data frequency register at 2 Hz. The sensor employed was LNCS Neo (Masimo®, Irvine, CA, USA) placed in postductal position. Near-infrared spectroscopy (NIRS)

monitoring of cerebral oxygenation has been employed in preterm infants to prevent brain injury [21-24]. rScO2 was continuously measured by NIRS (INVOS® – 5100; Medtronic®, Dublin, Ireland) at 0.09 Hz using a specific sensor (OxyAlert™ NIRSensor Infant/Neonatal Sensor; Medtronic®, Dublin, Ireland) located on the frontotemporal region, avoiding the venous sinus.

The monitoring records of all sessions were downloaded from the oximeters and NIRS monitors employing Masimo Instrument Configuration Tool – MICT software (Masimo®) – and INVOS™ Monitoring System Analytics Tool (Medtronic®), respectively. These data were imported into MATLAB R2022a (MathWorks Inc., Natick, MA, USA) writing the corresponding functions considering the specific format of the records. Then, timetable arrays were created for each session with the SpO2, HR, and rScO2 as variables.

2.3 Model selection and data pre-processing

Clustering algorithms are a key technique in unsupervised learning that aims to group datasets into clusters such that data points within the same cluster have a high degree of similarity while different clusters have a low degree of similarity between them [60]. These algorithms are widely used in various scenarios such as image analysis, market segmentation, and community detection in social networks [61]. There are various clustering methods including K-mean clustering, hierarchical clustering, DBSCAN and spectral clustering, etc. K-mean clustering optimises the quality of clusters by iteratively redistributing data points and updating the cluster centres [62], while DBSCAN relies on the density to form clusters, which is effective in dealing with noisy and anomalous data points [63]. Choosing the appropriate clustering algorithm usually depends on the characteristics of the data and the purpose of the study. A deeper understanding of the theoretical foundations and practical applications of these algorithms can significantly improve the quality and effectiveness of data analysis.

This project used the K-means algorithm and the DBSCAN algorithm for cluster analysis of the dataset. From the initial 30 or so features in the data, identified five key features through the process of pre-processing and feature selection. For these five features, two different experimental scenarios were designed and each of which selected three of the features to perform the clustering operation. With this methodological design, the data was effectively clustered and draw the relevant conclusions from my research. This process not only demonstrated the applicability and effectiveness of the chosen clustering algorithm, but also verified the importance of feature selection and its significant impact on the clustering results.

2.3.1 K-Means

k-means is an unsupervised learning algorithm which is used in clustering problems. The algorithm attempts to assign n observations to k clusters (k is a user-specified parameter) such that each observation belongs to the cluster corresponding to its nearest mean (i.e., cluster centre). It works as follows:

Initialisation: randomly select 'k' data points as initial cluster centres.

Assignment: assign each point to the nearest cluster centre to form k clusters.

Update: for each cluster, calculate the mean value of all points and set it as the new cluster centre.

Repeat: the assignment and update steps are repeated until a stopping condition is met (usually the cluster centres no longer change, or the change is less than a threshold, or a predetermined number of iterations is reached).

The k-means algorithm is simple and very popular in practice, but it has its limitations. For example, it assumes that clusters are convex and homogeneous, which means that it may not work well with clusters that vary greatly in size and density, or that are not spherical. In addition, since the initial cluster centres are chosen randomly, the

algorithm may fall into local optimal solutions, and different initialisations may lead to different results.

2.3.2 DBSCAN

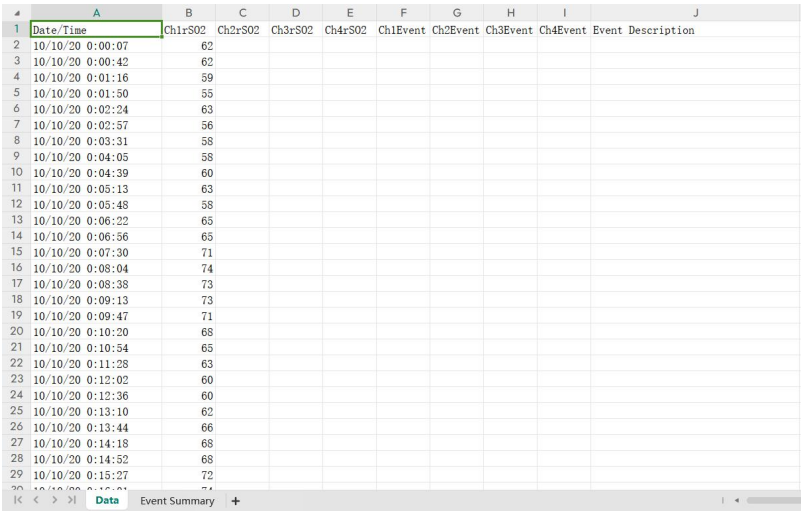
DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is a well-known clustering algorithm for density-based hiring. The main advantages of DBSCAN are that it does not require a pre-specified number of clusters, it can identify clusters of arbitrary shapes, and it can effectively deal with noise and anomalous data points. Due to its unique clustering characteristics and robustness, DBSCAN has been widely used in fields such as astronomical data analysis, geographic information systems, medical image analysis, and social network analysis.

The basic idea of DBSCAN is to cluster data points according to their density. There are two main parameters in the algorithm: ε (epsilon) and MinPts (minimum points). ε is the radius size of the neighbourhood, and MinPts is the minimum number of data points required to form a dense region.

2.3.3 Data Composition

Premature infants with bradycardic apneic syndrome with a gestational age less than 32 weeks who are stable at respiratory and metabolic levels will be included. During the study time, oxygen saturation will be continuously monitored by postductal pulse oximetry (24 hours a day for 7 days). Clinical parameters will be recorded (analysis of the pulse oximetry histogram and clinical variables) and markers of oxidative stress in urine and hypoxia in plasma (metabolites and microRNAs associated with hypoxia) will be determined.

The data consisted of two parts: the electronic data recording sheet, and the SpO2 and rScO2 (NRIS) data. electronic data recording sheet data format is described in detail in figure 7.2 data collection. the SpO2 and rScO2 (NRIS) data are in csv format and record two values from 114 different beds at different moments in time, with three to seven csv files storing the two types of data for each bed, totalling 10^9 levels of data.



	A	B	C	D	E	F	G	H	I	J
1	Date/Time	Ch1rSO2	Ch2rSO2	Ch3rSO2	Ch4rSO2	Ch1Event	Ch2Event	Ch3Event	Ch4Event	Event Description
2	10/10/20 0:00:07	62								
3	10/10/20 0:00:42	62								
4	10/10/20 0:01:16	59								
5	10/10/20 0:01:50	55								
6	10/10/20 0:02:24	63								
7	10/10/20 0:02:57	56								
8	10/10/20 0:03:31	58								
9	10/10/20 0:04:05	58								
10	10/10/20 0:04:39	60								
11	10/10/20 0:05:13	63								
12	10/10/20 0:05:48	58								
13	10/10/20 0:06:22	65								
14	10/10/20 0:06:56	65								
15	10/10/20 0:07:30	71								
16	10/10/20 0:08:04	74								
17	10/10/20 0:08:38	73								
18	10/10/20 0:09:13	73								
19	10/10/20 0:09:47	71								
20	10/10/20 0:10:20	68								
21	10/10/20 0:10:54	65								
22	10/10/20 0:11:28	63								
23	10/10/20 0:12:02	60								
24	10/10/20 0:12:36	60								
25	10/10/20 0:13:10	62								
26	10/10/20 0:13:44	66								
27	10/10/20 0:14:18	68								
28	10/10/20 0:14:52	68								
29	10/10/20 0:15:27	72								

Data | Event Summary | +

Figure 7.1_SpO2 csv file

	A	B	C	D	E	F	G	H	I	J	K
1	ID	StudyTime	GestationalAge	Days	Sex	Weight at birth	Weigth percentile	Multiple pregnar	prenatal corticos	Number of doses	Hours broken n
2	1	1	29	0	1	1330	66	1	1	2	
3	1	2	29	0	1	1330	66	1	1	2	
4	2	1	29	0	1	1350	69	1	1	2	
5	2	2	29	0	1	1350	69	1	1	2	
6	3	1	30	0	0	695	3	0	1	4	
7	3	2	30	0	0	695	3	0	1	4	
8	4	1	25	2	1	810	78	0	1	2	
9	4	2	25	2	1	810	78	0	1	2	
10	5	1	27	6	1	900	24	0	1	3	
11	5	2	27	6	1	900	24	0	1	3	
12	6	1	28	5	0	1400	78	0	1	2	
13	6	2	28	5	0	1400	78	0	1	2	
14	7	1	27	6	1	1150	66	1	1	2	
15	7	2	27	6	1	1150	66	1	1	2	
16	8	1	30	0	1	1500	65	1	1	2	
17	8	2	30	0	1	1500	65	1	1	2	
18	9	1	30	0	1	1500	65	1	1	2	
19	9	2	30	0	1	1500	65	1	1	2	
20	10	1	29	5	1	1390	57	0	0	0	
21	10	2	29	5	1	1390	57	0	0	0	
22	11	1	27	6	1	1020	43	1	1	2	
23	11	2	27	6	1	1020	43	1	1	2	
24	12	1	29	4	1	950	11	0	1	3	
25	12	2	29	4	1	950	11	0	1	3	
26	13	1	29	5	1	1005	13	1	1	2	
27	13	2	29	5	1	1005	13	1	1	2	

Figure 7.2_Clinical data collection

2.3.4 Data Pre-processing

For SpO2 and rScO2 data, the Data points with alarm messages (e.g., low perfusion, sensor off, ambient light, or low signal), HR <40 bpm, SpO2 < 60% (with abnormal pulse wave), or rScO2 < 15 were considered outliers and they were discarded. The obtained clean timetables were aligned employing the synchronize function resampling rScO2 with linear interpolation and the FtOE was computed for each point in percentage as FtOE = (SpO2-rScO2)/SpO2*100.

Hypoxic events were defined as mild when SpO2 < 90% and >85% for >5 s, moderate when SpO2 < 85% and >80% for >5 s, and severe when SpO2 < 80% for >5

s. Bradycardic events were defined as moderate when HR <100 bpm for >5 s and severe as HR <80 bpm for >5 s [10, 13, 14, 25, 26]. Besides, events that included both bradycardia and hypoxia were also analyzed. Furthermore, hemodynamic changes defined as HR decreases more than 20 bpm and as rScO2 increases or decreases more than 10 points were also analyzed. Finally, normal ranges were defined as SpO2 >90% in patients without supplementary oxygen and as SpO2 between 90% and 95% in patients with supplementary oxygen (FiO2 > 0.21) [27]. Likewise, it was considered cerebral regional hypoxia when rScO2 was <55 and cerebral hyperoxia when rScO2 was >85 [22].

According to the above definition, the purpose of this preprocessing step is to calculate the ratio of abnormal events to total time for SpO2 data and the ratio of hyperoxia and brain region hypoxia time to total time for rScO2 data using a python script program.

	A	B	C	D	E	F
1	55195E+12	Mar. 07. 2019;9:28:27;67;61;4. 3;;;;;;;;;				
2	55195E+12;Mar. 07. 2019;9:28:29;69;60;4. 5;;;;;;;;;					
3	55195E+12;Mar. 07. 2019;9:28:31;72;59;4. 6;;;;;;;;;					
4	55195E+12;Mar. 07. 2019;9:28:33;75;60;3. 4;;;;;;;;;					
5	55195E+12;Mar. 07. 2019;9:28:35;77;61;2. 8;;;;;;;;;					
6	55195E+12;Mar. 07. 2019;9:28:37;83;179;2. 4;;;;;;;;;					
7	55195E+12;Mar. 07. 2019;9:28:39;89;179;2. 7;;;;;;;;;					
8	55195E+12;Mar. 07. 2019;9:28:41;91;179;2. 6;;;;;;;;;					
9	55195E+12;Mar. 07. 2019;9:28:43;93;179;2. 7;;;;;;;;;					

Figure 8_SpO2 csv file 2

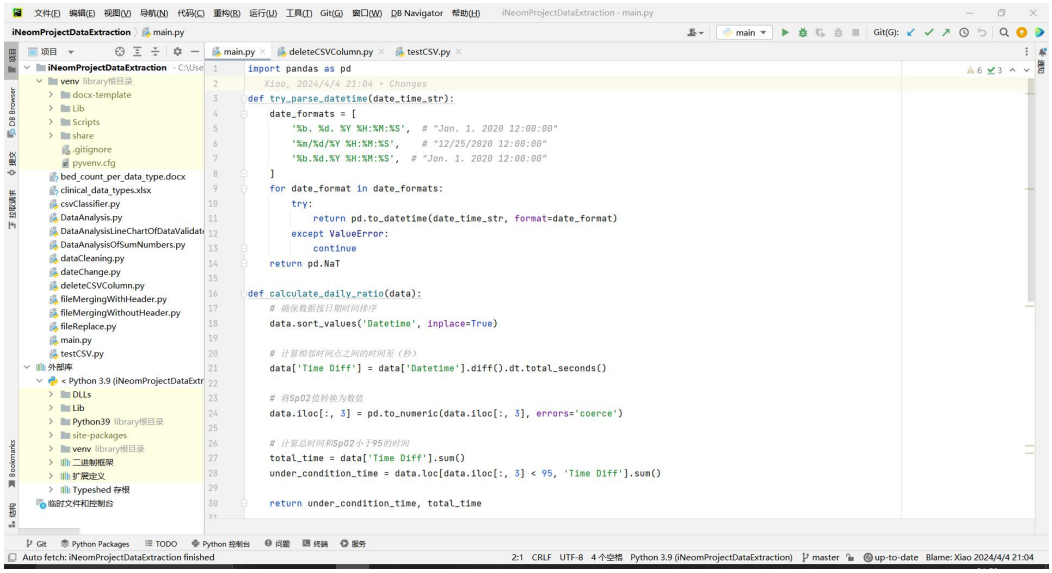


Figure 9.1_Python Script for data pre-processing

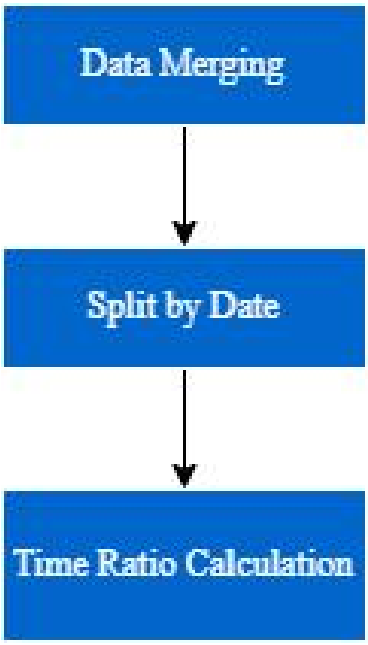


Figure 9.2_Python Script Structure

The data preprocessing script code can be divided into three parts: document merging, splitting based on date, and final scaling.

The initial csv document format is prem_n_1_spo_n_2.csv, where ns_1 is the bed number and n_2 is the document number. Each bed has three to seven different csv documents. The first step of the script is to merge the documents of the same beds into one and also, for the documents where headers exist, delete the duplicate headers.

For the merged documents, the data is fetched from different dates. So, the second step is to read the data from different dates separately and then calculate the percentage of time that does not satisfy the range. At the same time, the date data format of different beds is different, and it is also necessary to make a judgement in the code.

The reading interval of Spo2 and HR data is 2s, therefore, the time ratio can be calculated according to the formula r=n (amount of data with spo2<90, HR<100 and lasting for five seconds)/n (amount of total effective data). The calculation results are as follows:

File Name	SpO2<90	HR Incidents < 100
1	0.114588328	0.000284987
2	0.062630363	0.000216188
3	0.011289689	0.000536177
5	0.197590147	0.000290204
6	0.088409686	0.000455555
7	0.163815045	0.00070719
8	0.052276806	0.000442066
9	0.014061931	0.001102832
10	0.030531929	0.000394047
11	0.091502811	0.000675383
12	0.098045174	0.001036432

Figure 10_spo2 and HR data ratio

Two different approaches to normalization were tried: firstly box-cox normalization + normalization, which did not reach good enough results, so the second approach, simple normalization, was tried and the final clustering was better than after box-cox normalization.

SpO2<90	HR Incidents < 100	SpO2<90_log	HR Incidents < 100_log
0.346610397	0.06879642	0.750603354	0.335396238
0.18752318	0.04405011	0.621621722	0.253037684
0.030326009	0.159146119	0.305047806	0.521423373
0.600749077	0.070672788	0.875680746	0.340781091
0.266455463	0.130147417	0.694018788	0.473774383
0.497334962	0.220657246	0.831673204	0.601881117
0.155822198	0.125295654	0.584913638	0.46496155
0.038814183	0.362964452	0.341897589	0.729731437
0.089242761	0.108023655	0.480492102	0.431177689
0.275926132	0.209216887	0.701415001	0.588549464
0.295957832	0.339081327	0.716365499	0.711958981
0.043746312	0.374585519	0.36047844	0.737985212
0.087932478	0.850580144	0.47784567	0.956435221
0.792439115	0	0.942213618	0
0.018575729	0.169908793	0.238069445	0.537255263
0.349203525	0.31529479	0.752237088	0.693054968
0.018753614	0.226574637	0.239289654	0.608536907
0.763266574	0.376024406	0.933060046	0.738990333
0.286295806	0.028079204	0.709266839	0.184024587
0.340598133	0.191107189	0.74677451	0.566066806

Figure 11_Data after two procedures

Ph data, hco3 data and pco2 data were missing respectively. In order to avoid affecting the clustering effect, two ways of data supplementation were adopted: the first was to populate the mean values, which were 7.29 (ph), 24.3 (hco3) and 50.5 (pco2); the second was assisted by a test technologist (Dr Yue Zhang, Department of Clinical Medical Laboratory Medicine, Shandong Provincial Hospital affiliated to the First Medical University of Shandong, Shandong Province, China), who was assisted by a test technologist based on the kit reference interval and sample patient status for predictive filling.

Parameters	Range reference	Unit
pH	7.35～7.45	pH
pCO2	35～48	mmHg
pO2	83～108	mmHg
Na+	136～145	mmol/L
K+	3.4～4.5	mmol/L
Ca+	1.15～1.33	mmol/L
Cl-	98～107	mmol/L

Chart 1_Reference intervals for some parameters

编号	ph	eb	hco3	pco2	
615		7.27	-4	21.7	51
615		7.27	-4	21.7	51
620		7.26	-4.1	21.6	53
620		7.26	-4.1	21.6	53
892		7.27	-4.3	21.5	51
892		7.27	-4.3	21.5	51
321		7.34	-1.3	23.8	46
321		7.34	-1.3	23.8	46
495		7.39	-1.1	23.8	38
495		7.39	-1.1	23.8	38
		7.34	0.4	27.1	49
		7.34	0.4	27.1	49
494		7.31	1.3	22.1	50
494		7.31	1.3	22.1	50
		7.3	0	27	55
		7.3	0	27	55
		7.3	-4	21	44
		7.3	-4	21	44
455		7.36	2.1	26.6	52
455		7.36	2.1	26.6	52
		7.14	-8	22	64
		7.14	-8	22	64

Figure 11_Populated clinical data collection

For the other data selected for use: blood ph, hco3, pco2, neonatal weight and gestational age, normalization was taken for pre-processing.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1		Raw								Normalised				
2	File Name	Sp02<90	HR Incidents < 100	Sp02<90_log	HR Incidents < 100_log	ph	eb	hco3	pco2	Sp02<90	HR Incidents < 100	Sp02<90_log	HR Incidents < 100_log	ph
3	1	0.114588328	0.000284987	-1.895386717	-9.165009897	7.26	2.145883276	24.7	46.5	0.346610397	0.06879642	0.750603354	0.335396238	0.6792
4	2	0.062630363	0.000216188	-2.337829739	-9.513138236	7.27	1.626303632	24.5	45.5	0.18752318	0.04405011	0.621621722	0.253037684	0.6981
5	3	0.011289689	0.000536177	-3.423766692	-8.378676064	7.25	1.112896888	23.8	42	0.030326009	0.159146119	0.305047806	0.521423373	0.6603
6	5	0.197590147	0.000290204	-1.46633633	-9.142248208	7.34	0.4	27.1	49	0.600749077	0.070672788	0.875680746	0.340781091	0.8301
7	6	0.088409686	0.000455555	-2.089487582	-8.580087608	7.31	1.3	24.2	44	0.266455463	0.130147417	0.694018788	0.473774383	0.7735
8	7	0.163815045	0.00070719	-1.61729449	-8.038582416	7.3	0	27	55	0.497334962	0.220657246	0.831673204	0.601881117	0.7547
9	8	0.052276806	0.000442066	-2.463748721	-8.617339319	7.3	-4	21	44	0.155822198	0.123295654	0.584913638	0.46496155	0.7547
10	9	0.014061931	0.001102832	-3.297361644	-7.498161083	7.36	1.140619308	23.9	42.5	0.038814183	0.362964452	0.341897589	0.729731437	0.8679
11	10	0.030331929	0.000394047	-2.821943756	-8.760143178	7.14	-8	22	64	0.089242761	0.108023655	0.480492102	0.431177689	0.4528
12	11	0.091502811	0.000675383	-2.064116507	-8.094935108	7.21	-3.9	25.4	62	0.275926132	0.209216887	0.701415001	0.588549464	0.584
13	12	0.098045174	0.001036432	-2.012832123	-7.57328498	7.27	-4.7	18.7	48	0.295957832	0.339081327	0.716365499	0.711958981	0.6981
14	13	0.015672766	0.00113514	-3.233624136	-7.463272503	7.32	-3.9	22.1	42	0.043746312	0.374585519	0.36047844	0.737985212	0.792
15	14	0.03010399	0.002458498	-2.831021753	-6.539887678	7.35	-1.5	24	42	0.087932478	0.850580144	0.47784567	0.956435221	0.8490
16	15	0.260196209	9.37198E-05	-1.238109994	-10.58272463	7.26	-1.9	26.4	58	0.792439115	0	0.942213618	0	0.6792
17	16	0.007452041	0.000566099	-3.653521175	-8.311754905	7.31	-3.8	22.3	43	0.018575729	0.169908793	0.238069445	0.537255263	0.7735
18	17	0.115435244	0.000970301	-1.889782553	-7.653191953	7.33	-1.8	24.1	45	0.349203525	0.31529479	0.752237088	0.693054968	0.8113
19	18	0.007510139	0.000723641	-3.649335519	-8.010448495	7.37	3.9	30.4	51	0.018753614	0.226574637	0.239289654	0.608536907	0.8867
20	19	0.250668442	0.001139141	-1.269509303	-7.459023873	7.36	-2	23	40	0.763266574	0.376024406	0.933060046	0.738990333	0.8679
21	20	0.094889552	0.000171785	-2.037182508	-9.804855534	6.9	-13.5	17	90	0.286295806	0.028079204	0.709266839	0.184024587	
22	22	0.112624719	0.000625035	-1.908520723	-8.189968957	7.39	-1.9	23	37	0.340598133	0.191107189	0.74677451	0.566066806	0.9245
23	24	0.013428504	0.000568168	-3.324186261	-8.307262835	7.21	1.134285044	22.6	49	0.03687473	0.170652985	0.334077637	0.538317976	0.584
24	25	0.034154575	0.000670424	-2.749255876	-8.1039668	7.2	1.341545749	24.3	44.5	0.100334739	0.207433108	0.501682178	0.586412789	0.5660
25	26	0.217356063	0.000444179	-1.38817625	-8.611426727	7.27	-5.1	21.7	46	0.661269242	0.126053755	0.898466086	0.466360323	0.6981
26	27	0.104732613	0.001196862	-1.96341285	-7.399372012	7.39	-1.5	23.2	38	0.316433731	0.396786117	0.730772277	0.753102488	0.9245
27	28	0.012170576	0.000433917	-3.380910061	-8.640415983	7.34	1	27	51	0.03302315	0.122364391	0.317541433	0.459502182	0.8301
28	29	0.017287853	0.000287388	-3.175226899	-9.154483427	7.35	0.1	27.2	53	0.048691458	0.069659826	0.377502487	0.337886541	0.8490
29	31	0.107143696	0.000522509	-1.946270131	-8.410532509	7.01	-11.5	21	83	0.323816091	0.154229925	0.735769747	0.513886926	0.2071

Figure 12_Data sheet after perprocessing

Chapter 3. Modeling and Outcome

Based on the data characteristics of this project, the machine learning algorithm chosen is the unsupervised learning clustering algorithm. After comparison, Kmeans algorithm was selected for clustering operation. For the parameters from the e-clinical dataset, seven parameters that differed significantly between patients were selected for bivariate analysis. After bivariate analyses and comparisons, five data were selected, namely, the proportion of time with spo2<90, the proportion of time with hr<100, blood ph values, hco3 values, and pco2 values. Three types of data were randomly selected for cluster analysis, and three types of clusters were found to be more effective: spo2, hr, ph, spo2, hr, hco3 and spo2, hr, pco2, and the profile coefficients of the two clusters reached 0.86, 0.79, and 0.79, respectively.

3.1 Bivariate analysis

Binary analysis is an analytical method in statistics used to study the relationship between two variables. This type of analysis focuses on whether there is some association or dependence between two data variables and attempts to describe the nature and extent of this relationship. Of the more than thirty parameters included in the Clinical data collection, many binary data such as sex, whether or not there was a multiple pregnancy, and whether or not antenatal corticosteroids were used, which are difficult to analyse bivariately, as well as data such as the number of hours of rupture of membranes, rScO2, and other data with a percentage of absence of more than 40%, which could not be manually supplemented, were not included in the binary analyses. Seven clinical parameters were entered into the binary analysis: birth weight, gestational age, spo2 value <90, proportion of time with HR <100, blood ph, hco3 value and pco2 value.

After binary analysis, newborn weight and gestational age did not show significant correlation with the other parameters, and thus the other five parameters were selected for the next clustering operation.

3.2 Modeling Outcome

For the five selected parameters: the proportion of time with spo2<90, the proportion of time with hr<100, blood ph values, hco3 values, and pco2 values, we selected these two parameters in combination with the other three parameters based on the fact that oxygen saturation and heart rate are the most intuitive ways to reflect the state of tissue oxygenation. We selected these two parameters to be combined with the other three parameters to run the kmeans clustering algorithm. Among them, two clusters were set, the weights of spo2 and HR parameters were set to 1, and the weights of the remaining parameters were 0.5.

A combination of profile coefficients, the Davies-Bouldin index and the Calinski-Harabasz index were used to assess the clustering results. The contour coefficient is a measure of how similar each point is to other points in its cluster and how dissimilar it is to points in other recent clusters. Its value ranges from -1 to 1. A high contour coefficient means that the points within a cluster are similar and very dissimilar to the points in the nearest cluster; the Davies-Bouldin index evaluates the quality of clustering based on the closeness of the distances within a cluster and the separation of the distances between clusters. The smaller this index is, the better the clustering is; the Calinski-Harabasz index (also known as the variance ratio criterion) evaluates the effectiveness of clustering by the ratio of intraclass variance to interclass variance. The larger this ratio, the better the clustering is usually.

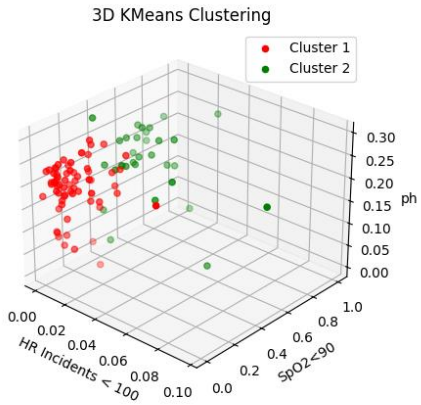


Figure 13.1_hr-spo2-ph clustering image

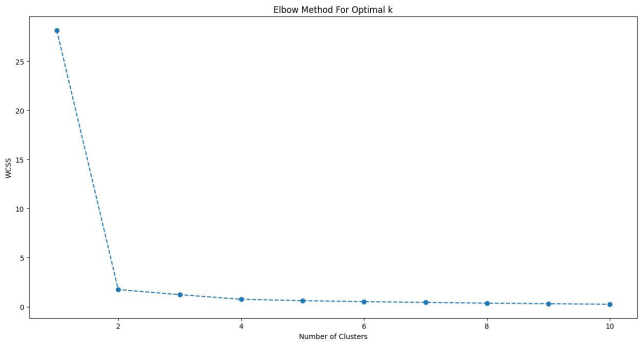


Figure 13.1_hr-spo2-ph clustering elbow

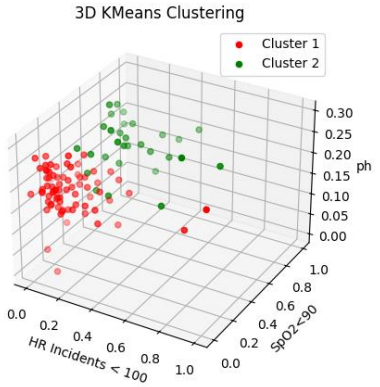


Figure 13.1_hr-spo2-hco3 clustering image

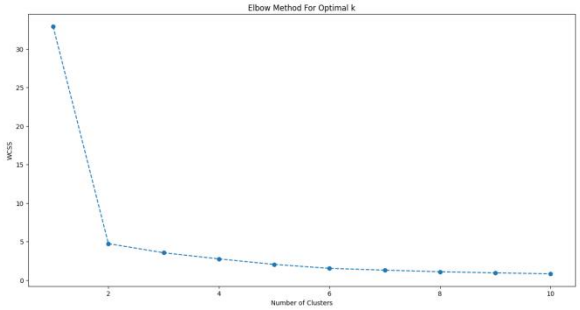


Figure 13.1_hr-spo2-hco3 clustering elbow

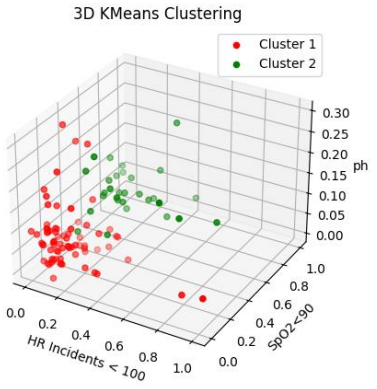


Figure 13.1_hr-spo2-pco2 clustering image

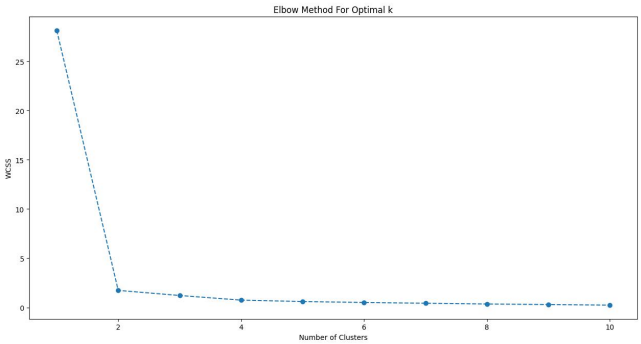


Figure 13.1_hr-spo2-pco2 clustering elbow

ph:

Silhouette Coefficient: 0.86

Davies-Bouldin Index: 0.218

Calinski-Harabasz Index: 1464.030

hco3:

Silhouette Coefficient: 0.79

Davies-Bouldin Index: 0.327

Calinski-Harabasz Index: 607.315

Pco2:

Silhouette Coefficient: 0.79

Davies-Bouldin Index: 0.329

Calinski-Harabasz Index: 595.849

The results show that by analysing data on spo2, hr and other blood gas metrics, patient data can be effectively clustered, laying the groundwork for the next steps in clinical validation in an operating environment under controlled conditions and pathophysiological risks identifications.

Chapter 4. Conclusion and Future work

In order to explore the prospect of the use of Artificial Intelligence in the Neonatal Intensive Care Unit (NICU), and to identify the development trend of Artificial Intelligence-driven technologies and their roles in the diagnosis, monitoring, and treatment of neonatal diseases, this project firstly selected 318 articles published in *MEDLINE, EMBASE, Cochrane*, and *IEEEXplore* for the period of January 2013 to December 2023, and finally selected 41 articles to form a systematic review paper. Through a series of screening processes, 41 articles were selected for systematic review, resulting in a review paper: A Systematic Review on the use of Artificial Intelligence in the Neonatal Intensive Care Unit: far beyond the potential impact, which is expected to be published. beyond the potential impact, which is expected to be published in *Paediatric Research*, the official journal of the American Academy of Paediatrics, the European Society for Paediatric Research and the Society for Paediatric Research. Meanwhile, based on the retrospective preterm physiological data given by the Neonatal Intensive Care Unit of the La Fe University and Polytechnic Hospital in Valencia, a kmeans clustering algorithm based on unsupervised learning of machine learning was used to select five physiological data for a retrospective analyses, yielding clustering results with profile coefficients of 0.86 and 0.79, respectively.

There are still some problems in the retrospective analysis part of the data in this project: the overall data set is small, and some outliers may interfere with the clustering effect; the data set is incomplete, and some important data, such as rScO2, are seriously missing leading to the impossibility of using it for clustering, and, at the same time, there is no exact quantitative relationship between certain physiological parameters of preterm infants, such as hco3, and others so far, leading to the impossibility of, for the filled in data, to guarantee that it is fully justified from a medical diagnostic point of view. Future work will be based on these issues and will focus on ensuring and validating the soundness and completeness of the dataset from a medical point of view. Also, as part of a joint project between the Universidad Politécnica de Valencia (UPV) and La Fe

University and Polytechnic Hospital in Valencia, the next step of the project will be to carry out a clinical validation in an operational environment under controlled conditions, leading to the delivery of a systematic validation report of iNeom in a period of approximately 24 months.

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Acknowledgement

Unwittingly, the moment has come to pen the acknowledgments for my first ever academic paper. Although it's neither a complex project nor a significant dissertation like a Ph.D. thesis, nor can it be considered scholarly at all-so much so that these acknowledgments might never be perused-I feel compelled to write something for myself in this inaugural instance. I can't let it vanish into oblivion like the posts on my public account after the initial proposal.

Last week, at this very time, as I grappled with the most challenging part of the project, I found myself tossing and turning in bed, unable to sleep, regretting my decision to embark on an overseas final project. Who could have known it would turn into such an ordeal?

This morning, as all coding tasks came to an end, I sat by the window where the Mediterranean sun, slightly obscured by thicker clouds than usual, bathed the side of my desk in light. Suddenly, a plump pigeon flew to the window and looked in at me, making everything seem surreal. Whether I regret the hectic days ten days ago when my computer’s hard drive nearly crashed, or the quiet moment now, staring at a strange pigeon, seems irrelevant. To seize the final opportunity of my college days to watch the pigeons of Valencia-well, that feels quite nice.

Of course, my experiences here are not limited to this pigeon. At ITCAC, in Building 4D, and in the virtual meeting rooms on Teams, my dedicated and friendly mentor provided tremendous support and help during my thesis development. I deeply admire his professionalism. Also, I’m grateful to the gentleman coordinating between UPV and QMUL, my first Spanish contact, who with his warm, approachable, and chatty nature, was always ready to assist us with any needs. Valencia is all the more beautiful because of you.

During the project, I must also thank my family: my father, mother, and maternal grandmother for their immense support of my decision to undertake an overseas final project, and my aunt, who provided substantial help with blood test analysis. I extend my heartfelt thanks to them all. A deep bow.

Four years have passed in the blink of an eye, and graduation is now upon us. Throughout my university life, my roommates and classmates have also offered me much help; I wish to express my respect and appreciation for them here.

As I looked up, the pigeon pecked gently at the glass, then flew away as swiftly as time, leaving not a feather behind.

April 23, 2024, in Valencia.

Appendices

Disclaimer

This report is submitted as part requirement for the undergraduate degree programme at Queen Mary University of London, and Beijing University of Posts and Telecommunications. It is the product of my own labour except where indicated in the text. The report may be freely copied and distributed provided the source is acknowledged.

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Date: 22/04/2024

北京邮电大学 本科毕业设计（论文）任务书

Project Specification Form

Part 2 - Student

学院 School	International School	**专业 Programme**	**Internet of Things Engineering**		
姓 Family name	Xiao	**名 First Name**	Longwei		
BUPT 学号 BUPT number	2020213690	**QM 学号 QM number**	200983941	**班级 Class**	2020215122
论文题目 Project Title	Development and implementation of an Intelligent Neonatal Monitoring system through the use of Big Data and Artificial Intelligence				
论文概述 Project outline **Write about 500-800 words** **Please refer to Project Student Handbook section 3.2**	1. Requirement Analysis Neonatal Intensive Care Units (NICUs) are specialized medical facilities dedicated to the critical care of newborns facing various health challenges[1]. Common reasons for neonates to require NICU care include premature birth, low birth weight, respiratory distress, concerns about infections, hypoglycemia, surgical needs, and genetic conditions. NICUs operate as complex ecosystems, staffed by skilled healthcare professionals with diverse roles and equipped with various medical devices, such as incubators, ventilators, and monitoring equipment[2]. The adoption of Electronic Medical Records (EMRs) in recent years has enabled the collection of comprehensive clinical data in the NICU. This data-rich environment offers opportunities for applying advanced analytics techniques, potentially improving healthcare outcomes for neonates[3-4]. During a neonate's stay in the NICU, a substantial amount of data is generated from diverse sources, including extensive imaging data, physiological data (heart rate, oxygen saturation, etc.), and data from monitoring devices. The integration of pervasive sensing technology and artificial intelligence has ushered in autonomous and granular healthcare monitoring. Analyzing this wealth of data may reveal critical factors influencing neonatal neurodevelopment[5-9]. In this context, AI and machine learning have the potential to enhance predictive capabilities and clinical outcomes in the NICU.This project aims to analyze data from various monitoring instruments in the NICU by using artificial intelligence and big data technologies, which can be used to help healthcare professionals predict clinical outcomes and give treatment recommendations. 2. Techniques to be employed Literature review: A comprehensive, structured analysis of existing scientific literature on the specific context of AI and NICUs will be performed. Based on PRISMA methodology, we aim to identify, evaluate, and synthesize relevant studies, providing a balanced summary of current knowledge about data sources, variables and modelling techniques.				

Supervised learning: Various prediction models and scoring systems have been developed to aid decision-making by providing early predictions of the onset of morbidities, mortality, and planned LOS. These models and scoring systems often utilize selected attributes (referred to as risk factors) in predicting the clinical state [10-14]. These measurements are done at different time points of a neonate's stay in NICU, capturing treatment data such as clinical assessments, medications, laboratory investigations, and procedures to generate standardized clinical scores. With the availability of voluminous EMR data for each neonate, scoring tools have improved and they can quickly update neonate-specific predictions.

3. Main Tasks

A. Technical specifications of the iNeom system (Document). Synthesis o the state of the art (outcomes of the systematic review) and specifications according to the functional requirements, type of devices, communication protocols and hardware connectivity.
B. Data modelling and clinical alerts in Neonatal ICU (Document and software). State of the art on predictive modelling techniques in the Neonatal ICU.
C. iNeoM Prototype (Software). Development of the software and hardware modules.
D. iNeom System Validation (Document). Testing of the models and the platform.

1. White RD, Smith JA, Shepley MM. Recommended standards for newborn ICU design, eighth edition. J Perinatol. 2013;33:S2–16.
2. Ellsworth MA, Lang TR, Pickering BW, Herasevich V. Clinical data needs in the neonatal intensive care unit electronic medical record. BMC Med Inform Decis Mak. 2014;14:92.
3. De Georgia MA, Kaffashi F, Jacono FJ, Loparo KA. Information technology in critical care: review of monitoring and data acquisition systems for patient care and research. Sci World J. 2015;2015:1–9.
4. Strickland NH. PACS (picture archiving and communication systems): filmless radiology. Arch Dis Child BMJ Publ Group Ltd. 2000;83:82–6.
5. Fairchild KD, Aschner JL. HeRO monitoring to reduce mortality in NICU patients. Rrn Dove Press. 2012;2:65–76.
6. Griffin MP, Lake DE, Bissonette EA, Harrell FE, Shea OTM, Moorman JR. Heart rate characteristics: novel physiomarkers to predict neonatal infection and death. Pediatrics Am Acad Pediatrics. 1999;116:1070.
7. Fairchild KD, Lake DE. Cross-correlation of heart rate and oxygen saturation in very low birthweight infants: association with apnea and adverse events. Am J Perinatol. 2018;35:463.
8. Davoudi A, Malhotra KR, Shickel B, Siegel S, Williams S, Ruppert M, et al. Intelligent ICU for autonomous patient monitoring using pervasive sensing and deep learning. Sci Rep. 2019;9:8020. https://doi.org/10.1038/s41598-019-44004-w.
9. Hee Chung E, Chou J, Brown KA. Neurodevelopmental outcomes of preterm infants: a recent literature review. Transl Pediatr. 2020;9:S3–8.
10. The CRIB (clinical risk index for babies) score: a tool for assessing initial neonatal risk and comparing performance of neonatal intensive care units. The international neonatal network. Lancet.1993;342:193–8.

	11. Lee SK, Aziz K, Dunn M, Clarke M, Kovacs L, Ojah C. et al. Transport risk index of physiologic stability, version II (TRIPS-II): a simple and practical neonatal illness severity score. Am J Perinatol Thieme Med Publishers. 2013;30:395–400. 12. Gagliardi L, Cavazza A, Brunelli A, Battaglioli M, Merazzi D, Tandoi F, et al. Assessing mortality risk in very low birthweight infants: a comparison of CRIB, CRIB-II, and SNAPPE-II. Arch Dis Child Fetal Neonatal Ed. 2004;89:F419–22. 13. Parry G, Tucker J, Tarnow-Mordi W, Group UNSSC. CRIB II: an update of the clinical risk index for babies score. Lancet. 2003;361:1789–91. 14. Kim SY, Kim S, Cho J, Kim YS, Sol IS, Sung Y, et al. A deep learning model for realtime mortality prediction in critically ill children. Crit Care. 2019;23:279.
道德规范 **Ethics**	Please confirm by checking the box: ☐ I confirm that I have discussed ethical issues with my supervisor.

Please discuss ethical issues with your supervisor using the ethics checklist in Project Handbook Appendix 1.	1. Data privacy and security: When training with open datasets, sensitive personal health information may be involved, and the collection, storage and processing of this data needs to comply with relevant data protection regulations. Solution: 1. Ensure data anonymisation or de-identification to protect individual privacy. 2. Comply with local and international data protection laws and regulations, such as the EU's General Data Protection Regulation (GDPR). 3. Implement strict data security measures, such as encryption and access control. 2. Algorithmic bias and accuracy: Machine learning algorithms may be biased by biases in the training data, leading to an increased risk of misdiagnosis for certain groups. Solution: 1. Use diverse and representative datasets for training to reduce bias. 2. Regularly review and adjust the algorithms to ensure the accuracy of their judgements and predictions. 3. Collaborate with healthcare professionals to ensure the medical accuracy and applicability of the algorithms. 3. Legal responsibility and accountability: Determining liability attribution can be complicated when a system error or failure results in patient harm. Solution: 1. Clarify system usage guidelines and liability limitations. 2. Establish error reporting and response mechanisms to ensure issues are addressed in a timely manner. 3. Work with legal experts to develop an appropriate liability framework. 4. Infant's right to privacy: Although infants are unable to make their own decisions, their medical information and biometric data are still protected by the right to privacy. Solution: 1. Obtain explicit consent from parents or legal guardians for data collection and use. 2. Ensure that strict privacy protection standards are adhered to during data processing. 5. Parent and Family Involvement: Health monitoring of infants not only involves the healthcare team, but also profoundly affects their family members. Solution: 1. Provide parent education and training to help them understand the system's capabilities and limitations. 2. Facilitate communication between parents and the healthcare team to ensure they are adequately involved in the decision-making process. 6. Compliance with Child Protection Laws and Ethical Guidelines: Child protection laws and ethical guidelines require that any medical intervention with children, including infants, should be done with extreme caution. Solution: 1. Strictly adhere to relevant child protection laws and ethical guidelines. 2. The well-being of infants is always the first priority in the design and

	implementation of the system. 7. Incidental findings: When analyzing retrospective data, unexpected information may be discovered, such as undiagnosed diseases or genetic risks. These findings can have significant implications for patients and families. How to deal with these unexpected findings, especially when they may influence healthcare professionals' decisions about patient care, is a complex ethical issue. Solution: 1. Establish clear protocols for handling: Develop clear guidelines on how to handle unanticipated discoveries, including when and how to notify health-care workers and patients' families, and ensure that these protocols are consistent with medical ethics and legal requirements. 2. Before using retrospective data, make clear to the patient or family the likelihood that unknown information may be found and ensure that they understand and agree to the process in such cases. The project has been approved by the Ethical Committee on Clinical Research of the Universidad Politécnica de Valencia(UPV) and the partner hospital.
中期目标 **Mid-term target.** **It must be tangible outcomes, E.g. software, hardware or simulation.** **It will be assessed at the mid-term oral.**	1. Complete the technical specifications of the iNeom system (Document). 2. Completion of predictive modelling and clinical alerts prototype in Neonatal ICU. 3. Complete the analysis of the state of the art on predictive modelling techniques in the Neonatal ICU.

Work Plan (Gantt Chart)

Fill in the sub-tasks and insert a letter X in the cells to show the extent of each task

	Nov 1-15	Nov 16-30	Dec 1-15	Dec 16-31	Jan 1-15	Jan 16-31	Feb 1-15	Feb 16-28	Mar 1-15	Mar 16-31	Apr 1-15	Apr 16-30
Task 1 Technical specifications of the iNeom system (Document). Specifications according to the functional requirements, type of devices, communication protocols and hardware connectivity.												
Summary of the types, functions and data types of the devices used.				X	X	X	X					
Selecting and testing communication protocols.						X	X					
Test the viability of the existing hardware used to read data from different devices.						X	X					
Write technical specification documents of the iNeom system.				X	X	X	X	X				
Task 2 Data modelling and clinical alerts in Neonatal ICU. State of the art on predictive modelling techniques in the Neonatal ICU.												
Relevant papers read, collected and screened	X	X	X									
An analysis of state of the art on predictive modelling techniques in the Neonatal ICU.		X	X	X	X	X						
Summarize data types for each device and build analytical models.						X	X	X				
Debugging and testing for the model.							X	X	X	X		
Task 3 iNeoM Prototype (Software). Development of the software and hardware modules.												
Data analysis and data set selection.					X	X	X	X				
Model selection and training.							X	X	X	X		
Software front-end construction.									X	X	X	X
Task 4 iNeom System Validation (Document). Testing of the models and the platform.												
Data validation: validate data set quality and data decoding process					X	X	X	X				
Testing of data models							X	X	X	X		
System Integration Testing								X	X	X	X	X

Security and privacy testing										X	X	X

北京邮电大学 本科毕业设计（论文）初期进度报告

Project Early-term Progress Report

学院 School	International School	**专业 Programme**	**Internet of Things Engineering**		
姓 Family name	Xiao	**名 First Name**	Longwei		
BUPT 学号 BUPT number	2020213690	**QM 学号 QM number**	200983941	**班级 Class**	2020215122
论文题目 Project Title	Development and implementation of an Intelligent Neonatal Monitoring system through the use of Big Data and Artificial Intelligence				

1. Literature search

Literature sources：PubMed, IEEE, SCOPUS.
Keywords：neonates OR neonatal OR newborn OR NICU"big data" OR A OR "artificial intelligence"OR oxygen OR heart OR respiratory OR blood OR ventilation OR monitoring OR "real time
Exclusion: Adult, Children, Animal
Year Range: 5 years.
Search result: 133 papers in total (excluding duplicate articles)

2. Paper Screening

Method: System Review

Step 1: Exclusion
The article must not meet all three of the following criteria in order to proceed to the next step:

EXCLUSION Criterion 1: Not NICU: The article must include NICU-related content.
EXCLUSION Criterion 2: Not including stats and modelling: the article must include data analysis.
EXCLUSION Criterion 3: Not clinical outcome: articles must include clinical outcomes.

A total of 42 articles met all three Exclusion criteria.

Step 2: Inclusion
The article must meet all three of the following criteria in order to be successfully selected:

INCLUSION Criterion 1: Retrospective/Prospective trial. This criterion has the objective of only including studies which were implemented on real data. This data can be prospective or retrospective, so it also includes existing data sets (private or open). The idea is to exclude theoretical or design studies which do not use data for modelling/validation.

INCLUSION Criteria 2: Description of Methods and data sources. Apparently no problem with this.

INCLUSION Criteria 3: Defines Specific Clinical Outcome in NICU. The objective of this criterion is to include studies which have a clear and concrete principal clinical outcome in the context of the NICU. This clinical outcome can be a clinical condition or an event (e.g.: high blood pressure, apnea, low body temperature.. etc). As clinical outcome we can classify them with ICD codes (bronchopulmonary dysplasia, respiratory distress syndrome, persistent fetal circulation, anemia, meningitis, sepsis, bradycardia….). Note that this criterion does not refer to the

context/location of the study – only to the presence of a clinical objective.

A total of 10 articles fulfilled the above three Inclusion conditions.

Step 3: Data Extraction

3. Literature Review

In Neonatal Intensive Care Units (NICU), newborns are monitored extensively, generating a vast array of data. This includes detailed imaging, physiological measurements like heart rate and oxygen levels, and other metrics captured by advanced monitoring systems. The integration of pervasive sensor technology with artificial intelligence has enabled more precise and continuous medical surveillance. Analyzing this comprehensive data set is crucial for identifying factors that influence the neurological development of neonates. Artificial intelligence and machine learning technologies are increasingly seen as vital tools for enhancing predictive accuracy and overall clinical results in NICUs. The goal of this initiative is to apply AI and big data solutions to interpret the data gathered from various NICU monitoring tools. This approach aims to assist medical professionals in forecasting clinical outcomes and formulating appropriate treatment strategies.

In the field of neonatal intensive care, monitoring haemodynamic conditions is essential as they often indicate the severity of cardiovascular and other diseases. Xiu-Lin Chen, Bo-Sheng Lin, and their team developed a sophisticated system for non-invasive monitoring of blood perfusion, which aids in determining the severity of illnesses. This system first calculates specific indices by measuring changes in haemoglobin parameters using a multi-wavelength approach for optical density attenuation. It then selects key indicators through various feature selection methods, including the t-test, Kruskal-Wallis test, Relief, and several entropy-based methods such as information gain, information gain ratio, and symmetric uncertainty. These indicators are used as inputs for a Radial Basis Function Neural Network (RBFNN), which serves as the classifier. Experimental findings revealed significant differences in blood perfusion indicators among neonates with varying levels of disease severity. Furthermore, the neural network proved effective in differentiating between mild and severe cases of the disease.

In neonatal intensive care units (NICUs), newborns are often at risk for respiratory failure that may necessitate tracheal intubation. Timely intubation is critical, as delays can lead to increased complications and mortality, particularly in emergency situations. Accurate and real-time prediction of intubation needs can allow for better preparation, reducing the risks associated with late intubation and enhancing overall safety.

Jueng-Eun Im and colleagues conducted a retrospective analysis on 128 neonates with respiratory distress in the NICU. They developed a multimodal network capable of predicting the need for intubation up to three hours in advance. This network combines two subsystems: a multilayer perceptron (MLP) for analyzing numerical data and a transformer block for handling time series data. The network integrates feature vectors from both systems into a fully connected layer to estimate the likelihood of needing intubation.

Péter Földesy and his team created a novel deep learning algorithm for a camera-based respiratory monitoring system. This algorithm identifies significant respiratory patterns by analyzing periodic movements and incrementally trains a deep neural network to detect breathing in complex situations, like bursty or motion-intensive environments. The algorithm, which continuously evolves without a forgetting mechanism, can adapt to varying breathing patterns.

S Navaneeth and associates utilized thermography and deep learning to classify respiratory rates non-invasively. They developed a neural network using Keras, which categorizes breathing into

four types: rapid, slow, healthy, and inconclusive. The model demonstrated high recall and precision rates, evidencing its effectiveness in identifying respiratory disorders.

The traditional approach for early detection of neurodevelopmental disorders in premature infants involves manual inspection of their movement patterns by skilled professionals. To streamline this labor-intensive and qualitative process, Lucia Migliorelli and her team have introduced a novel deep learning model designed for precise estimation of limb positions using depth images. Their algorithm, named TwinEDA, employs a convolutional neural network with specialized architectural units. These units are optimized to perform fewer computations without compromising on the accuracy of predictions. This network was tested on a substantial dataset comprising 27,000 depth video frames from 27 preterm infants, gathered in actual clinical settings. When compared to leading algorithms in the field, TwinEDA demonstrated a twofold increase in processing speed for individual depth frames and required only a quarter of the memory, while maintaining a comparable level of accuracy, as indicated by a Dice similarity coefficient of 0.88.

Cristhyne León and her team conducted a study focused on neonatal late-onset sepsis (LOS), a significant cause of morbidity and mortality in very preterm infants. Their research in a neonatal intensive care unit (NICU) involved analyzing heart rate variability (HRV) data from 49 preterm infants. These infants were divided into two groups: one that received antibiotics post-birth (LOS group) and a control group that did not receive antibiotics. The study compared the HRV characteristics of the LOS group against those of the control group, as well as against baseline values established during a calibration period. Using automated feature selection, they trained four machine learning models: k Nearest Neighbours (KNN), Logistic Regression (LogR), Random Forest (RandF), and Support Vector Machines (SVMs). Logistic regression emerged as the most effective in detecting LOS, highlighting the value of incorporating a visibility chart index in HRV analysis for predicting neonatal sepsis.

In a separate study, Saim Ervura and colleagues aimed to identify respiratory abnormalities in newborns using a non-invasive, non-ionizing method: thermography. They employed CNN models and data augmentation techniques to detect respiratory issues in neonates. The study categorized newborns into two groups: those with respiratory abnormalities and those with cardiovascular or abdominal issues. The accuracy of classifying these conditions improved from 84.5% to 90.9% when the number of images was quadrupled through data enhancement. This increase underscores the impact of data augmentation on the classification results in medical diagnoses using artificial intelligence.

Critical congenital heart disease (CCHD) is a subset of CHD and represents the most severe form of CHD. delayed or missed detection of CCHD can lead to severe, preventable morbidity as well as death. However, approximately 900 newborns with CCHD are still missed each year in the U.S. Zhengfeng Lai et al. designed an interpretable machine-learning model that can be directly incorporated into current stand-alone SpO2 screening systems with automated feature selection to further improve the sensitivity of CCHD detection with minimal impact on specificity[12].

Neonatal apnea, a critical condition observed in preterm infants, is characterized by a pause in breathing for over 20 seconds, often accompanied by a slowed heartbeat, skin discoloration (bruising or pallor), and decreased muscle tone. This condition poses a significant risk of brain damage and is predominantly found in preterm infants. To address this, Omiya Hassan and colleagues developed a machine learning-based hardware model for detecting neonatal respiratory failure in neonatal intensive care units (NICU). Their system includes a pyroelectric transducer-based respiratory monitor and a pulse oximeter for identifying apnea episodes. The system captures signals from the transducer, which are then digitized and processed. The respiratory data, enhanced through a charge amplifier, is digitized in a range between 0 and 1. In contrast, pulse oximetry data is normalized within a 0 to 5 range. This data is then analyzed using a Fully Connected Neural Network (FCNN) to determine the presence of apnea, particularly effective in cases where both respiratory rate and SpO2 levels are low. Omiya Hassan's model boasts a remarkable accuracy rate

of about 99% in detecting respiratory failure in neonates.

Reference:

[1] Fairchild KD, Aschner JL. HeRO monitoring to reduce mortality in NICU patients. Rrn Dove Press. 2012;2:65–76.

[2] Griffin MP, Lake DE, Bissonette EA, Harrell FE, Shea OTM, Moorman JR. Heart rate characteristics: novel physiomarkers to predict neonatal infection and death. Pediatrics Am Acad Pediatrics. 1999;116:1070.

[3] Fairchild KD, Lake DE. Cross-correlation of heart rate and oxygen saturation in very low birthweight infants: association with apnea and adverse events. Am J Perinatol. 2018;35:463.

[4] Davoudi A, Malhotra KR, Shickel B, Siegel S, Williams S, Ruppert M, et al. Intelligent ICU for autonomous patient monitoring using pervasive sensing and deep learning. Sci Rep. 2019;9:8020. https://doi.org/10.1038/s41598-019-44004-w.

[5] H. -L. Chen, B. -S. Lin, K. -H. Chen and B. -S. Lin, "An Intelligent Systemic Circulation Monitoring System for Neonatal Illness Severe Severity Evaluation," in IEEE Access, vol. 11, pp. 127468-127478, 2023, doi: 10.1109/ACCESS.2023.3331826.

[6] J. -E. Im, S. -A. Yoon, Y. M. Shin and S. Park, "Real-Time Prediction for Neonatal Endotracheal Intubation Using Multimodal Transformer Network," in IEEE Journal of Biomedical and Health Informatics, vol. 27, no. 6, pp. 2625-2634, June 2023, doi: 10.1109/JBHI.2023.3267521.

[7] L. Burne et al., "Ensemble Approach on Deep and Handcrafted Features for Neonatal Bowel Sound Detection," in IEEE Journal of Biomedical and Health Informatics, vol. 27, no. 6, pp. 2603-2613, June 2023, doi: 10.1109/JBHI.2022.3217559.

[8] Migliorelli, L., Cacciatore, A., Ottaviani, V. et al. TwinEDA: a sustainable deep-learning approach for limb-position estimation in preterm infants' depth images. Med Biol Eng Comput 61, 387–397 (2023). https://doi.org/10.1007/s11517-022-02696-9

[9] C. León, G. Carrault, P. Pladys and A. Beuchée, "Early Detection of Late Onset Sepsis in Premature Infants Using Visibility Graph Analysis of Heart Rate Variability," in IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 4, pp. 1006-1017, April 2021, doi: 10.1109/JBHI.2020.3021662.

[10] Ervural, S., Ceylan, M. (2021). Convolutional neural networks-based approach to detect neonatal respiratory system anomalies with limited thermal image. Traitement du Signal, Vol. 38, No. 2, pp. 437-442. https://doi.org/10.18280/ts.380222

[11] P. Földesy, Á. Zarándy and M. Szabó, "Reference Free Incremental Deep Learning Model Applied for Camera-Based Respiration Monitoring," in IEEE Sensors Journal, vol. 21, no. 2, pp. 2346-2352, 15 Jan.15, 2021, doi: 10.1109/JSEN.2020.3021337.

[12] Z. Lai et al., "Enhanced Critical Congenital Cardiac Disease Screening by Combining Interpretable Machine Learning Algorithms," 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Mexico, 2021, pp. 1403-1406, doi: 10.1109/EMBC46164.2021.9630111.

[13] O. Hassan, S. Shamsir and S. K. Islam, "Machine Learning Based Hardware Model for a Biomedical System for Prediction of Respiratory Failure," 2020 IEEE International Symposium on Medical Measurements and Applications (MeMeA), Bari, Italy, 2020, pp. 1-5, doi: 10.1109/MeMeA49120.2020.9137291.

[14] S. Navaneeth, S. Sarath, B. Amba Nair, K. Harikrishnan and P. Prajal, "A Deep-Learning Approach to Find Respiratory Syndromes in Infants using Thermal Imaging," 2020 International Conference on Communication and Signal Processing (ICCSP), Chennai, India, 2020, pp. 0498-0501, doi: 10.1109/ICCSP48568.2020.9182231.

是否符合进度? On schedule as per GANTT chart?

YES

下一步 Next steps:

An analysis of state of the art on predictive modelling techniques in the Neonatal ICU.

北京邮电大学 本科毕业设计（论文）中期进度报告

Project Mid-term Progress Report

学院 School	International School	**专业 Programme**	**Internet of Things Engineering**		
姓 Family name	Longwei	**名 First Name**	Xiao		
BUPT 学号 BUPT number	2020213690	**QM 学号 QM number**	200983941	**班级 Class**	2020215122
论文题目 Project Title	Development and implementation of an Intelligent Neonatal Monitoring system through the use of Big Data and Artificial Intelligence				

是否完成任务书中所定的中期目标？Targets met (as set in the Specification)?
Completed with Exceptions.
Reasons for non-completion of established tasks: Otitis media prevented normal work; was overly optimistic in setting goals for the previous phase of the assignment, underestimated the amount of work involved in the systematic review of the assignment, and did not realize that Supervisor wants to write a review paper when he set the goals.
Catch up plan: The planned Task 1: iNeom system technical specifications (documentation) and Task 3: iNeom prototype (software) need to be carried out after the completion of the current tasks (i.e. the system review) and the preliminary analysis of the monitoring data on or around 3 March. The two tasks can be carried out simultaneously and compressed to be completed by the end of March.

已完成工作 Finished work:

1. System review of An analysis of state of the art on predictive modelling techniques in the Neonatal ICU.

Literature sources：PubMed, IEEE, SCOPUS.
Keywords：neonates OR neonatal OR newborn OR NICU"big data" OR A OR "artificial intelligence"OR oxygen OR heart OR respiratory OR blood OR ventilation OR monitoring OR "real time
Exclusion: Adult, Children, Animal
Year Range: 5 years.
Search result: 260 papers in total (excluding duplicate articles)

Paper Screening:

Method: System Review

Step 1: Exclusion
The article must not meet all three of the following criteria in order to proceed to the next step:

EXCLUSION Criterion 1: Not NICU: The article must include NICU-related content.
EXCLUSION Criterion 2: Not including stats and modelling: the article must include data analysis.
EXCLUSION Criterion 3: Not clinical outcome: articles must include clinical outcomes.

Step 2: Inclusion
The article must meet all three of the following criteria in order to be successfully selected:

INCLUSION Criterion 1: Retrospective/Prospective trial. This criterion has the objective of only including studies which were implemented on real data. This data can be prospective or retrospective, so it also includes existing data sets (private or open). The idea is to exclude theoretical or design

studies which do not use data for modelling/validation.

INCLUSION Criteria 2: Description of Methods and data sources. Apparently no problem with this.

INCLUSION Criteria 3: Defines Specific Clinical Outcome in NICU. The objective of this criterion is to include studies which have a clear and concrete principal clinical outcome in the context of the NICU. This clinical outcome can be a clinical condition or an event (e.g.: high blood pressure, apnea, low body temperature.. etc). As clinical outcome we can classify them with ICD codes (bronchopulmonary dysplasia, respiratory distress syndrome, persistent fetal circulation, anemia, meningitis, sepsis, bradycardia….). Note that this criterion does not refer to the context/location of the study – only to the presence of a clinical objective.

A total of 42 articles fulfilled the above three Inclusion conditions, which are finally selected for data extraction.

Step 3: Data Extraction

	Objective			Data			
Authors	Title	Journa	Year	DOI	Source	RETRIE	EXCLUSIO	EXCLUDED?	ICD-11 3º level	ICD Disease Name	Aim (develop	Accessibility (	Data treatme	Study design	Origin
E. Groob	Noisy Neonatal Chest Sound Separat	IEEE Jou	2023	10.1109	IEEE			FALSE	?胸音分离	Chest Sound Sepration	Develop	Private	Comparison vs cc	Case report	Own st
Z. Peng;	A continuous late-onset sepsis predic	IEEE Jou	2023	10.1109	IEEE			FALSE	KA60 新生儿败血症	Sepsis of fetus or newborn	Develop	Private	Cohorts	Case report	Own St
Matić V.;	Improving Reliability of Monitoring Bi	IEEE Tra	2016	10.1109	SCOPUS			FALSE	8B24 缺氧缺血性脑病	Hypoxic-ischaemic encephi	Develop	Private	Cohorts	Case report	Own St
Y. J. Cher	High-Reliability Non-Contact Photop	IEEE Acc	2023	10.1109	IEEE			FALSE	? 通过视频监测心率	HR monitoring	Develop	Public	Cohorts	Not reported / Ur	Own st
C. León;	Evaluation of Maturation in Preterm I	IEEE Jou	2022	10.1109	IEEE			FALSE	? 婴儿成熟度评估	Evaluation of Maturation	Develop	Private	Cohorts	Not reported / Ur	Own st
C. Matac	End-to-End Automatic Morphologica	IEEE Jou	2022	10.1109	IEEE			FALSE	8D60颅内高压	Increased intracranial press	Develop	Private	Cohorts	Not reported / Ur	Own st
E. Groob	Real-Time Multi-Level Neonatal Hea	IEEE Acc	2022	10.1109	IEEE			FALSE	?心肺音质量评估	Heart and Lung Sound Qua	Develop	Private	Cohorts	Not reported / Ur	Own st
Ervural S	Classification of neonatal diseases wit	Multime	2022	10.1007	SCOPUS			FALSE	KB23, LA8Y	Respiratory distress of newl	Develop	Private	Cohorts	Not reported / Ur	Own st
Juraev F.	Multilayer dynamic ensemble model	Journal	2022	10.1016	SCOPUS			FALSE	?	mortality prediction	Develop	Public	Cohorts	Not reported / Ur	Own st
J. Egede;	Automatic Neonatal Pain Estimation:	2019 8th	2019	10.1109	IEEE			FALSE	MG3Z疼痛分析	Pain, unspecified	Develop	Public	Cohorts	Not reported / Ur	Own st
R. Góme	Development of a Non-Invasive Proc	2019 IEE	2019	10.1109	IEEE			FALSE	KA60	General symptoms, signs or	Develop	Private	Comparison vs cc	Not reported / Ur	Own st
Semenov	Prediction of short-term health outc	Comput	2019	10.1016	SCOPUS			FALSE	BA2Z	General symptoms, signs or	Develop	Private	Comparison vs cc	Not reported / Ur	Own st
Y. Hu; V.	An Application of Convolutional Neu	2019 Int	2019	10.1109	IEEE			FALSE	KA60	General symptoms, signs or	Develop	Private	Comparison vs cc	Not reported / Ur	Own st
K. E. S. Fe	CRISP-TDM0 for standardized knowl	2017 IEE	2017	10.1109	IEEE			FALSE	9B71	Diseases of the visual system	Develop	Private	Cross-over arms	Not reported / Ur	Own st
A. Thomm	A Rule-Based Temporal Analysis Method for	2014 IEEE	2014	10.1109/E	IEEE			FALSE	MD11	Symptoms, signs or clinical f	Develop	Private	Cross-over arms	Not reported / Ur	Own st
Chen W.;	A random forest model based classifi	BioMedi	2014	10.1186	SCOPUS			FALSE	8E47, 8A63	Diseases of the nervous syst	Develop	Private	Cross-over arms	Not reported / Ur	Own st
Honoré A	Vital sign-based detection of sepsis in	Acta Pae	2023	10.1111	SCOPUS			FALSE	KA60 新生儿败血症	General symptoms, signs or	Develop	Private	Cross-over arms	Not reported / Ur	Own St
D. G. Kyr	Transfer Learning Approaches for Ne	2022 IEE	2022	10.1109	IEEE			FALSE	? head position detection	?	Develop	Private	Single group	Not reported / Ur	Own St
R. Joshi;	Predictive Monitoring of Critical Card	IEEE Jou	2019	10.1109	IEEE			FALSE	? early prediction of critical	?	Develop	Private	Single group	Not reported / Ur	Own St
H. Singh;	Neo-Bedside Monitoring Device for I	IEEE Acc	2019	10.1109	IEEE			FALSE	?监护系统	?	Develop	Private	Single group	Not reported / Ur	Own St
G. Marvii	Explainable Feature Learning for Pre	2021 IEE	2021	10.1109	IEEE			FALSE	?预测NICU入院	?	Develop	Private	Single group	Not reported / Ur	Own st
Kim Y.; Ki	Early prediction of need for invasive r	BMC Pe	2023	10.1186	SCOPUS			FALSE	CB41 呼吸衰竭	?	Develop	Private	Single group	Not reported / Ur	Own st
H. -L. Ch	An Intelligent Systemic Circulation M	IEEE Acc	2023	10.1109	IEEE			FALSE	?	?	Develop	Private	Single group	Not reported / Ur	Own st
	Real-Time Prediction for Neonatal Er	IEEE Jou	2023	10.1109	IEEE			FALSE	CB40.Y 呼吸困难	Pleural, diaphragm or media	Develop	Private	single group	Prospective coho	Own st
Stancules	A hierarchical switching linear dynam	Uncertai	2014	https://d	SCOPUS			FALSE	KA60	Certain infectious or parasit	Develop	Private	Comparison vs cc	Case report	Own st
L. Burne;	Ensemble Approach on Deep and Ha	IEEE Jou	2023	10.1109	IEEE			FALSE	?肠鸣音		Develop	Private	Single group	RCT	Own st

RETRIEVAL AND ELIGIBILITY - XX | DATA EXTRACTION - XYZ papers | DATA ANALYSIS - XYZ papers

Columns:

Objective	ICD-11 3º level
	ICD Disease Name
	Aim (develop, update, validate a model, Re-development...)
Data	Accessibility (Public/Private)
	Data treatment from study
	Study design
	Origin
Participants (descriptores de alto nivel)	Participant recruitment method
Outcome quality (grano grueso)	Outcome description
	Outcome in AI
	Purporse of AI
	Was the outcome defined (described) and used consistently in all patients (otucome and measure)?
	Single or combined outcome?
	Blinded outcome? (Y/N) *As outcome assessed without knowledge of the candidate predictors
Predictors	Type of predictors (nature, type - continuous/categorical)
	Timing of predictor measurement
	Preprocessing of predictors? (categorization, normalization, etc···)
Sample Size	Sample Size calculation and statistical power (Y/N)

	Number of participants
	Nº samples with outcome
Missing data	Mentions missing data?
	Nº Samples with missing data
	Handling of missing data
Model development	Type of modeling (statistical, Supervised, Unsupervised, Semi, RL)
	Type of model (regression, bayesian, SVM, CNNs, ……)
	Method for selection of candidate predictors
	Shrinkage of predictors
Model Performance	Calibration
	Classification/Discrimination Measures (metric: S, Sp, AUC, C-statistic, Accuracy….)
	Model significance (Y/N)
Model Evaluation	Type Validation
	Method for testing model
	Adjusting or updating the model?
	Performance metrics (actual value)
Discussion	Interpretation of models (Y/N)
	Comparison of models with other studies (Y/N)
	Challenges (Ctrl+V)
	Opportunities (Ctrl+V)

Summary:

1. Objective

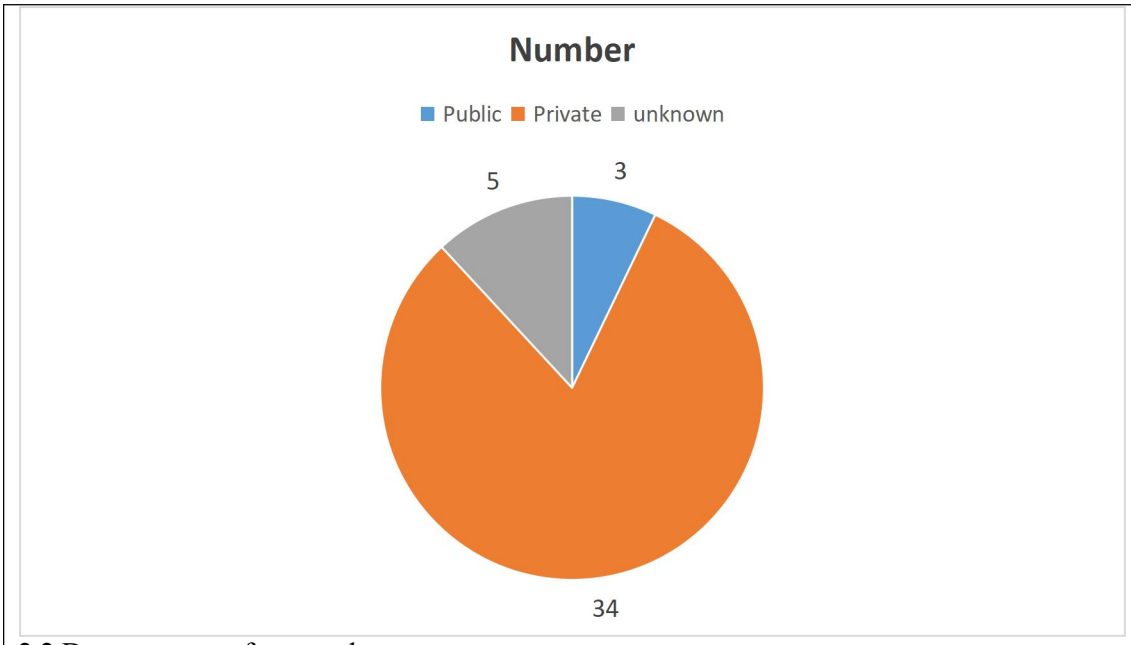
1.1 ICD Disease Group Analysis

ICD Disease Group	Number of Articles
Unknown (Monitor Only)	16
General symptoms, signs or clinical findings	8
Disorders of cerebrospinal fluid pressure or flow	1
Symptoms, signs or clinical findings of the respiratory system	2
Structural developmental anomalies of the circulatory system	2
Diseases of the nervous system	4
Certain infectious or parasitic diseases	1
Cerebrovascular diseases	1
Pleural, diaphragm or mediastinal disorders	4
Functions of the cardiovascular, haematological, immunological and respiratory systems	1

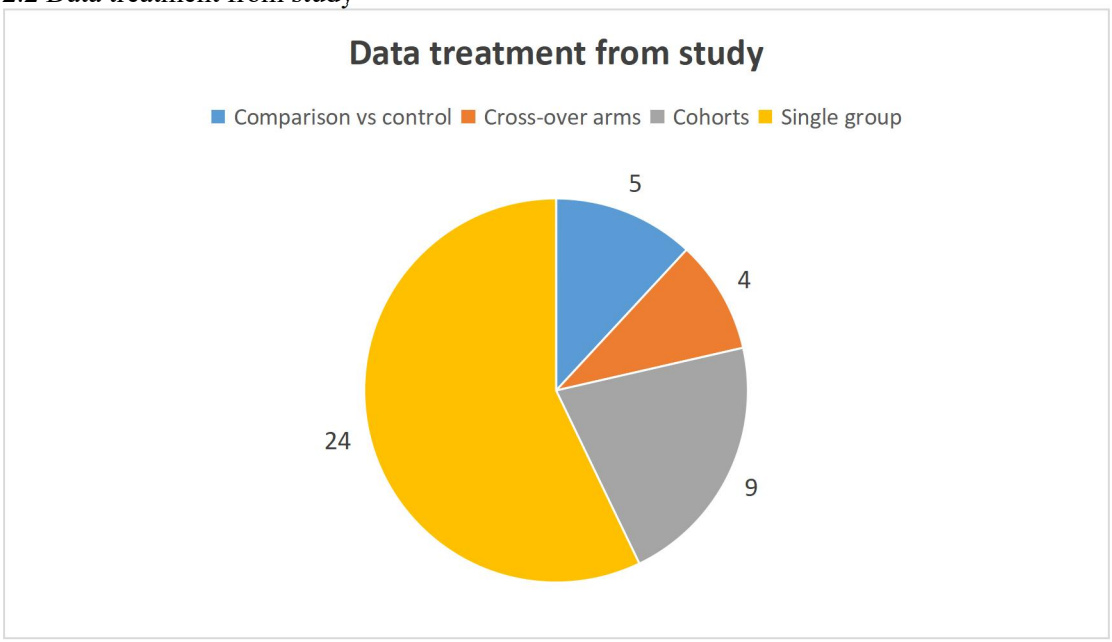
1.2 Aim: All Developed

2. Data

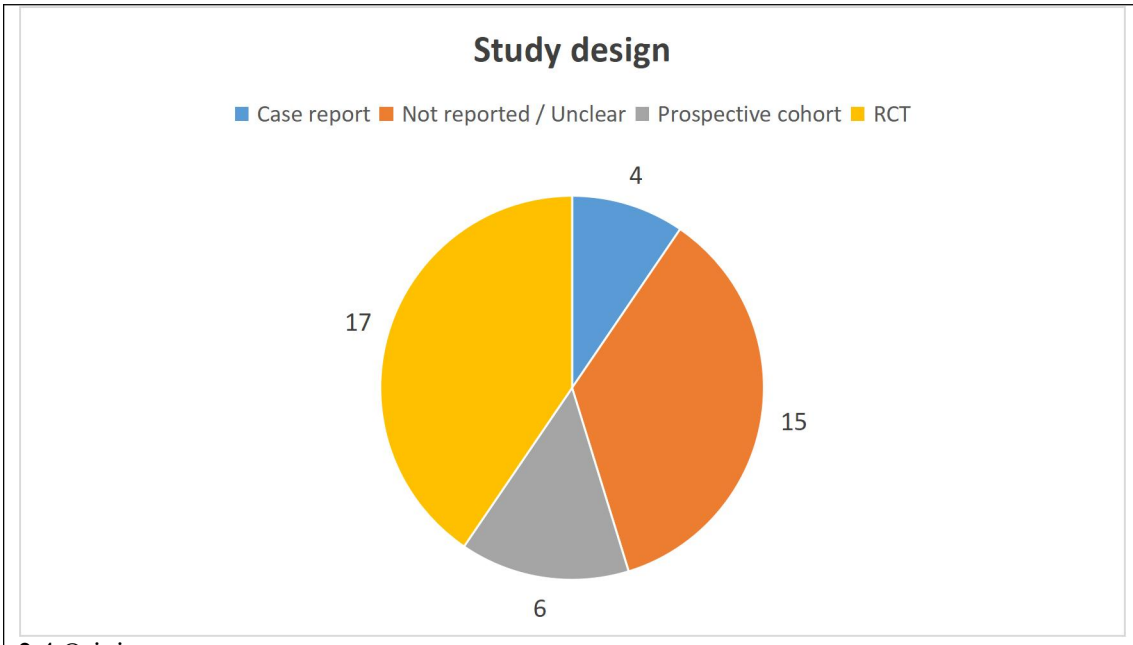
2.1 Accessibility



2.2 Data treatment from study

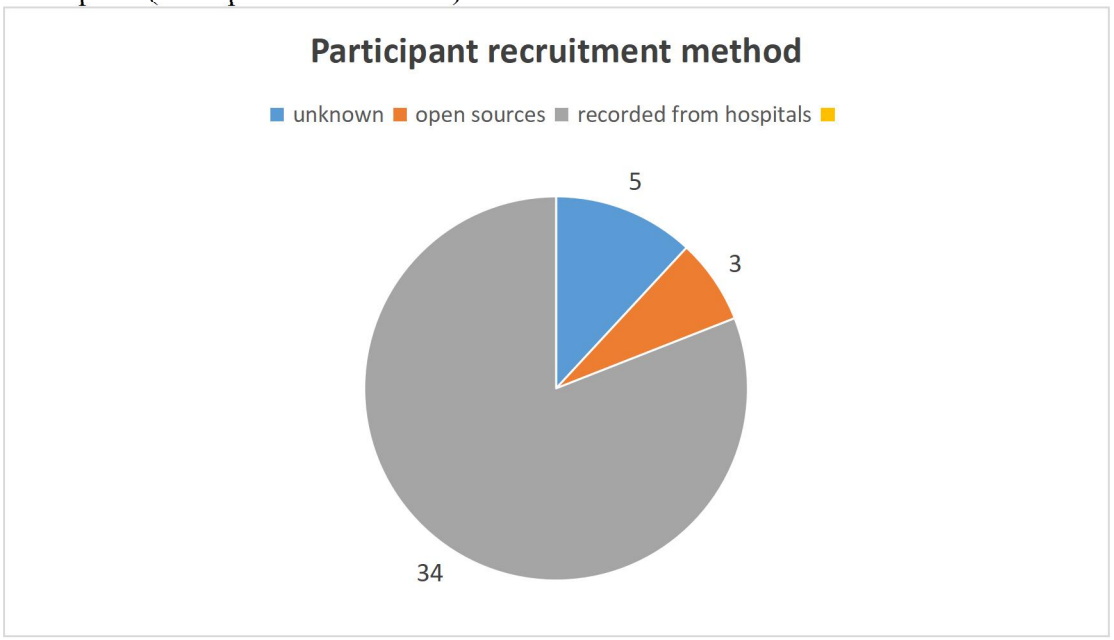


2.3 Study design

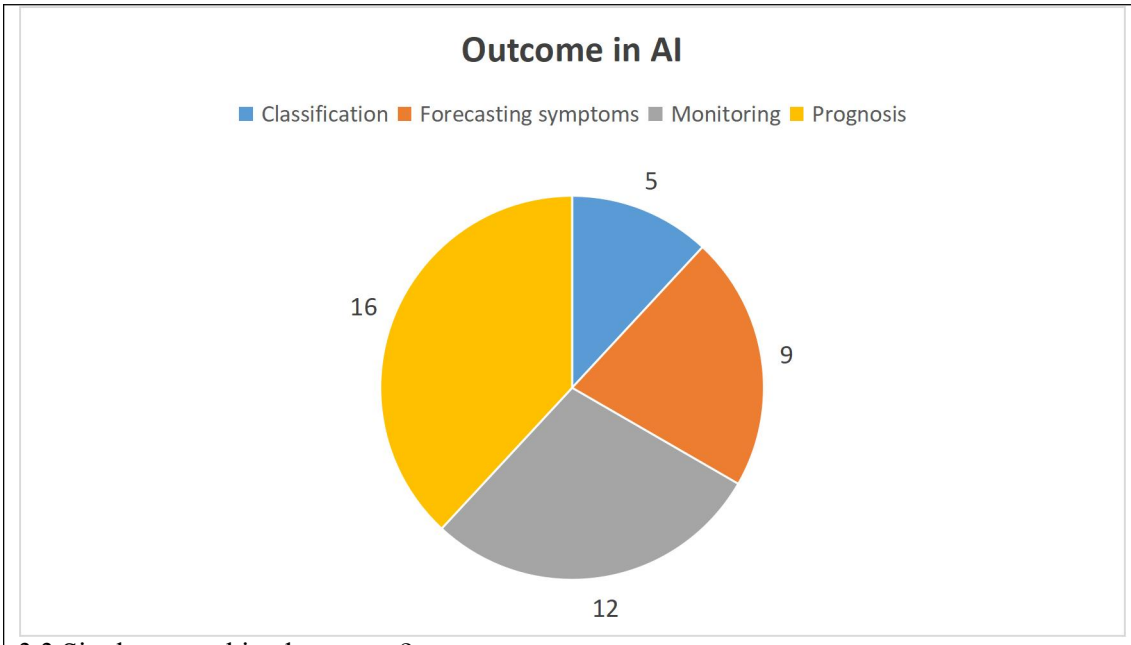


2.4 Origin
All Own Study

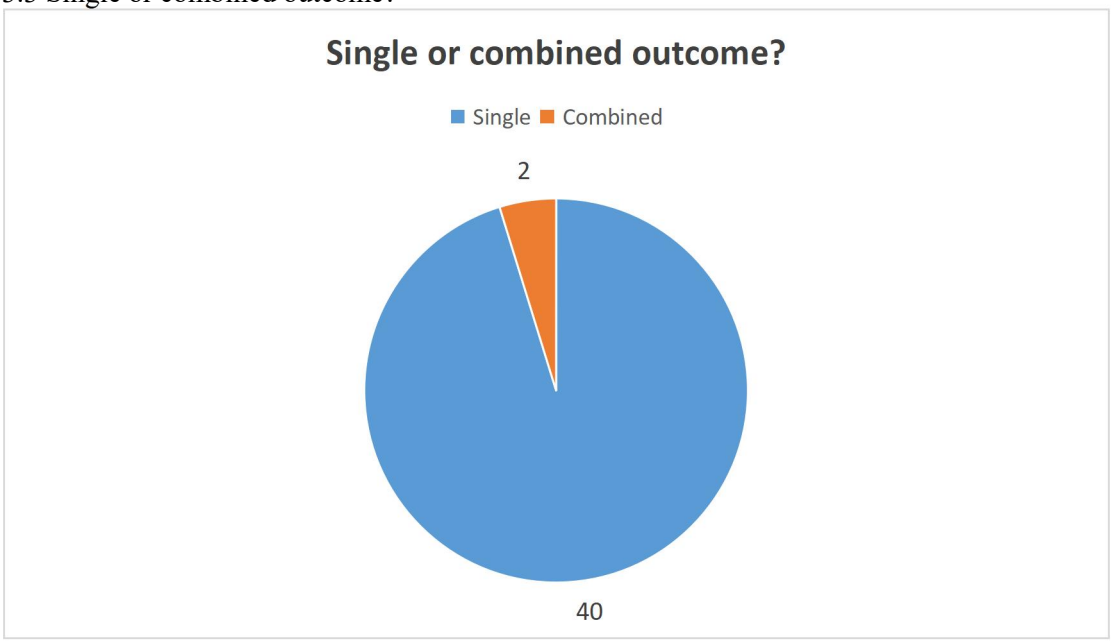
Participants (descriptores de alto nivel)
Participants (descriptores de alto nivel)



3. Outcome quality (grano grueso)
3.2 Outcome in AI

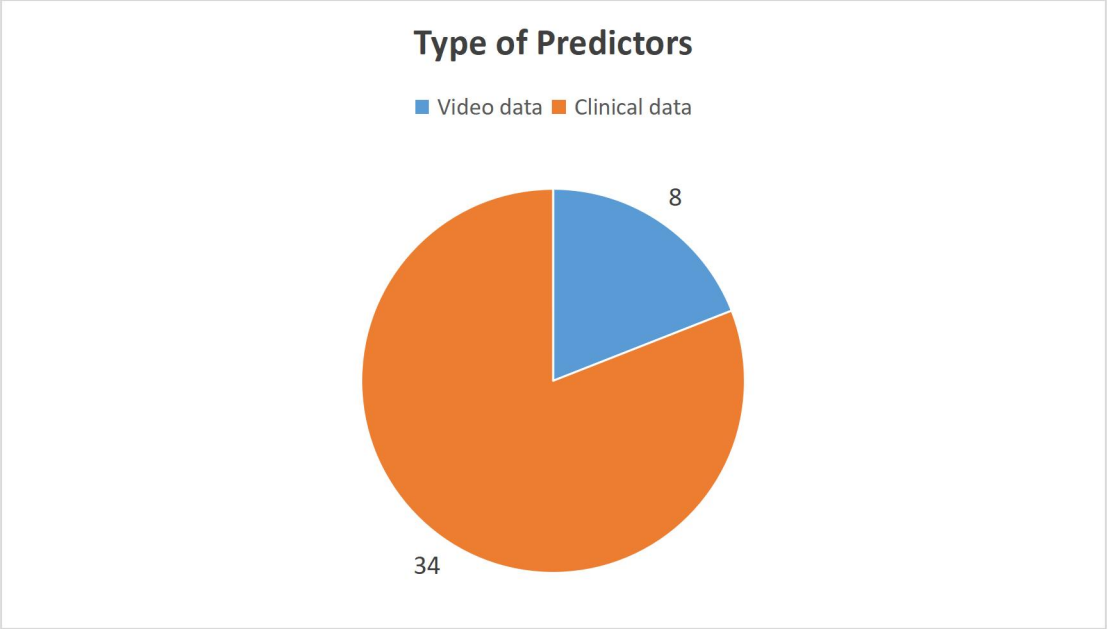


3.3 Single or combined outcome?

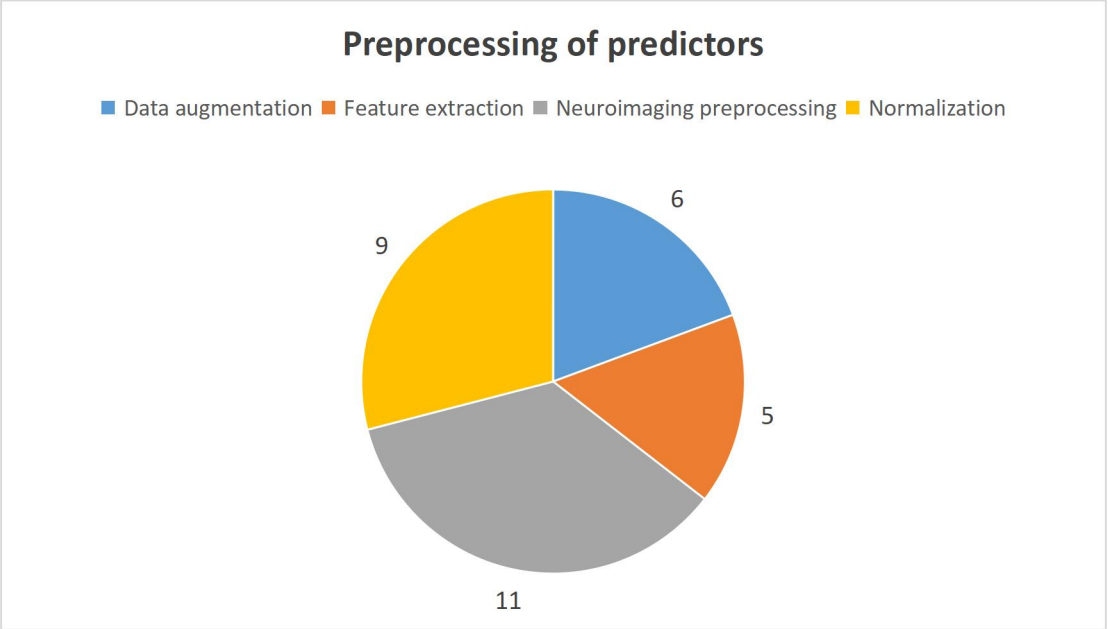


3.4 Blind outcome?
No blind outcome

4. Predictors
4.1 Type of predictors



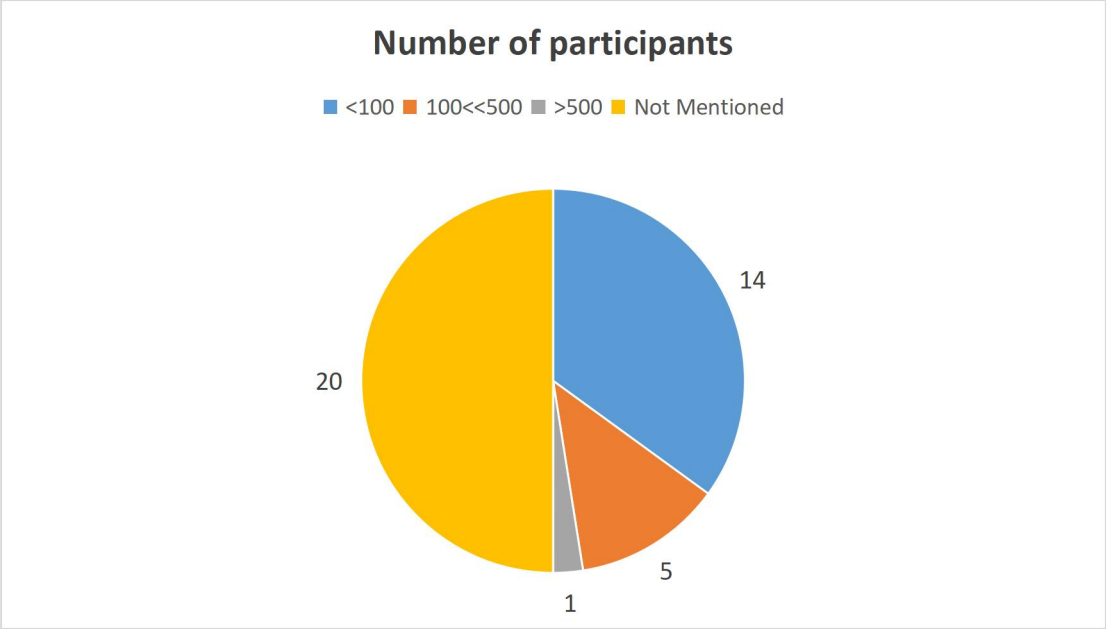
4.2 Preprocessing of predictors? (categorization, normalization, etc…)



5. Sample Size

5.1 Sample Size calculation and statistical power (Y/N): Y

5.2 Number of participants



6. Missing data

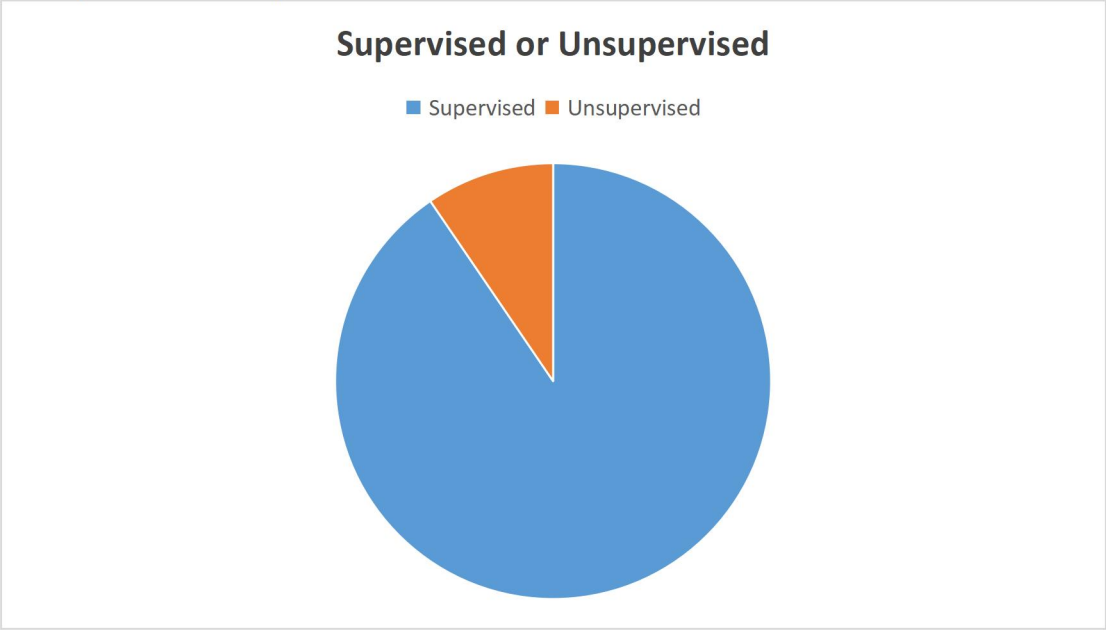
6.1 Mentioned missing data: 6 Articles have mentioned

6.2 Handling of missing data

N-fold cross-validation
fill with average value
fill with average value
fill with average value
data imputation
Decision Tree

7. Model development

7.1 Supervised or Unsupervised



7.2 Type of model (regression, bayesian, SVM, CNNs, ……)

CNN	14
LSTM	5
KNN	4
SVM	4

RF	4
DNN	3
Decision trees	3
XGB	3
LR	3
DNN	3
NB	2
RBFNN	2

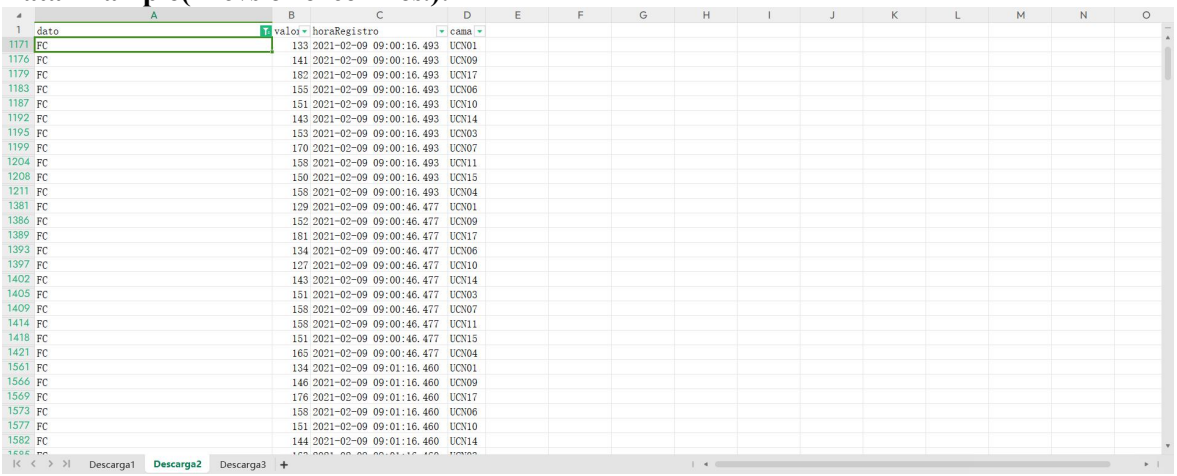
8. Model Performance
8.2 Classification/Discrimination Measures (metric: S, Sp, AUC, C-statistic, Accuracy….)

Not Reported	9
ACC	11
AUC	5
AUROC	3
Sen	6
Spc	6
F1-Score	2
DSC	1
RMSE	1
MAE	1
PCC	1
SDR	1
SIR	1

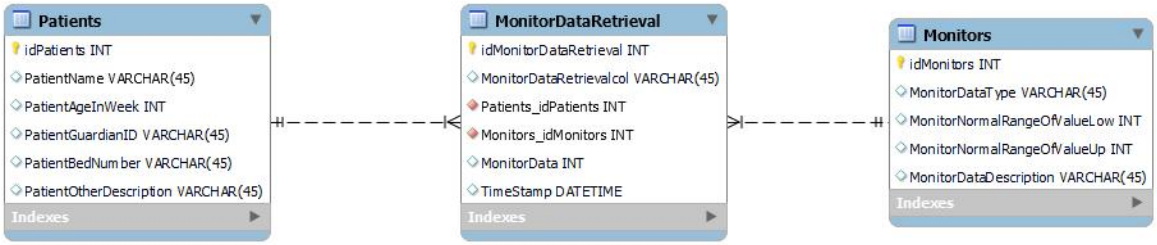
2. Analysis of monitor data examples and database construction

This task consists of two parts: the creation of the database and the writing of the python scripts used to understand the data and organise the data. The data given to the monitors was in xls format, and the data has been changed to csv format in order to make it easier for the script to analyse. The data has a total of four columns, which are data type, value, timestamp and temperature box number. There are more than 600,000 pieces of data in total.

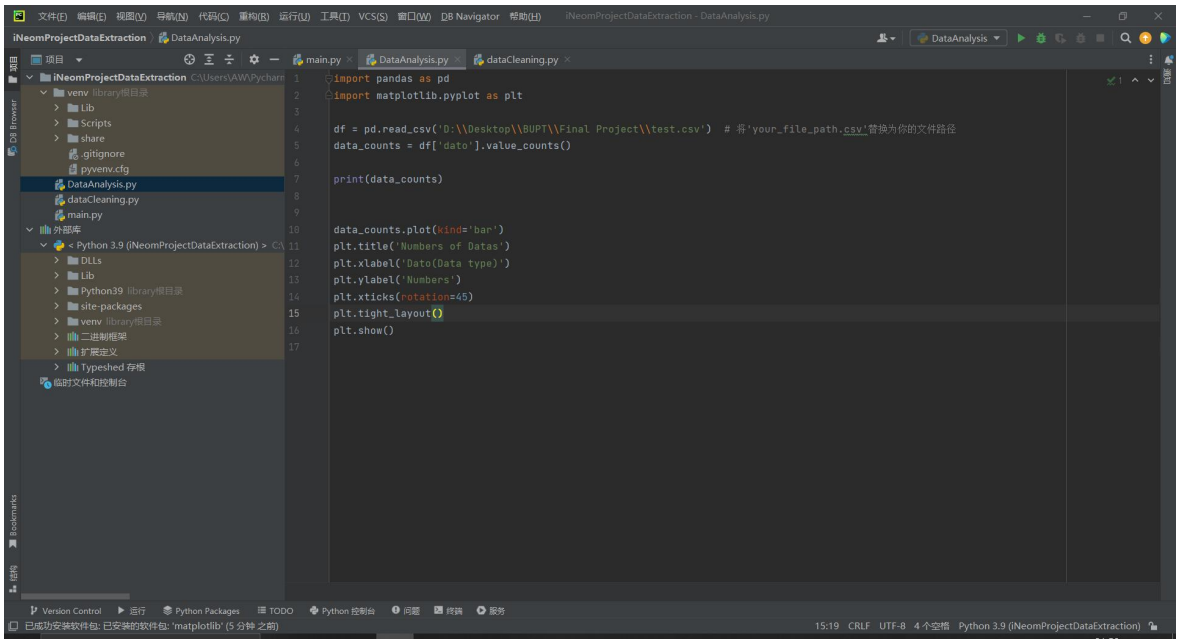
Data Example(in cvs or excel files.):



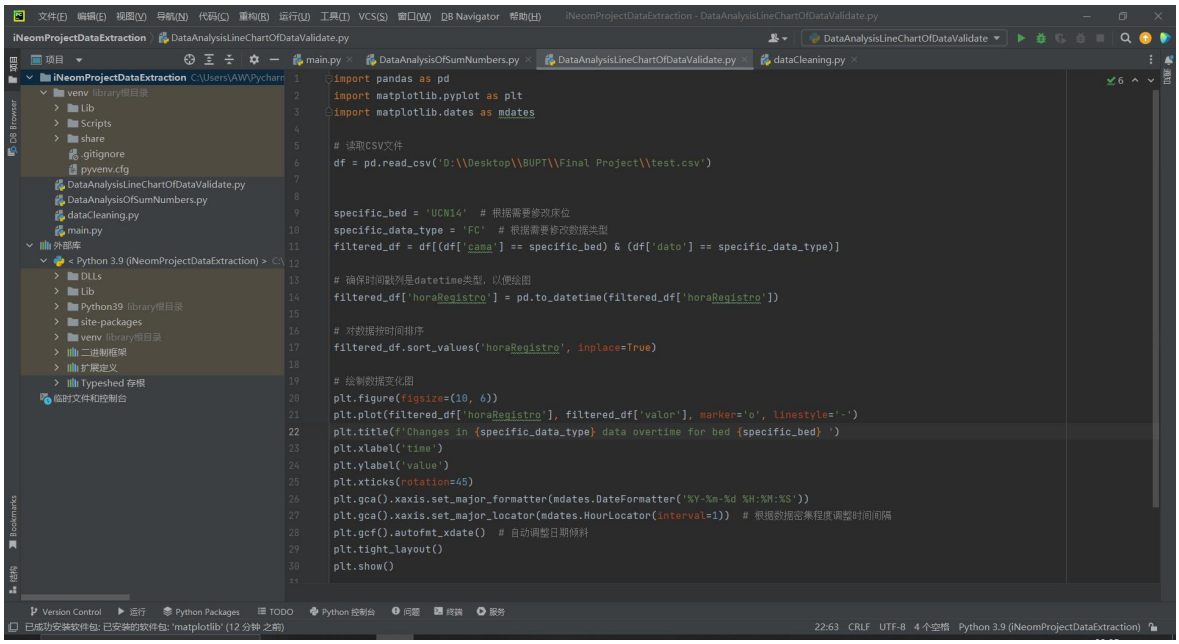
For the database, a total of three tables were created: patient, monitor and data table.



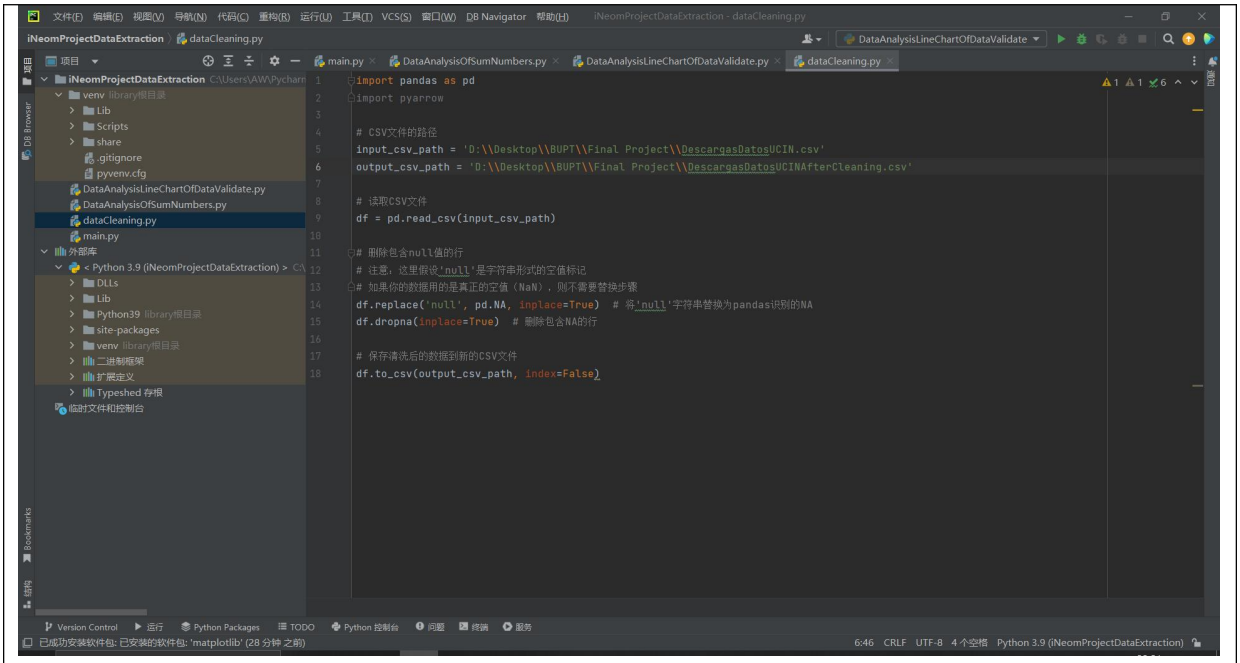
For scripts, two types have been prepared so far. The first is a script that summarizes the number of data types, used to summarize how many different types of monitor data there are in total; the second is the change in a particular piece of data over time for a single bed, which can be used to analyse the patient's condition; and the third is used to clean the data by deleting all rows in the table that contain null for import into the sql database.



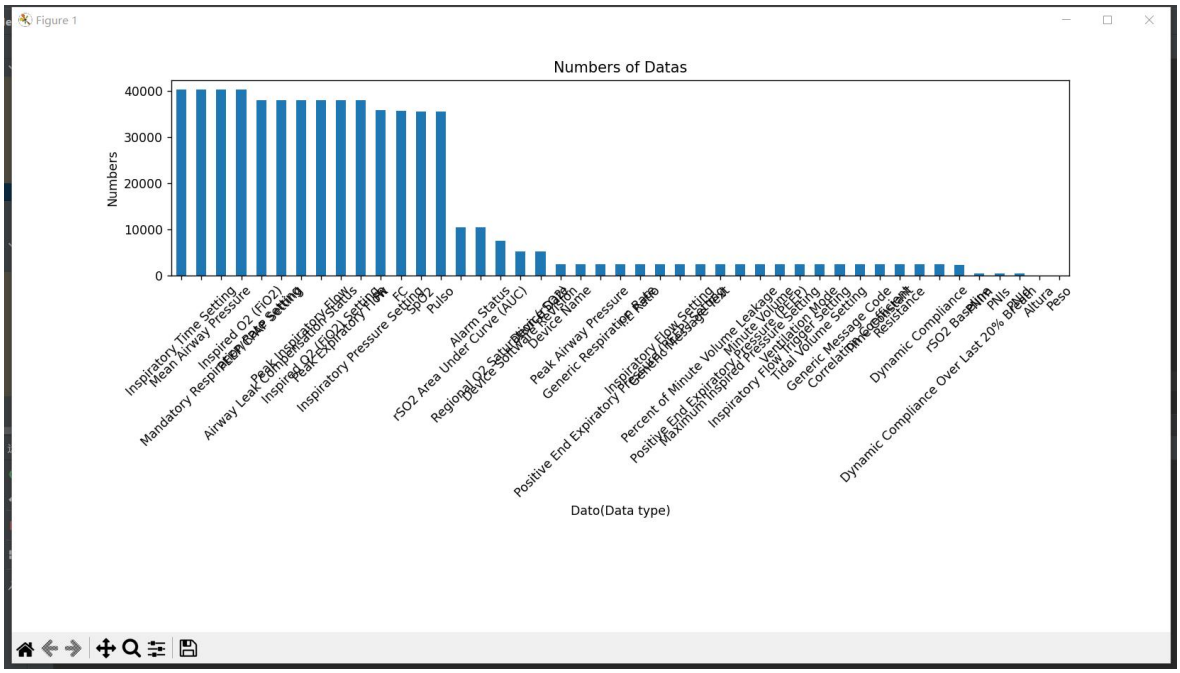
```
import pandas as pd
import matplotlib.pyplot as plt

df = pd.read_csv('D:\\Desktop\\BUPT\\Final Project\\test.csv')  # 将'your_file_path.csv'替换为你的文件路径
data_counts = df['dato'].value_counts()

print(data_counts)


data_counts.plot(kind='bar')
plt.title('Numbers of Datas')
plt.xlabel('Dato(Data type)')
plt.ylabel('Numbers')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

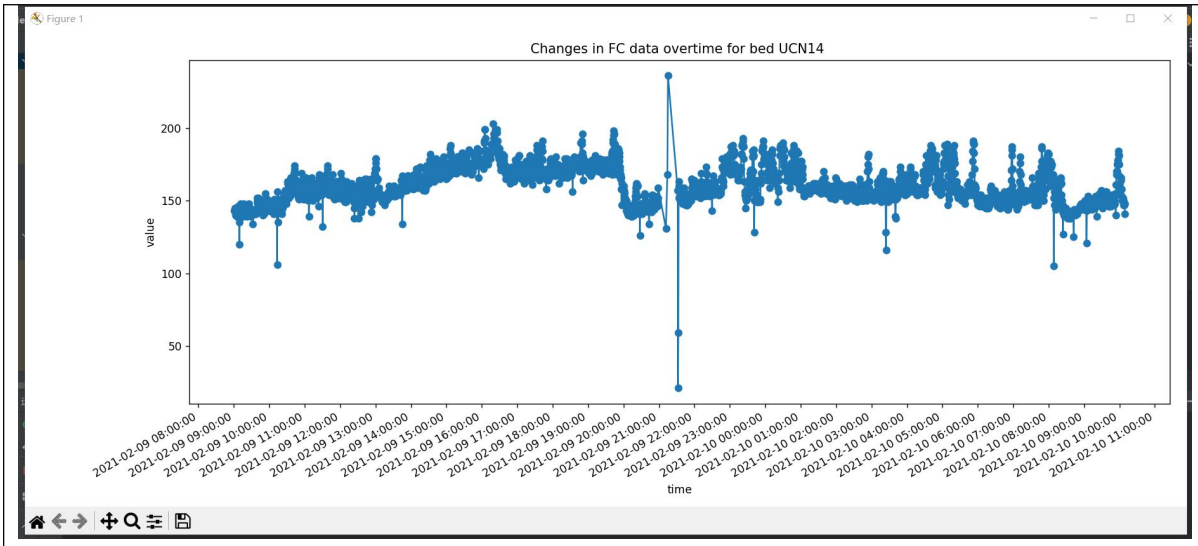


```
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.dates as mdates

# 读取CSV文件
df = pd.read_csv('D:\\Desktop\\BUPT\\Final Project\\test.csv')


specific_bed = 'UCN14'  # 根据需要修改床位
specific_data_type = 'FC'  # 根据需要修改数据类型
filtered_df = df[(df['cama'] == specific_bed) & (df['dato'] == specific_data_type)]

# 确保时间戳列是datetime类型，以便绘图
filtered_df['horaRegistro'] = pd.to_datetime(filtered_df['horaRegistro'])

# 对数据按时间排序
filtered_df.sort_values('horaRegistro', inplace=True)

# 绘制数据变化图
plt.figure(figsize=(10, 6))
plt.plot(filtered_df['horaRegistro'], filtered_df['valor'], marker='o', linestyle='-')
plt.title(f'Changes in {specific_data_type} data overtime for bed {specific_bed} ')
plt.xlabel('time')
plt.ylabel('value')
plt.xticks(rotation=45)
plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m-%d %H:%M:%S'))
plt.gca().xaxis.set_major_locator(mdates.HourLocator(interval=1))  # 根据数据密集程度调整时间间隔
plt.gcf().autofmt_xdate()  # 自动调整日期倾斜
plt.tight_layout()
plt.show()
```



```python
import pandas as pd
import pyarrow

# CSV文件的路径
input_csv_path = 'D:\\Desktop\\BUPT\\Final Project\\DescargasDatosUCIN.csv'
output_csv_path = 'D:\\Desktop\\BUPT\\Final Project\\DescargasDatosUCINAfterCleaning.csv'

# 读取CSV文件
df = pd.read_csv(input_csv_path)

# 删除包含null值的行
# 注意，这里假设'null'是字符串形式的空值标记
# 如果你的数据用的是真正的空值（NaN），则不需要替换步骤
df.replace('null', pd.NA, inplace=True)  # 将'null'字符串替换为pandas识别的NA
df.dropna(inplace=True)  # 删除包含NA的行

# 保存清洗后的数据到新的CSV文件
df.to_csv(output_csv_path, index=False)
```





尚需完成的任务 Work to do:

1. Write technical specification documents of the iNeom system.
2. Build analytical models.
3. Model selection and training.
4. Front-end construction.
5. Testings.

存在问题 Problems:

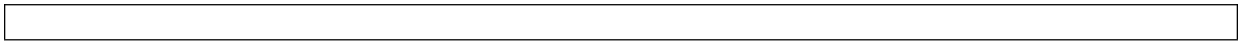
Data types are complex and difficult to understand, and the data formats of each monitoring instrument are different and complex.

拟采取的办法 Solutions:

Data cleansing is performed using scripts to convert non-compliant data formats.

论文结构 Structure of the final report: (Chapter headings and section sub headings)

Abstract
Keywords
1. Introduction
    1.1 Background Information
    1.2 Formal Studies
2. Design and Implementation
    2.1 Hardware Introduction
    2.2 Data Composition and Pre-processing
    2.3 Modelling
3. Results and Discussion
    3.1 Result Analysis
4. Conclusion and Future Work.
5. References
6. Acknowledgement



Supervision log

Date: 24/10/2023
Supervision type: Email
Summary: Say hello and book a time for the next formal meeting

Date: 16/11/2023
Supervision type: Online
Summary: Project introduction and discussion of project specification

Date: 23/11/2023
Supervision type: Online
Summary: Systematic review introduction and tasking

Date: 8/12/2023
Supervision type: Online
Summary: Progress review and discussion about Exclusion Criterion(Part of System review)

Date: 15/12/2023
Supervision type: Online
Summary: Progress review and discussion about Inclusion Criterion (Part of System Review)

Date: 26/12/2023
Supervision type: Online
Summary: Progress review and discussion about the early term report

Date: 10/01/2023
Supervision type: Online
Summary: Discussion about the early term report

Date: 14/01/2023
Supervision type: Online
Summary: Progress review and discussion about the System Review

Date: 18/01/2023
Supervision type: Face-to-face
Summary: Discussion about the System Review

Date: 03/02/2023
Supervision type: Face-to-face
Summary: Progress review, discussion about the System Review and introducing the data examples analysis

Date: 19/02/2023
Supervision type: Face-to-face
Summary: Progress review, discussion about the System Review the data examples analysis

Date: 25/02/2023
Supervision type: online
Summary: Progress review, discussion about the midterm report

Date: 04/03/2023
Supervision type: online
Summary: Progress review, discussion about the further tasks

Date: 15/03/2023
Supervision type: online
Summary: Progress review, discussion about the System Review data extraction file

Date: 22/03/2023
Supervision type: online
Summary: Meeting with the physician to discuss the envisaged target and procedures of regression analysis of the data modeling

Date: 28/03/2023
Supervision type: online
Summary: Systematic review of draft mandate notifications and assignments

Date: 08/04/2023
Supervision type: online
Summary: Discuss the draft final report

Date: 11/04/2023
Supervision type: online
Summary: Discuss the draft of the systematic review

Date: 18/04/2023
Supervision type: online
Summary: Discussed the harmonization of icon formats in draft systematic review papers and the data analysis procedures

Additional Appendices

Abbreviations

AI: artificial intelligence

CONSORT: Consolidated Standards of Reporting Trials

CHARMS: Critical Appraisal and Data Extraction for Systematic Reviews of Prediction Modelling Studies

EQUATOR: Enhancing the Quality and Transparency of Health Research

ICD-11: International Classification of Diseases 11th Revision

IEEE: Institute of Electrical and Electronics Engineers

MI-CLAIM: Minimum Information About Clinical Artificial Intelligence Modeling

PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses

PROBAST: Prediction Model Risk of Bias Assessment Tool

RCT: randomized clinical trial

SPIRIT: Standard Protocol Items: Recommendations for Interventional Trials

SVM: support vector machine

TRIPOD: Transparent Reporting of a Multivariable Prediction Model of Individual Prognosis or Diagnosis

Illustration

Figure1_ paper funneling

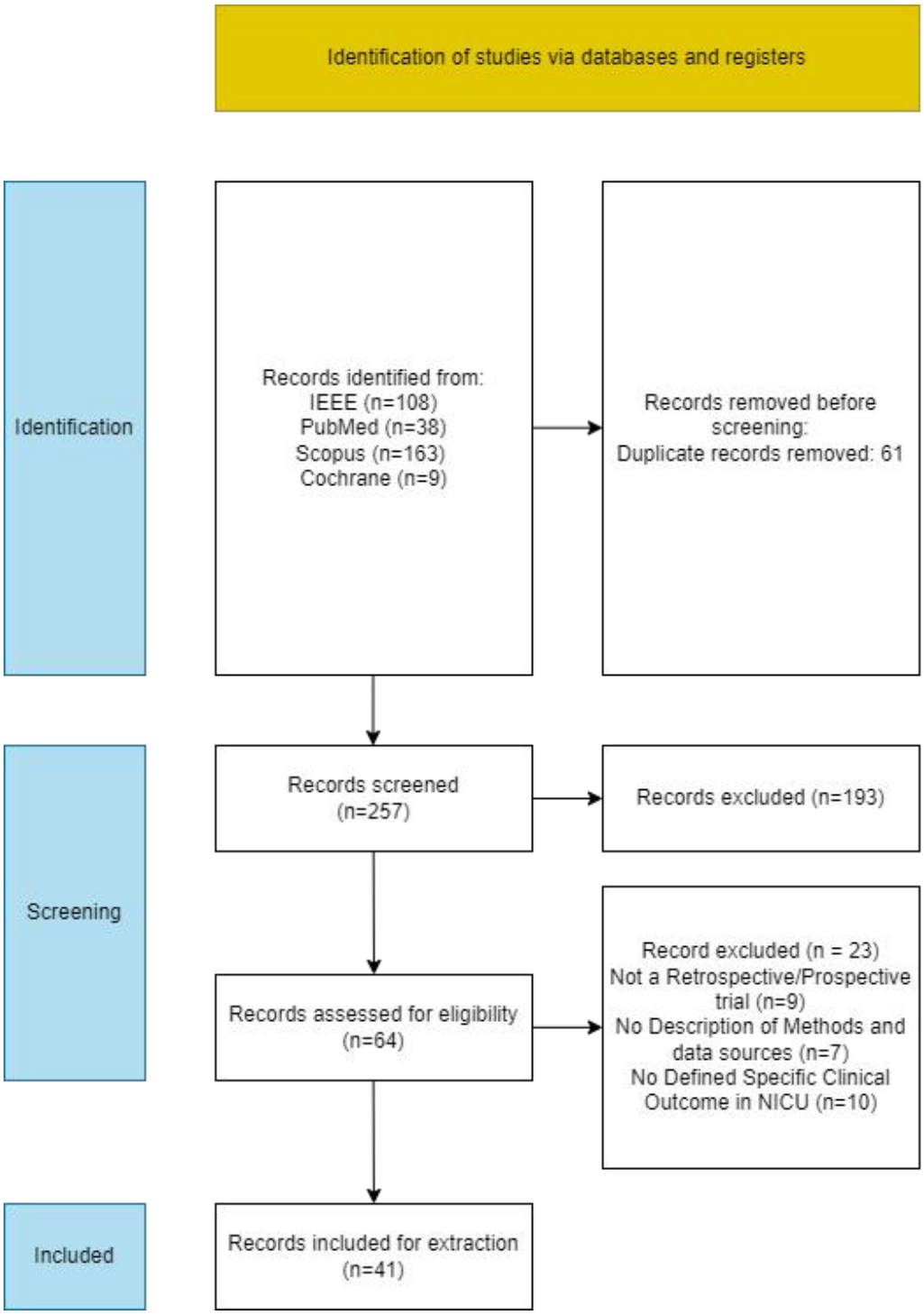


Table 1: Summary of Review

Health Area	Type of modelling	Data type
Cardiovascular	Deep Learning[20, 28, 41, 44,47] Traditional ML Models[33, 39,46] Other Models[46]	BLOOD PERFUSION INDEXES and HEMOGLOBIN[20]; HR, SpO2, PIA[33]; Skin Image[38]; EEG[39]; RR[41]; Video of infants[28]; HR[46]; ECG, HR, RR, SpO2[47]; Chest Sound[44]
Digestive	Deep Learning[34, 37]	Bowel Sound[34, 37];
Infections	Deep Learning[19]; Traditional ML Models[14, 29, 30, 54] Other Models[15]	ECG[14, 15, 29, 30]; HR[15, 19, 30, 54]; RR, SpO2[19, 54]; CI[14]
Microvascular	Other Models[26]	SpO2[26]
Mortality	Traditional ML Models[42]	vital signs, hospital records, fluid information, laboratory tests, treatment orders, and free-text medical records[42]
Neural/Brain	Deep Learning[16, 21, 27, 48] Feature Engineering Models[23] Traditional ML Models[17, 22]	EEG[16, 17, 27] Video of infants[16, 21] Image of infants[23] ICP[48]
Not disease	Deep Learning[28, 49] Ensemble Learning[36] Feature Engineering Models[43] Traditional ML Models[28, 30]	HR[28, 30, 43] SpO2[28, 43] StO2[28] GA[30] Not Mentioned[36] Video of infants[28, 49]
Respiratory	Deep Learning[24, 25, 40, 50, 51] Traditional ML Models[31] Other Models[18, 44]	SpO2[18, 31, 40, 50] RR[40, 50] HR[18, 31, 50] BP, PR, GA,...[31] Thermal imaging[24, 25] Video of infants[51] Chest Sound[44]

Possible Risks

Description of risks	Description of impact	Likelihood rating	Impact rating	Preventative actions
When predictive analysis is performed on real patients in the NICU, the patient's family may have opinions that prevent the experiment from being conducted	The experiment was interrupted and samples were selected again for analysis	2	3	The patient's family should be informed in detail before the experiment, and other spare samples should be selected in advance