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# Integrating an Automated Action Recognition with a Simulation Approach to Analyze the Risks of the Newborn Life Support Algorithm

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The Newborn Life Support (NLS) algorithm is an evidence-based protocol to resuscitate and stabilize a compromised baby. The resuscitation team should perform this in a timely and effective manner. Both technical and social aspects of this procedure can influence its outputs. Therefore, a comprehensive study integrating these aspects to analyze the performance of the NLS procedure is essential. Previous studies have investigated the significance of either the technical or non-technical aspects of the procedure using video recordings. However, this requires manual analysis of the recordings, making it lengthy and burdensome for clinicians. Therefore, an automated analysis of the recorded videos to identify variations in the NLS protocol would be highly beneficial. Our research introduces a potential solution to address these issues. We developed an integrated automated action recognition and simulation model that can be used to analyze the risks of the resuscitation procedure. The first element of the solution is the NLS simulation model developed using the Colored Petri Net approach. It considers both technical and non-technical aspects of the procedure, such as different types of respiratory devices, the levels of doctor's experience, and the ability of the clinical staff to cope with the stressful situation during the procedure. The second element is the automated variation recognition system, which is built on a combination of image segmentation and action recognition techniques. The integration involves automated identification of the status of the wet towel removal step in the input NLS recordings, which is fed into the simulation model to analyze the risk of the clinical procedure in the long run. The risk is observed through the changes in the proportion of satisfactory conditions, resuscitation duration, and baby's final heart rate. A simple graphical interface for this integrated system was also developed, allowing users to experiment with different NLS activity settings.

*Keywords*: Newborn Life Support, Colored Petri Nets, Action Recognition, Integrated Simulation Model, Clinical Risks, Healthcare Modelling

## 1. Introduction

The Newborn Life Support (NLS) protocol is an evidence-based procedure to resuscitate and stabilize a compromised baby. According to the European Resuscitation Council Guidelines 2021 (Madar et al. 2021), there are approximately

15% of babies needing support after birth. This includes 10% where only drying, stimulation, and airway opening procedure are needed, while the remaining five percent require breathing support with positive pressure ventilation (PPV) in the majority of cases and occasionally more advanced actions such as compressions. The NLS protocol is undertaken by a team and it is crucial for them to deliver the steps in a timely and effective manner. Poor support given to the baby may increase the risk of death or morbidity.

Unfortunately, errors are common in the NLS procedure. A literature study found that the error rate can be as high as 55% (Tsang et al. 2022). The guidelines for the NLS procedure have been established and widely taught, but both technical and social aspects during the resuscitation may affect the actual performance of the team. Influential factors may include a technical issue on the types of respiratory devices used in the procedure (Szyld et al. 2014) and non-technical aspects of leadership and teamwork (Brogaard et al. 2022). A comprehensive study to understand the characteristics of the NLS procedure that involves these two aspects is essential.

However, there are two main issues with this approach. Direct observation or field experiments integrating these two aspects can be disruptive and impact flow of procedures, as well as potentially compromise safety. The second issue is the long duration of NLS data collection and analysis. The use of video recordings to study the NLS procedure is common (Boer et al. 2021). It can help to reduce distractions and inconveniences during the procedure. However, manual analysis of these recordings is lengthy and burdensome for the clinicians.

In this paper, we integrate an automated action recognition method into an NLS simulation model to simultaneously address the above two issues. The first element involves a representative NLS model that captures both technical and non-technical aspects of the procedure and their interactions. The purpose is to enable researchers or clinicians to quantify any variations in the NLS procedure and estimate their risks and consequences on the newborn without causing disruption to the actual procedure. The Colored Petri Nets approach was applied to this procedure (Tan et al. 2025) to capture its complexity.

The second element of our integrated system is an automated data analysis method. It automatically informs us of the types of actions performed by the clinical team, recorded in the videos. Currently, it is designed as a post-processing step of NLS recordings, aiming to reduce the burden of manually evaluating the performance of participants of NLS, allowing their actions to be quantified and analyzed for the NLS simulation. For this purpose, the method provides information on the types and time points of actions, as well as their duration. It is further transformed into relevant statistics or action status that determines how the simulation model works.

The integration of the NLS model and the action recognition method is demonstrated by automatically identifying the availability of the wet towel removal step and its duration in an input NLS recording. This status will determine how the NLS model simulates the development of the newborn's body temperature during the procedure. A user interface prototype enabling users to experiment with several NLS parameters is also developed. This integrated system will finally provide information on the proportion of successful procedures, the median of the baby's final heart rate, and the average duration of the NLS procedure. These indicators are used to evaluate the risks of the NLS variations given a specific condition of the wet towel removal step identified in the procedure.

The rest of the paper is organized into five main sections. Section 2 briefly explains the structure of the NLS model and its parameters. Section 3 explains the development of the action recognition model. Section 4 shows the integration of the two main elements in the system as well as its user interface. Section 5 presents a discussion on the pros and cons of the system integration. Finally, Section 6 concludes what has been completed in this research and presents some potential future works in this area.

## 2. Colored Petri Nets Model

This section describes the Colored Petri Nets (CPN) model developed for the NLS protocol. It particularly covers aspects that we use to demonstrate the system integration. In general, the

CPN was developed following the NLS algorithm, which consists of seven major steps:

(i) Stimulation and thermal treatment
(ii) Initial condition assessment
(iii) Initial airway assessment and action
(iv) Inflation
(v) Ventilation
(vi) Chest compression
(vii) Drug administration

### 2.1. *CPN structure*

The CPN is built using four types of tokens, 62 places, and 67 transitions. There are 78 colors distributed to 4 types of tokens and 40 functions that define the logic of token processing in the CPN. The four types of tokens are defined to model the resuscitation job, heart rate change signal, body temperature change signal, and the effect of body temperature on baby's condition, respectively. The 62 places are also divided into four categories, according to the types of tokens. The CPN transitions are mostly used to represent the NLS steps. However, additional transitions are needed to model a number of mechanisms that represent alternative conditions of a certain NLS step and the development of baby's condition.

The first mechanism includes the missing wet towel removal condition. This is a possible missing action in the thermal treatment at the beginning of the NLS procedure. The second aspect involves the baby's heart rate adjustment mechanism, body temperature development process, and heart rate assessment. Most of these aspects are modelled based on empirical incident reports about their effect on certain clinical conditions. One of them is the type of thermal treatments that determine the deterioration rate of body temperature. Additional relationships in the integrated model are described in the following section.

### 2.2. *Relationships of NLS aspects*

The first relationship {1} describes the changes in the inner body temperature of a baby given a certain type of thermal treatment. Data from (Dahm and James 1972) is used to model the baby's body temperature as a function of time ($t$) of the NLS duration. This relationship is also separately defined for vigorous and depressed babies. Three types of thermal treatments are considered. Eq. (1)-(3) show three regression functions for the changes of body temperature of a vigorous baby using complete thermal care, radiant heater only care, and an absence of thermal care, respectively. Uncertainty in the body temperature is described by the last component in the function that is assumed to follow a Normal distribution $(\mu, \sigma)$.

$$f_1(t) = 37.18 - 0.0131t + \mathrm{N}(0,0.0519) \quad (1)$$

$$f_2(t) = 37.12 - 0.0286t + \mathrm{N}(0,0.0893) \quad (2)$$

$$f_3(t) = 37.10 - 0.0619t + \mathrm{N}(0,0.1120) \quad (3)$$

Changes in the body temperature will affect the heart rate of a baby. This second relationship {2} is modelled following information from two studies of (Wood and Thoresen 2015) and (Hanna and Greenes 2004).

The third relationship {3} describes the intubation duration and its success rate for different levels of doctor's experience. Resident, fellow, and consultant doctors are modelled (O'Donnell et al. 2006). The effect is extended to the deterioration of a baby's heart rate, which is modelled based on (O'Donnell et al. 2006) and (Maheshwari et al. 2016). The fourth relationship {4} is developed following an association between types of respiratory devices and intubation rate. Based on (Szyld et al. 2014), two conditional probabilities of choosing intubation as the next NLS step given failed intubation using a certain type of respiratory device are estimated.

The last relationship {5} describes how non-technical skills of clinical staff determine error conditions in the NLS procedure. We defined a connection between the ability of the technical staff to cope with stress (Brogaard et al. 2022) and its associated error in the heart rate assessment step (Voogdt et al. 2010). A set of scenarios describing various levels of clinical staff ability to handle a stressful situation during the NLS procedure and the accuracy of their heart rate measurement step is defined. All relationships are applied as functions in the CPN model. These determine how the values of the NLS procedure-related indicators change and affect the final output of a simulated NLS protocol.

### 2.3. *Model validation*

A simulation is developed based on the CPN model. Twenty indicators are observed from the simulation model for validation purposes. This process aims at ensuring that the model can adequately represent the actual NLS procedure and hence can be useful for further study of the NLS characteristics. The 20 indicators involve the proportion of full resuscitation cases, the time point of particular NLS events, median and average of baby's final heart rate, as well as the baby's final body temperature for vigorous and depressed babies at four time points (i.e., 1-minute, 5-minutes, 10-minutes, and 20-minutes) during the simulated NLS procedure. The benchmark statistics for all indicators in the validation process come from several publications, including (Fawke et al. 2021) and (Dahm and James 1972). Statistical tests were performed to check if all model indicators can be statistically inferred to be equal to the values in the references. Further information on our model can be found in (Tan et al. 2025).

## 3. Automated Action Recognition Model

This section describes the components of the action recognition system. These include the high-level structure of the system and the optimized model of image segmentation and action classification.

### 3.1. *Action recognition pipeline*

The action recognition process aims at identifying a set of actions occurring in an NLS recording. The dataset used to develop this system comes from (Smith et al. 2019). The number of data available for the procedure is limited. Twenty-three NLS videos were collected and used in our research. Dealing with this constraint, the idea of image segmentation and action classification integration suggested by (Smith et al. 2019) is applied in our research. However, some modifications are performed to improve the classification performance. Figure 1 shows the general pipeline of our action recognition system.

A video is constituted by a number of still images (frames). To simplify variations in these images, an image segmentation technique is applied to every video frame. This method locates the 18 types of NLS-related objects, which include towel, hat, plastic bag, and dry towel. Other objects included in this step can be found in our initial work (Tan et al. 2023). The output of the segmentation process will inform the action recognition step of the availability of a certain object to help identify a particular step in the NLS procedure.

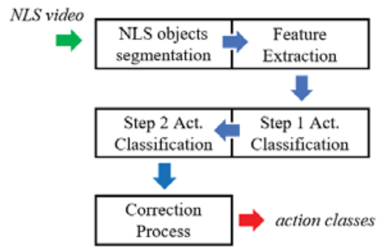

Fig 1. Action Recognition Method

The feature extraction step follows the image segmentation process. Since we use a traditional machine learning (non-deep learning) approach in the action classification steps, a set of input features is manually defined and extracted. Every feature provides information for the action classification model to identify types of actions occurring. This feature is generated from a collection of segmented frames. Therefore, these extracted features contain information on the characteristics of objects in a specific time duration.

The extracted features become inputs for machine learning models of action classification. The system is trained to recognize eight NLS actions (see Table 1). Since there could be multiple actions occurring at the same time point, every action is designed to have its own binary classification model. In step 1, the model will identify the occurrence of the action only from the extracted action features. The second step aims at improving the action prediction by considering the predicted occurrence of NLS action categories resulting from step 1, which can be associated with the occurrence of another particular action class. These associations are empirically estimated from the dataset. The initial extracted features are combined with the confidence level of the associated actions prediction generated in step 1 to conclude the occurrence of a particular action category.

To further improve the prediction accuracy, two correction steps are suggested at the end of the pipeline. These steps are the final evaluation procedure of the prediction based on the probability of action availability at a standardized time point location in an NLS procedure timeline, as well as the possibility of an action sequence in the procedure.

Table 1. Action Categories

| Code | Action |
|---|---|
| 0 | Inflation breath |
| 1 | Tracheal intubation |
| 2 | Heart rate assessment |
| 3 | Ventilation |
| 4 | Removing a wet towel |
| 5 | Normal baby head positioning |
| 6 | Covering baby with a dry towel |
| 7 | Covering baby with a polythene bag |

The first correction step is technically performed by eliminating the positive action prediction signal (i.e., informing of an occurrence of an action) if it is found at the impossible time location following the common distribution of the action time point in the NLS procedure. On the contrary, the predicted absence of an action at a particular time point may be transformed into a positive signal. This process considers the confidence score of the action prediction model and the likelihood of the action occurrence following the action time point distribution. The probability distribution of action time locations is empirically derived from the dataset.

The second correction step introduces an action transition matrix that is also empirically generated from the dataset. This is produced by analyzing NLS step sequences in all NLS videos. Information in this matrix is applied by eliminating the predicted positive signal of an action that is impossible to follow a certain previous action. This process also reduces overpredictions found in the model outputs. The initial action prediction resulting from action classification steps goes through these two correction processes and becomes the final action prediction signal to use.

### 3.2. *Image segmentation*

The U-net Deep Learning structure (Ronneberger, Fischer, and Brox 2015) is used for the image segmentation model. The input size of our model is 128 × 128 pixels. Since we only have a limited dataset, the model is first trained on a subset of 10,000 COCO dataset (Lin et al. 2014). This dataset contains images with more general object categories, but with a much larger dataset. This is to give the model an initial ability to discern basic image features. Eleven experiments on different hyperparameter configurations produce the best result of 75.13% segmentation accuracy on the validation dataset.

Following the first training step, a collection of 1,141 images is extracted from the NLS videos for the fine-tuning process of the image segmentation model. A proportion of 70% and 30% is allocated for the training and validation dataset, respectively, throughout several training steps. A number of experiments are performed in every step. These involve modifications of the learning rate, the loss function, and the trainable layers of the model. The model is evaluated based on the Intersection over Union (IoU) indicator on the validation dataset. The best model is obtained by applying the Focal loss function ($\gamma = 9$), retraining all the decoder layers of the U-net model, setting the learning rate to 0.001 with a learning rate decay of exp (-1/650), applying a batch size of 32, and training the model for 3,250 epochs. The model achieves an average IoU of 0.639 (range: 0.308-0.917) with 68.4% objects having an IoU larger than 0.5 (the maximum value of IoU is 1).

### 3.3. *Action classification*

The action classification model analyses every 5-second segment of NLS videos that is generated with a stride of 30 video frames each. The feature extraction process collects four points of information from every video segment. These include the time location of the video segment relative to the entire NLS video duration, the proportion of every NLS object appearance in the video segment, the correlation between the time order of the video frames and the distance of every NLS object to a baby in every frame, and the correlation of the time order of the video frame with the distance of NLS objects to the hand of the clinical staff. The last two features are used to inform the model of the movement of the NLS equipment. Further examination of these features is performed, resulting in a final set of 32 input features to use.

The action classification model is optimized through 23 × 4-fold cross-validation processes. This includes the training and validation step with the 4-fold cross-validation strategy utilizing data generated from 22 NLS videos and a testing step with a single video. There are 23 combinations of cross-validation processes. Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting (GB), and LightGBM (LG) are applied and evaluated for every action category. This includes an experiment with 7, 9, 32, 32, and 16 combinations of hyperparameters, respectively, for every algorithm. Four different random seeds are also applied to include possible variations of the model performance in the analysis. The highest average of F1score (F1) on the validation dataset is used as a criterion to choose the best model for every action class. Table 2 presents the best algorithm for every action class along with the average F1score.

Table 2. The Best Action Class Algorithm

| Act | Alg. | F1 | Act | Alg. | F1 |
|---|---|---|---|---|---|
| 0 | SVM | 0.628 | 4 | SVM | 0.641 |
| 1 | SVM | 0.838 | 5 | SVM | 0.737 |
| 2 | LG | 0.575 | 6 | GB | 0.611 |
| 3 | SVM | 0.664 | 7 | SVM | 0.694 |

These models are further evaluated on the test dataset with two additional correction strategies to determine if the strategies would be included in the action classification system for a particular action class. The evaluation shows significant improvement for action code 0, 1, 6, and 7. Therefore, these correction steps are applied.

## 4. Integrated NLS Simulation Model

The integration starts with the user providing the input NLS video, defining the settings of the NLS procedure to simulate, and determining the number of model iterations. Figure 2 shows the flow of the NLS procedure data processing and analysis.

To demonstrate the system integration, the action classification system is used to identify the availability of the wet towel removal step. The status of this action determines how the baby's body temperature changes over time, as explained in Section 2.2. The duration of the available wet towel removal step is also computed. This information is then fed into the simulation model. Along with the predetermined NLS settings of types of doctors, respiratory equipment, and the non-technical skill level of clinical staff, the NLS simulation model is run. It follows the predefined number of model iterations to capture the probabilistic aspects of the procedure, such as action durations, outputs of NLS steps, and baby's conditions.

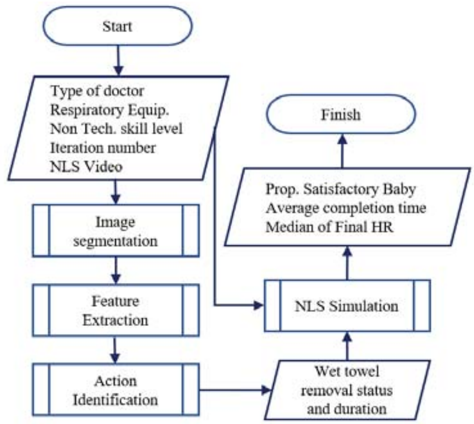


Fig 2. Integration System Flow

A platform prototype of the NLS study integrated system is developed with a user interface shown in Figure 3.

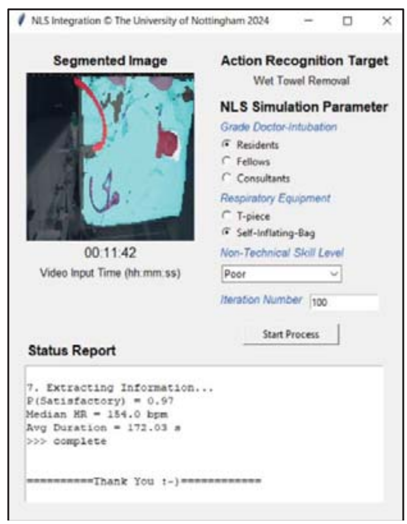


Fig 3. System Platform Interface

In Figure 3, the NLS setting is defined to have resident doctors in the team, a self-inflating bag as respiratory equipment, and poor skill of clinical staff to deal with pressure during the procedure. The input video duration is 11 minutes 42 seconds. It is analyzed to inform the simulation model of the status of the wet towel removal step. The segmented image window in the platform presents the segmentation process of video frames. In the end, the performance of the procedure can be observed from the Status Report window. We aim at getting a high successful proportion of resuscitation cases, above 100 beats per minute for the baby's final heart rate, and efficient execution of the NLS procedure.

## 5. Discussion

Considering all the integrated elements presented above, the system will be beneficial to learn and estimate significant differences in the NLS performances within various NLS settings without causing significant disturbance to the actual NLS process. This system can also predict the likelihood of the NLS outcomes following the status of a certain action automatically identified during an actual procedure.

Executing this system with our computing resource (i.e., 2.21 GHz CPU) on the case in Section 4 takes around 3.5 hours to complete. The two heaviest parts are the video segmentation and the feature extraction process. The U-net Deep Learning structure involves a high number of parameters, which signify a large number of numerical processing steps to produce the final output. In addition, there are a large number of frames the model needs to segment. Given a constant video duration, the recording speed determines the number of frames the model needs to segment. Our video dataset has a 30 frame per second recording speed.

The duration of feature extraction processes also depends on the number of video frames and how the video is partitioned into units of analysis. Our method divides a video into five-second (150 frames) video segments with 1-second (30 frames) interval of video segment generation. Based on this method, an example video of five-minute duration will then have 296 units of 5-second video segments for the feature extraction process, which also includes the collection of 32 feature values to extract from each segment. The complexity is even higher since it also involves a computation process on information recorded in every image cell, which relates to the size of the input image. Graphical Processing Unit (GPU) with sufficient memory capacity will be very useful to speed up the analysis. However, this system is not currently designed to support real-time analysis of the NLS procedure. To achieve this, additional work of an embedded system is required to ensure a compact and efficient computing process.

Overall, our system contributes to the development of a clinical decision support system and the utilization of artificial intelligence methods as part of essential emerging technology requirements desired by leading clinicians in neonatal care (Batey et al. 2024). We highlight the benefits of the current approach as the first steps towards an embedded, live system. Further work on simplified video analysis strategies and feature extraction techniques with competitive or even higher performance accuracy would be very beneficial.

## 6. Conclusion and Future Works

Our integrated system considers two major elements. The NLS model is developed by incorporating technical and non-technical aspects of the procedure to accommodate a holistic study of the protocol. However, it is not yet a comprehensive model. Future works may consider additional relevant factors to improve the model. The integration strategy and the experimental NLS parameters can be expanded.

The action recognition model has been generated, leaving some potential areas of exploration. The use of traditional machine learning techniques in our research aims at reducing the total duration of the action recognition process. However, challenges appear in handcrafting a set of useful features for the classification models. Other useful features from multimodal input data can be applied to improve our current performance.

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**References**

Batey, Natalie, Caroline Henry, Shalabh Garg, Michael Wagner, Atul Malhotra, Michel Valstar, Thomas Smith, et al. 2024. "The Newborn Delivery Room of Tomorrow: Emerging and Future Technologies." *Pediatric Research* 96 (3): 586–94. https://doi.org/10.1038/s41390-022-01988-y.

Boer, Maria C den, Mirjam Houtlosser, Ruben S G M Witlox, Roosmarijn van der Stap, Martine C de Vries, Enrico Lopriore, and Arjan B te Pas. 2021. "Reviewing Recordings of Neonatal Resuscitation with Parents." *Archives of Disease in Childhood - Fetal and Neonatal Edition* 106 (4): 346. https://doi.org/10.1136/archdischild-2020-320059.

Brogaard, Lise, Lone Hvidman, Gitte Esberg, Neil Finer, Kristiane R Hjorth-Hansen, Tanja Manser, Ole Kierkegaard, Niels Uldbjerg, and Tine B Henriksen. 2022. “Teamwork and Adherence to Guideline on Newborn Resuscitation—Video Review of Neonatal Interdisciplinary Teams.” *Frontiers in Pediatrics* 10. https://www.frontiersin.org/articles/10.3389/fped.2022.828297.

Dahm, Lida Swafford, and L Stanley James. 1972. “NEWBORN TEMPERATURE AND CALCULATED HEAT LOSS IN THE DELIVERY ROOM.” *Pediatrics* 49 (4): 504–13. https://doi.org/10.1542/peds.49.4.504.

Fawke, Joe, Sean Ainsworth, Adam Benson Clarke, T’ng Chang, Andy Coleman, Karen Cooper, Jonathan Cusack, et al. 2021. *Newborn Life Support*. Edited by Sean Ainsworth and Joe Fawke. 5th ed. London, England: Resuscitation Council UK.

Hanna, Colleen M, and David S Greenes. 2004. “How Much Tachycardia in Infants Can Be Attributed to Fever?” *Annals of Emergency Medicine* 43 (6): 699–705. https://doi.org/https://doi.org/10.1016/j.annemergmed.2003.10.002.

Lin, Tsung-Yi, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. 2014. “Microsoft COCO: Common Objects in Context.” In *Computer Vision – ECCV 2014*, edited by David Fleet, Tomas Pajdla, Bernt Schiele, and Tinne Tuytelaars, 740–55. Cham: Springer International Publishing.

Madar, John, Charles C Roehr, Sean Ainsworth, Hege Ersdal, Colin Morley, Mario Rüdiger, Christiane Skåre, et al. 2021. “European Resuscitation Council Guidelines 2021: Newborn Resuscitation and Support of Transition of Infants at Birth.” *Resuscitation* 161: 291–326. https://doi.org/https://doi.org/10.1016/j.resuscitation.2021.02.014.

Maheshwari, Rajesh, Mark Tracy, Nadia Badawi, and Murray Hinder. 2016. “Neonatal Endotracheal Intubation: How to Make It More Baby Friendly.” *Journal of Paediatrics and Child Health* 52 (5): 480–86. https://doi.org/https://doi.org/10.1111/jpc.13192.

O’Donnell, Colm P F, C Omar F Kamlin, Peter G Davis, and Colin J Morley. 2006. “Endotracheal Intubation Attempts During Neonatal Resuscitation: Success Rates, Duration, and Adverse Effects.” *Pediatrics* 117 (1): e16–21. https://doi.org/10.1542/peds.2005-0901.

Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. 2015. “U-Net: Convolutional Networks for Biomedical Image Segmentation.” In *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*, edited by Nassir Navab, Joachim Hornegger, William M Wells, and Alejandro F Frangi, 234–41. Cham: Springer International Publishing.

Smith, Thomas J., Michel Valstar, Don Sharkey, and John Crowe. 2019. “Clinical Scene Segmentation with Tiny Datasets.” In *2019 IEEE/CVF International Conference on Computer Vision Workshop (ICCVW)*, 1637–45. IEEE. https://doi.org/10.1109/ICCVW.2019.00203.

Szyld, Edgardo, Adriana Aguilar, Gabriel A Musante, Nestor Vain, Luis Prudent, Jorge Fabres, and Waldemar A Carlo. 2014. “Comparison of Devices for Newborn Ventilation in the Delivery Room.” *The Journal of Pediatrics* 165 (2): 234-239.e3. https://doi.org/https://doi.org/10.1016/j.jpeds.2014.02.035.

Tan, Alfian, Rasa Remenyte-Prescott, Joy Egede, Don Sharkey, and Michel Valstar. 2025. “Coloured Petri Nets-Based Approach for Modelling Effects of Variation on the Reliability of the Newborn Life Support Procedure.” *Reliability Engineering & System Safety* 260: 111001. https://doi.org/https://doi.org/10.1016/j.ress.2025.111001.

Tan, Alfian, Rasa Remenyte-Prescott, Joy Egede, Michel Valstar, and Don Sharkey. 2023. “Identifying Variation in the Newborn Life Support Procedure: An Automated Method.” In *Proceedings of the 33rd European Safety and Reliability Conference (ESREL)*, edited by Mario P. Brito, Terje Aven, Piero Baraldi, Marko Cepin, and Enrico Zio, 607–14. Southampton: Research Publishing, Singapore. https://doi.org/10.3850/978-981-18-8071-1_p314-cd.

Tsang, Kishan D, Mendel K Ottow, Arno F J van Heijst, and Timothy A J Antonius. 2022. “Electronic Decision Support in the Delivery Room Using Augmented Reality to Improve Newborn Life Support Guideline Adherence: A Randomized Controlled Pilot Study.” *Simulation in Healthcare* 17 (5). https://journals.lww.com/simulationinhealthcare/fulltext/2022/10000/electronic_decision_support_in_the_delivery_room.2.aspx.

Voogdt, Kevin G J A, Allison C Morrison, Fiona E Wood, Ruurd M van Elburg, and Jonathan P Wyllie. 2010. “A Randomised, Simulated Study Assessing Auscultation of Heart Rate at Birth.” *Resuscitation* 81 (8): 1000–1003. https://doi.org/https://doi.org/10.1016/j.resuscitation.2010.03.021.

Wood, Thomas, and Marianne Thoresen. 2015. “Physiological Responses to Hypothermia.” *Seminars in Fetal and Neonatal Medicine* 20 (2): 87–96. https://doi.org/https://doi.org/10.1016/j.siny.2014.10.005.