Department of Electronic and Telecommunication Engineering
University of Moratuwa, Sri Lanka

NeoCare - Contactless Neonatal Health Monitoring System

SUPERVISORS:

Dr. Sampath K. Perera
Dr. Pranjeevan Kulasingham
Dr. Anusha Withana
Prof. Nishani Lucas

MEMBERS:

S.M.S.M.B.Abeyrathna	210005H
A.A.W.L.R.Amarasinghe	210031H
M.K.I.G.Morawakgoda	210391J
U.M.Y.B.Alahakoon	210027C

Final Year Project Proposal

October 24, 2025

Approval

Approval of the project supervisor(s).

Supervisor: Dr. Sampath K. Perera

Signature: . .  . . . . . .

Date: . . .24/10/2025 . . . . . .

Supervisor: Dr. Pranjeevan Kulasingham

Signature:  . . . . . .

Date: . . .24/10/2025 . . . . . .

Supervisor: Prof. Nishani Lucas

Signature:  . . . . . .

Date: . . .24/10/2025 . . . . . .

Supervisor: Prof. Anusha Withana

Signature:  . . . . . .

Date: . . .24/10/2025 . . . . . .

Abstract

Despite significant progress in neonatal care, continuous monitoring of vital signs in newborns remains heavily dependent on contact-based sensors such as pulse oximeters. These devices, though effective, can cause skin irritation, discomfort, and even infection risks in premature and low-birth-weight infants due to their fragile skin. Moreover, the presence of multiple wires and sensors can restrict movement and complicate clinical workflows in neonatal intensive care units (NICUs). Recent advancements in remote photoplethysmography (rPPG) and video-based physiological measurement have opened the possibility for contactless, non-invasive monitoring of vital signs such as heart rate and blood oxygen saturation. Leveraging deep learning architectures, including convolutional networks and transformers have demonstrated improved accuracy and robustness even under varying illumination, motion, and skin tone conditions.

However, extending rPPG to neonatal care presents challenges including small facial regions, subtle skin tone variations, motion artifacts, and limited datasets. Furthermore, as video-based monitoring inherently involves capturing sensitive visual data of infants, ensuring data privacy, ethical handling, and secure storage becomes critically important. Privacy preserving AI frameworks such as on-device processing, encrypted data transmission, and anonymizing data are therefore essential for clinical adoption.This body of work underscores the urgent need for reliable, contactless neonatal monitoring and highlights how the convergence of computer vision, signal processing, and machine learning can transform neonatal healthcare by enabling safer, more comfortable, and continuous vital sign assessment in NICUs.

Contents

Abstract **3**

1 Introduction **8**
1.1 Importance of the Project 8
1.2 Objectives 10

2 Literature Review **11**
2.1 Heart Rate Estimation Using rPPG 11
2.2 SpO_2 Estimation Using rPPG 12
2.3 Neonatal Jaundice Detection 12
2.4 Privacy-Preserving Techniques 12
2.5 rPPG Methods for Neonatal Care 13
2.6 Gaps in the Literature 13

3 Methodology **14**
3.0.1 Phase 1: Algorithm Enhancement and Design 14
3.0.2 Phase 2: Dataset Collection and Ground Truth Acquisition 18
3.0.3 Phase 3: Edge Deployment and Privacy-Preserving Implementation 19
3.1 Details of Participants 19
3.2 Details of Proposed Data Collection 19
3.3 Timeline 19
3.4 Study Location/Setting 20
3.5 Sample Size Calculation 20
3.6 Criteria for Participant Inclusion and Exclusion 20
3.7 Recruitment Procedure 20
3.8 Experimental Procedure 21
3.8.1 For rPPG 21
3.8.2 For Jaundice 21
3.9 Data Analysis and Processing 21
3.10 Plan for Dissemination 21

4 Ethical Considerations **22**
4.1 Risks and Benefits 22
4.2 Consent 23
4.3 Confidentiality 23
4.4 Data Security 23
4.5 Rights of Participants 24
4.6 Responsibilities of the Researcher 24

5 Conclusion **25**

List of Figures

1.1 Hour-Specific Serum Bilirubin Nomogram for Neonates [21]. 9

2.1 The skin reflection model that contains specular and diffuse reflections [1]. 11

3.1 Overall Architecture 14
3.2 Preprocessing - rPPG Estimation System 15
3.3 Preprocessing - Jaundice Estimation System 15
3.4 Project Timeline. 19

List of Tables

3.1 Comparison between Signal Processing and Deep Learning Approaches for rPPG Estimation [20, 21] 16
3.2 Comparison of Deep Learning Architectures for rPPG Estimation [20, 22, 23] 16
3.3 State-of-the-art HR estimation methods for adults on the PURE dataset [20] 16
3.4 State-of-the-art HR estimation methods for neonates on the NBHR dataset [24] 17
3.5 State-of-the-art SpO_2 estimation methods for adults on the VIPL-HR dataset [26] 17
3.6 State-of-the-art SpO_2 estimation method for neonates on the NBHR dataset 17
3.7 Comparison of Machine Learning vs Deep Learning Approaches [27] . . . 18
3.8 Comparison of Existing Jaundice Detection Models [27] 18
3.9 Planned data collection parameters for rPPG estimation 19
3.10 Planned data collection parameters for Jaundice detection 19

Chapter 1

Introduction

This project focuses on developing a non-contact method for monitoring vital signs, specifically heart rate (HR) and blood oxygen saturation (SpO_2) as well as enabling the detection of jaundice through a mobile application. It is an extension of the previous group project, ***VideoPulse: Physiological Signal Extraction from Video***, which was carried out by the 20^{th} batch, consisting of students from the Departments of Biomedical Engineering and Electronic and Telecommunication Engineering at the University of Moratuwa, under the permission of both Ethics Review Committees from University of Moratuwa and De Soysa Hospital for Women Colombo.

What sets our project apart is the inclusion of jaundice detection, along with the goal of developing a complete and privacy-preserving mobile solution to ensure data security and protect sensitive information.

By collecting and analyzing video data of neonates, this research seeks to enhance the accuracy and reliability of non-contact monitoring systems. The ultimate objective is to improve patient care in neonatal intensive care units (NICUs) and other clinical settings by enabling continuous, non-invasive monitoring of vital signs.

1.1 Importance of the Project

The importance of this project is strongly emphasized by the current limitations in neonatal care practices in Sri Lankan hospitals. Prof. Nishani Lucas highlighted the urgent need for objective methods for monitoring vital signs, particularly jaundice detection, due to the subjectivity while using manual methods. This re- search aims to introduce a practical, accurate, and low-cost solution tailored to the local healthcare context.

Critical Need in Neonatal Care

Non-contact monitoring is particularly important in neonatal care units, where even minimal physical interference can compromise the safety, comfort, and well-being of fragile newborns. At present, Sri Lankan hospitals rely heavily on contact-based devices such as pulse oximeters for measuring heart rate (HR) and blood oxygen saturation (SpO_2), whereas many other countries are transitioning to non-contact alternatives. These contact-based devices can restrict movement, cause skin irritation, spread infections, and become detached during infant motion, leading to unreliable readings and frequent adjustments.

Jaundice Detection

Neonatal jaundice affects a significant number of newborns in Sri Lanka. Globally, approximately 60% of term infants and 80% of preterm infants develop jaundice within the first week of life [4]. While most cases are benign, if left undiagnosed or untreated, severe jaundice can lead to kernicterus—a rare but fatal condition that causes permanent brain damage or death. UNICEF Sri Lanka estimates that 2 in every 5 newborns require treatment for jaundice in the country.

In hospitals, the first step in detecting neonatal jaundice is visual screening, where healthcare staff assess the baby's skin color. Based on this initial assessment, infants are categorized into negative (no visible jaundice) and positive (possible jaundice) groups. The positive cases are then referred for the gold standard diagnostic method—serum bilirubin measurement through invasive blood sampling. This test further classifies babies into negative (no treatment required) and positive cases. Among the positive cases, bilirubin levels and the age determine whether the infant requires phototherapy or not. Devices like transcutaneous bilirubinometers used abroad are often prohibitively expensive for Sri Lankan hospitals [20].

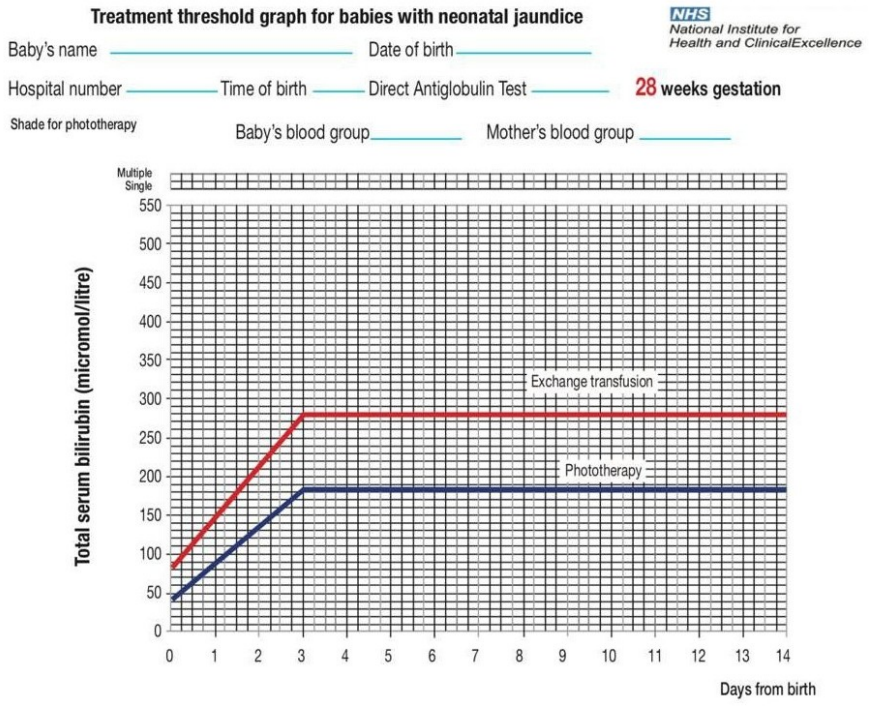

Figure 1.1: Hour-Specific Serum Bilirubin Nomogram for Neonates [21].

Affordable Innovation for a Pressing Need

This project proposes a low-cost, non-contact solution using facial video analysis, making it feasible even for under-resourced healthcare systems. It eliminates the need for frequent physical interaction, reduces reliance on costly equipment, and offers a scalable alternative that could benefit both hospitals and homes. With features like jaundice detection and privacy preserving schemes included in one mobile solution, this system could greatly reduce the workload of medical staff and minimize diagnostic delays.

Moreover, in Sri Lanka's context, where hospital resources are stretched, this solution is both timely and crucial. Continuous, accurate, and remote monitoring can optimize healthcare delivery for newborns.

Home Use and Parental Assurance

Beyond the clinical setting, this tool could empower parents with a safe and user-friendly way to monitor their newborns at home. Early detection of abnormal vital signs allows for timely medical intervention, giving parents peace of mind and reducing unnecessary hospital visits.

1.2 Objectives

Our project focuses on four primary objectives:

1. Enhance existing non-contact, video-based algorithms to accurately estimate heart rate (HR), blood oxygen saturation (SpO_2) and jaundice in neonates.
2. Create new datasets specifically for neonates to validate these algorithms.
3. Develop a mobile application for contactless monitoring of neonatal vital signs.
4. Implement privacy-preserving techniques through on-device processing and secure data handling.

The limited availability of neonatal datasets for non-contact vital sign monitoring underscores the critical importance of data collection to ensure the success of this project. We plan to collect up to 4 minutes of video data from neonates, along with their SpO_2, heart rate and reference PPG signal readings. For jaundice status, we will create a separate dataset consisting of neonatal images specifically for this purpose. These comprehensive datasets will provide a vital foundation for the development, training, and validation of our algorithms, enabling accurate and reliable estimation of these health indicators.

Chapter 2

Literature Review

This section presents project-specific knowledge gathered through an extensive literature review. It covers key methodologies for estimating heart rate and (HR) blood oxygen saturation (SpO_2)using remote photoplethysmography (rPPG). Additionally, it explores neonatal jaundice detection using images, offering a comparative analysis of existing estimation techniques. The review also examines privacy-preserving approaches, noise modeling strategies in rPPG, rPPG methods tailored for neonatal care, and identifies critical gaps in the current body of research.

2.1 Heart Rate Estimation Using rPPG

The core idea behind heart rate estimation using remote photoplethysmography (rPPG) is to extract the rPPG waveform from facial video. This involves analyzing the reflected light from the skin, which consists of intensity, specular, and diffuse components. The diffuse component, which carries information from beneath the skin, is key for deriving the rPPG waveform.

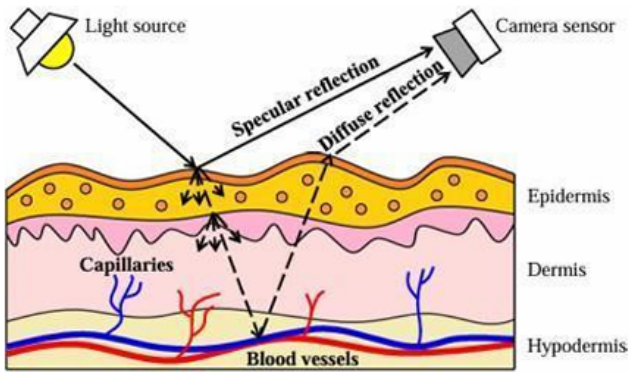

Figure 2.1: The skin reflection model that contains specular and diffuse reflections [1].

Since all the existing methods followed supervised learning approaches, recent work in contrastive unsupervised learning for rPPG has shown promise in addressing data scarcity by training models using pairs of videos, pulling similar predictions closer and pushing dissimilar ones apart. The physiological signal estimation via the non-contrastive unsupervised learning (SiNC) framework [8] simplifies this approach by applying loss directly to predictions, shaping the frequency spectrum, and encouraging variance over a batch

of inputs. This method allows for the discovery of periodic signals in video data without the need for ground truth vitals.

2.2 SpO_2 Estimation Using rPPG

Traditional contact-based methods for SpO_2 measurement use pulse oximeters that operate on the Ratio of Ratios principle, relying on red and infrared light absorption differences between oxygenated and deoxygenated hemoglobin [9]. Recent research has explored using RGB cameras for SpO_2 estimation by replacing infrared components with blue light, which has similar absorption characteristics.

The Ratio of Ratios can be adapted for RGB video as follows:

$$\mathrm{SpO}_2 = A - B \cdot \left(\frac{AC_{\mathrm{RED}}/DC_{\mathrm{RED}}}{AC_{\mathrm{BLUE}}/DC_{\mathrm{BLUE}}} \right)$$

Here, A and B are empirically determined parameters. The AC and DC components correspond to the red and blue channels' pulsatile and baseline signals.

Recent methods extract red and blue channel signals from facial video and use a calibration curve to estimate SpO_2. Although HR and RR estimation via deep learning have advanced, SpO_2 remains challenging. Spatial-temporal maps (STMaps), used in HR estimation, are being explored for SpO_2 estimation. Cheng et al. proposed a method using STMaps and an EfficientNet-B3 regression model for this purpose [9].

2.3 Neonatal Jaundice Detection

Neonatal jaundice results from elevated bilirubin levels. Traditional detection relies on visual inspection or serum bilirubin tests — the latter being invasive and requiring lab access [15]. Visual methods are subjective and less accurate for dark skin tones.
Modern techniques include transcutaneous bilirubinometers and image-based analysis. The latter analyzes skin or sclera color but often requires calibration, controlled lighting, or manual preprocessing, limiting practicality in real-world use [17, 19].

2.4 Privacy-Preserving Techniques

Since rPPG involves facial video, privacy is a key concern. To comply with ethical and legal standards, this project incorporates the following:

- **Region Masking**: Only forehead and cheeks are used; rest of the face is blurred or masked to prevent re-identification.
- **Derived Signal Storage**: Raw video is discarded after processing. Only HR, SpO, and RR signals are saved.
- **On-Device Processing**: Signal extraction is performed on the mobile device, avoiding cloud transmission.
- **Template Hashing**: If facial features are stored temporarily, they are hashed or encrypted to protect identity [14].

2.5 rPPG Methods for Neonatal Care

Most rPPG techniques are developed for adults. NBHRNet is a notable exception, designed for neonatal HR estimation using the Newborn Baby Heart Rate (NBHR) dataset [10]. It features:

- Lightweight model suitable for devices without GPUs.
- Components for ROI detection (KCF tracking), PPG estimation, and HR regression.
- Data augmentation for robustness.

Currently, there is no published rPPG-based RR method specifically for neonates.

2.6 Gaps in the Literature

- **Neonate-specific Research**: Few datasets and models are tailored for neonates.
- **Skin Tone Bias**: Most rPPG models perform poorly on darker skin tones.
- **Unified Multimodal Models**: Few models estimate HR, SpO, and RR simultaneously.
- **Robustness**: Existing methods are sensitive to motion and lighting.
- **Explainable AI (XAI)**: Lack of transparency in rPPG models.
- **Noise Modeling**: Limited handling of rolling shutter effects in video.
- **Few-shot Personalization**: Most models lack personalized adaptation with minimal data.
- **Privacy**: Existing datasets often store full facial videos unprotected.
- **Clinical Validation**: Few models undergo continuous, real-world clinical evaluation.

Chapter 3

Methodology

3.0.1 Phase 1: Algorithm Enhancement and Design

The project begins with enhancing existing algorithms to improve the estimation of heart rate (HR), blood oxygen saturation (SpO_2) and jaundice status in neonates. The focus will be on reducing computational load while maintaining clinical accuracy. From the outset, these algorithms will be designed with edge deployment in mind to ensure seamless integration into mobile platforms.

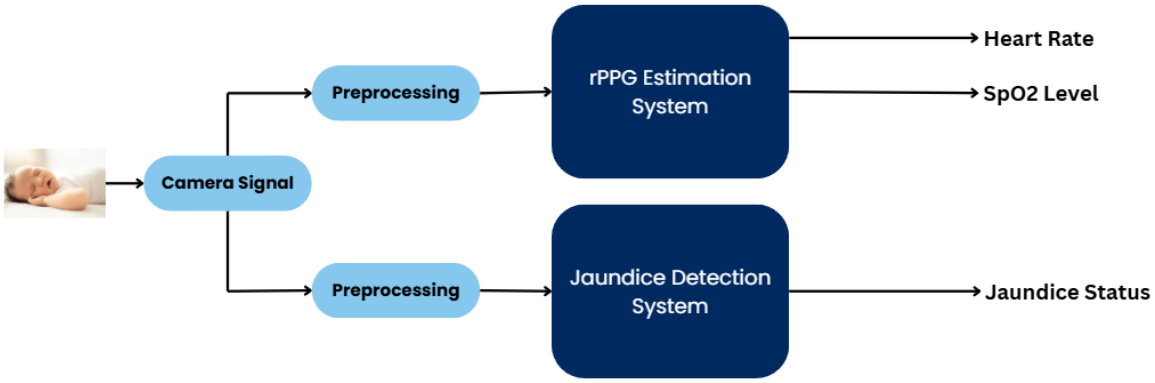

Figure 3.1: Overall Architecture

The above diagram shows the main workflow of our project. The camera records the baby's video signal, which is then preprocessed and sent to two separate systems. The rPPG system estimates the baby's heart rate and oxygen level, while the jaundice detection system checks the baby's jaundice condition. Both systems use lightweight deep learning models that are optimized for mobile devices and designed to protect privacy through edge-based processing. Together, they create a complete, camera-based, non-contact monitoring system.

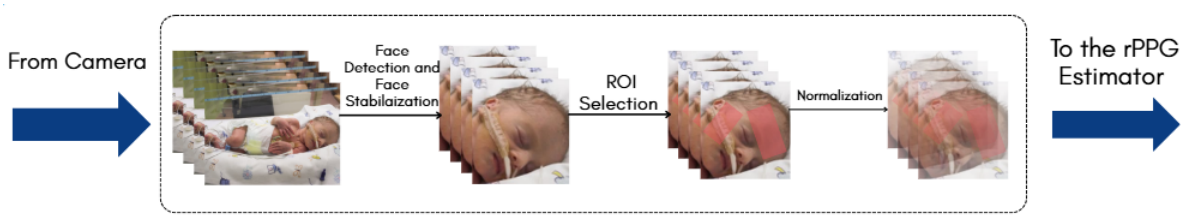

Figure 3.2: Preprocessing - rPPG Estimation System

The preprocessing stage prepares the video frames for physiological signal extraction. First, the baby's face is detected and stabilized across frames to minimize motion artifacts. Then, regions of interest (ROIs), specifically the forehead and cheeks are selected, as these areas provide the most reliable blood flow information. Finally, the selected ROIs are normalized to ensure consistent lighting and color balance before being passed to the rPPG estimator.

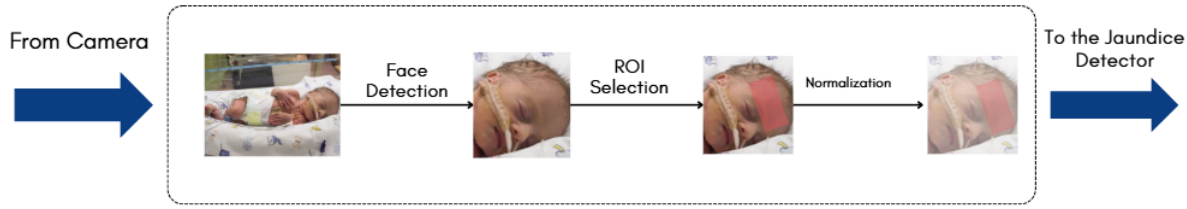

Figure 3.3: Preprocessing - Jaundice Estimation System

The preprocessing stage readies the input image from the camera for the jaundice detector. First, face detection is performed on the initial image to isolate the baby's face from the surrounding environment. Then, a specific region of interest (ROI), forehead and cheeks are selected from the detected face. Finally, this selected ROI undergoes normalization to correct for lighting inconsistencies and color balance, ensuring the skin tone data is standardized before being passed to the jaundice detector for analysis.

For rPPG estimation, 3D-CNNs, Vision Transformers, and Mamba models are ideal for capturing subtle color changes in video frames. For jaundice estimation, CNN-based models are preferred for their effectiveness in detecting skin color variations.

rPPG Estimation

For remote photoplethysmography (rPPG) estimation, two main approaches are commonly used: **Signal Processing–based Approaches** and **Deep Learning–based Approaches**.

Table 3.1: Comparison between Signal Processing and Deep Learning Approaches for rPPG Estimation [20, 21]

Aspect	**Signal Processing Approaches**	**Deep Learning Approaches**
Data Used	Color signals	Video frames
Noise Handling	Rule-based filtering	Learns noise patterns from data
Motion Robustness	Sensitive to motion	Robust to motion artifacts
Adaptability	Limited	Highly adaptive
Accuracy	Relatively low	High

Traditional signal processing approaches rely on handcrafted filtering pipelines and rule-based algorithms to isolate the pulsatile component from RGB color traces. Although computationally lightweight, these methods are sensitive to noise, motion artifacts, and illumination changes, limiting their robustness in real-world neonatal monitoring.

In contrast, deep learning–based approaches have emerged as the dominant paradigm due to their ability to automatically learn spatiotemporal representations directly from video data. By modeling both spatial texture variations and temporal pulse patterns, they achieve significantly higher accuracy and adaptability across varying conditions such as lighting, skin tone, and infant motion.

Among deep learning architectures, three primary model families are commonly explored for rPPG-based estimation: 3D Convolutional Neural Networks (3D CNNs), Vision Transformers (ViTs), and the recently introduced Mamba models.

Table 3.2: Comparison of Deep Learning Architectures for rPPG Estimation [20, 22, 23]

Architecture	**Compute Cost**	**Sequence Handling**	**Accuracy**
3D CNN	Low	Short–Medium	Moderate
Transformers (ViT)	High	Long	High
Mamba	Low	Long	High

In our case, **3D CNN** and **Mamba based architectures** are identified as the most suitable candidates. These models offer an optimal balance between computational efficiency and accuracy, enabling real-time inference and on-device preprocessing on mobile hardware. In contrast, ViT-based models, while accurate, incur higher computational overheads that are less suitable for mobile deployment.

To assess model performance, state-of-the-art methods for HR and SpO estimation in both adults and neonates were analyzed.

Table 3.3: State-of-the-art HR estimation methods for adults on the PURE dataset [20]

Method	**Architecture**	**MAE (bpm)**	**Parameter Size (M)**
PhysMamba	Mamba	0.25	0.56
RhythmFormer	Vision Transformer (ViT)	0.27	3.25
FactorizePhys	3D CNN	1.04	0.05

Table 3.4: State-of-the-art HR estimation methods for neonates on the NBHR dataset [24]

Method	**Architecture**	**MAE (bpm)**	**Parameter Size (M)**
NBHRnet-2s	2D CNN + LSTM	3.97	0.91
PhysNet (Previous Group)	3D CNN	2.97	0.77

Deep learning models, particularly those based on the Mamba and ViT architectures, achieve the highest accuracy for HR estimation in adults. PhysMamba demonstrates the best trade-off between accuracy and model size, while 3D CNN-based methods such as FactorizePhys remain efficient and lightweight. For neonates, only two methods; PhysNet and NBHRNet are currently available, indicating the limited exploration of rPPG-based HR estimation in neonatal populations.

Table 3.5: State-of-the-art SpO_2 estimation methods for adults on the VIPL-HR dataset [26]

Method	**MAE (%)**
Past Analytic (Ratio of Ratios)	3.334
EfficientNet-B3 + RGB	1.274
Multi-Model Fusion Method	1.000

Table 3.6: State-of-the-art SpO_2 estimation method for neonates on the NBHR dataset

Method	**MAE (%)**
Modified PhysNet (Previous Group)	1.69

Deep learning-based approaches significantly outperform traditional analytical methods in SpO_2 estimation for adults, with EfficientNet and multi-model fusion techniques achieving the lowest error rates. However, for neonates, only a single method, the Modified PhysNet, has been proposed so far, highlighting the need for further research and dataset expansion in neonatal SpO_2 estimation.

Jaundice Estimation

The jaundice detection component in this project uses a neonatal facial image to identify early manifestations of hyperbilirubinemia in a fully non-contact manner. Since visible yellow discoloration first appears on the forehead and cheeks, the system detects the infant's face and segments these two specific regions using facial landmarks or a lightweight segmentation model. This ensures that only clinically meaningful skin areas are analyzed, while background and unrelated features are removed. After segmentation, the extracted regions undergo a colour-normalization stage to minimize variations caused by different lighting conditions, camera settings, and skin tones. For this purpose, the images are transformed into more stable colour spaces such as YCbCr or Lab, and normalization techniques like gray-world correction or histogram matching are applied to maintain consistency across inputs.

To determine the best prediction strategy, both machine learning and deep learning approaches were examined. Machine learning methods require handcrafted colour features from the segmented skin, such as chrominance averages or red–green ratios, which

are then used by classifiers or regression algorithms like Random Forest or SVM. However, these feature-based techniques can struggle with generalizability across diverse neonate populations and environments.

Table 3.7: Comparison of Machine Learning vs Deep Learning Approaches [27]

Criteria	**Machine Learning (ML)**	**Deep Learning (DL)**
Feature Handling	Manual feature selection	Learns features directly from images
Complexity	Low	High
Adaptability	Limited	Highly adaptive
Accuracy	Low	High

Therefore, NeoCare uses a deep learning approach for jaundice detection. A lightweight CNN model learns relevant features from the normalized forehead and cheek regions and predicts either the bilirubin level or a risk category. Data augmentation improves robustness, and basic evaluation metrics ensure the model performs reliably in real conditions.

In recent years, several non-invasive jaundice detection methods have been introduced, mainly focusing on analyzing neonatal skin colour to estimate bilirubin levels. These approaches range from traditional colour-based algorithms and mobile apps to more advanced deep learning-based models that leverage facial images for improved accuracy. Each method offers different strengths in terms of performance, practicality, and clinical readiness.

Table 3.8: Comparison of Existing Jaundice Detection Models [27]

Study	**Accuracy**
ResNet50 with image augmentation	84.1%
Smartphone-based skin color segmentation	93.0%
Spectral-Spatial Graph Neural Network (SSGNN)	**96.5%**

3.0.2 Phase 2: Dataset Collection and Ground Truth Acquisition

To train and validate the models, a dedicated neonatal dataset will be collected under ethical approval. This will involve recording facial video data of neonates in the postnatal ward using both a webcam and a mobile phone camera, along with synchronized ground truth measurements of heart rate (HR), blood oxygen saturation (SpO_2) and jaundice status. Ground truth for HR and SpO_2 will be obtained using an FDA-approved neonatal pulse oximeter/patient monitor. For jaundice, a separate dataset consisting of neonatal images will be created and assessed using standard bilirubin measurement techniques based on previously collected blood samples. Data collection will be conducted with the support of medical personnel and supervised by Prof. Nishani Lucas at De Soysa Hospital for Women, Colombo. These datasets will form the foundation for training, testing, and benchmarking the proposed models.

3.0.3 Phase 3: Edge Deployment and Privacy-Preserving Implementation

In the final phase, the mobile application will be developed to integrate the preprocessing components of the refined algorithms, enabling contactless monitoring of neonatal vital signs. The aim is to minimize data transmission, enhancing privacy and ensuring compliance with healthcare data protection standards. The system will be optimized for low power consumption, thermal safety, and clinical reliability, making it suitable for neonatal intensive care environments.

3.1 Details of Participants

The participants for this study will be neonates in the postnatal ward.

3.2 Details of Proposed Data Collection

Description	Value
Total number of recording sessions	400
Total number of neonates	100
Video length per session	1 minute
Average number of videos per neonate	4

Table 3.9: Planned data collection parameters for rPPG estimation

Description	Value
Total number of images	250
Total number of neonates	50
Average number of images per neonate	5

Table 3.10: Planned data collection parameters for Jaundice detection

3.3 Timeline

Figure 3.4: Project Timeline.

The data acquisition period is planned for September–October 2025 and December 2025–January 2026 (16 weeks). Data will be collected once or twice a week, with recordings from

approximately 6–8 neonates per day. Each neonate will participate in four 1-minute video sessions.

3.4 Study Location/Setting

The data collection will be conducted in the university postnatal ward of De Soysa Hospital for Women, under the direct supervision of Prof. Nishani Lucas (Co-investigator).

3.5 Sample Size Calculation

Based on similar research in neonatal monitoring for HR, a sample size of 257 was used. Since this dataset is primarily for algorithm validation, a validation dataset of around 50 samples would be typical using a 5:1 training-to-validation ratio. However, to improve robustness, we have increased the sample size to 100 neonates after consultation with the hospital team.

3.6 Criteria for Participant Inclusion and Exclusion

Inclusion Criteria

Neonates admitted to the postnatal ward with stable vital signs and no congenital abnormalities affecting skin color or perfusion.

Exclusion Criteria

Neonates with severe congenital conditions, skin disorders, or any medical condition that could interfere with accurate photoplethysmography readings.

Rationale

These criteria ensure that the data collected is accurate and relevant to the study's objectives, focusing on typical neonatal physiology.

3.7 Recruitment Procedure

The recruitment will be conducted ethically and sensitively:

1. Parents or guardians will be approached by a member of the research team.
2. They will be given an information sheet explaining the study's purpose, procedures, risks, and benefits.
3. Informed written consent will be obtained before participation.

Participation is voluntary, and parents/guardians may withdraw at any time without consequences.

3.8 Experimental Procedure

3.8.1 For rPPG

1. Place the neonate on the cot attached to the mother's bed.
2. Fix a high-resolution camera on a tripod and position a mobile phone camera for an additional angle.
3. Attach an FDA-approved clinical pulse oximeter to monitor HR and SpO_2.
4. Conduct 10–15 minute video recording sessions with synchronized oximeter data.
5. Remove the equipment and ensure the neonate's comfort after recording.

3.8.2 For Jaundice

1. Capture neonatal images using a mobile phone attached to a tripod.
2. Record serum bilirubin results from previous clinical tests to estimate the jaundice status (treatment required or no treatment required).
3. Ensure the infant's safety and comfort after data collection.

3.9 Data Analysis and Processing

Ground truth data will be synchronized with video recordings and manually reviewed to remove outliers caused by motion, lighting, or noise. Preprocessing (normalization, filtering, transformation) will prepare the data for machine learning model training and validation. Model accuracy will be evaluated by comparing predictions with ground truth.

3.10 Plan for Dissemination

Results will be published in peer-reviewed journals or conferences. Any shared dataset will be anonymized to ensure no personal identification is possible.

Chapter 4

Ethical Considerations

4.1 Risks and Benefits

Risks and Risk Mitigation

The primary risks associated with this study include potential breaches of patient confidentiality and the challenges of ensuring data security. Neonates are a particularly vulnerable population, and their data must be handled with the utmost care, adhering strictly to ethical and privacy standards.

Physically, the risks are minimal, as no invasive procedures or exposure to radiation are involved. The use of video cameras and FDA-approved pulse oximeters ensures that the data collection process remains non-invasive and does not cause discomfort or harm to the participants.

Jaundice status will be determined using total serum bilirubin (TSB) levels obtained from previously collected blood samples as part of routine clinical procedures, eliminating the need for additional invasive tests. Trained medical staff assigned by Prof. Nishani Lucas from the postnatal ward will assist the researchers by providing access to serum bilirubin reports for babies who have undergone bilirubin estimation. These staff will also ensure the safety of the infants during data collection.

Risk Mitigation Strategies:

- Follow recommended clinical procedures for acquiring data.
- Implement stringent data encryption methods to secure all collected data.
- Restrict access to the data only to investigators.
- Conduct regular audits and monitoring of data handling processes to prevent unauthorized access.
- Ensure that the data collection devices and software comply with the latest healthcare data protection regulations.
- Educate the research team on the importance of maintaining patient confidentiality and handling sensitive data appropriately.

Benefits

The primary benefit of this study is to contribute to research that could lead to potential improvement in neonatal care through enhanced monitoring techniques. By developing and validating a method to accurately monitor vital signs using non-invasive technology, the study aims to reduce the risk of infection and discomfort associated with traditional contact-based monitoring methods.

The research could lead to better health outcomes for neonates, particularly in resource-limited settings where advanced monitoring equipment may not be available.

4.2 Consent

Informed consent will be obtained from the parents or legal guardians of the neonates before participation in the study. They will be provided with an information sheet detailing the study's purpose, procedures, risks, and benefits in Sinhala, English, and Tamil to ensure clear understanding.

The consent form will require a signature to confirm participation. Parents will be informed that participation is voluntary and that they can withdraw their consent at any time without any impact on the medical care provided to their child.

4.3 Confidentiality

To ensure the confidentiality of the participants, all data will be anonymized before analysis. No identifying information will be linked to the data in any publications or reports. The raw data will be stored in secure, encrypted storage systems, with access restricted to the research team.

Participants' identities will remain confidential, and no information that could identify them will be shared publicly.

4.4 Data Security

Data security is a top priority in this study. All patient data collected via the FDA-approved pulse oximeter and video cameras will be securely transmitted and stored on a laptop equipped with encrypted storage.

We will use secure, HIPAA-compliant software platforms for data collection, storage, and management to ensure compliance with medical data protection standards. Regular backups will be performed, and these backups will also be encrypted and stored securely to prevent data loss.

To further protect patient privacy, we plan to implement data anonymization techniques such as masking identifiable features and segmenting only the necessary regions of interest in the videos/images. Access to all collected data will be strictly limited to authorized personnel trained in data privacy and security.

All data handling procedures will adhere to the latest cybersecurity protocols to guard against unauthorized access, data breaches, and other potential threats.

4.5 Rights of Participants

Withdrawal from the Study

Participants, or in this case, the guardians of neonates, may withdraw from the study at any time by notifying the research team in writing or verbally. No additional data will be collected from them following their withdrawal, and previously collected data will be discarded if requested. Withdrawal or refusal to participate will not affect their medical care.

Questions and Complaints

Participants or their guardians can ask questions or raise concerns at any stage of the study. A designated contact person will be available to address any inquiries or complaints regarding the research process, participation rights, or other issues.

Contact Person: Lasitha Amarasinghe (+ 94 717577914). Contact details for all members of the research team will be provided.

Provision of Results

Once the research findings have been finalized, participants or their guardians can request a summary of the results. The research team will ensure that the results are communicated in an understandable manner and will inform participants of any insights relevant to neonatal care.

4.6 Responsibilities of the Researcher

The researchers are responsible for ensuring that the data collection process is conducted without interfering with the neonates' regular medical procedures. Data collection will only occur when neonates are not undergoing medical checkups and when guardians are available and comfortable.

If participants wish to adjust the timing, they can notify the research team verbally. The researchers will prioritize the safety and well-being of the neonates. Medical care will remain uninterrupted during the study, and participants will continue to receive their standard treatment after the research is completed. Any conflicts will be managed transparently in accordance with hospital guidelines. .

Chapter 5

Conclusion

This feasibility study has reviewed the current state-of-the-art techniques in contactless physiological monitoring using video-based methods and artificial intelligence. The literature highlights significant progress in remote photoplethysmography (rPPG), deep learning models, and non-invasive vital sign estimation, particularly for critical applications such as neonatal care. Advances in convolutional attention networks, transformer architectures, and privacy-preserving AI frameworks demonstrate that accurate and reliable measurement of heart rate, blood oxygen saturation, and jaundice detection is achievable without physical contact.

The study also recognizes the importance of specialized datasets and benchmarks that support the development and validation of these technologies in sensitive environments like NICUs. Challenges remain in ensuring robustness under diverse lighting conditions, motion artifacts, and variations in skin tones, but ongoing research shows promising solutions.

Overall, the project is feasible and aligns well with the urgent need for non-invasive monitoring solutions in clinical and low-resource settings. The integration of these AI-driven approaches into practical healthcare systems can enhance patient comfort, reduce infection risks, and enable continuous monitoring.

As the next steps, it is recommended to develop a prototype system combining deep learning models with real-time video capture, followed by rigorous validation using neonatal datasets. Collaboration with healthcare providers will be essential to tailor the system to clinical requirements and to conduct pilot studies for effectiveness and usability assessment. Additionally, attention should be given to data privacy and regulatory compliance to ensure safe deployment in healthcare environments.

Bibliography

[1] W. Wang, A. C. den Brinker, S. Stuijk, and G. de Haan, "Algorithmic principles of remote PPG," *IEEE Trans. Biomed. Eng.*, vol. 64, no. 7, pp. 1479–1491, 2017.

[2] X. Niu, H. Han, S. Shan, and X. Chen, "SynRhythm: Learning a deep heart rate estimator from general to specific," in *Proc. 24th Int. Conf. on Pattern Recognit. (ICPR)*, 2018, pp. 3580–3585.

[3] C. Hu, K.-Y. Zhang, T. Yao, S. Ding, J. Li, F. Huang, and L. Ma, "An end-to-end efficient framework for remote physiological signal sensing," in *Proc. IEEE/CVF Int. Conf. Comput. Vis. Workshops (ICCVW)*, 2021, pp. 2378–2384.

[4] W. Chen and D. McDuff, "DeepPhys: Video-based physiological measurement using convolutional attention networks," *arXiv preprint* arXiv:1805.07888, 2018. [Online]. Available: https://arxiv.org/abs/1805.07888

[5] Z. Yu, Y. Shen, J. Shi, H. Zhao, P. Torr, and G. Zhao, "PhysFormer: Facial video-based physiological measurement with temporal difference transformer," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2022, pp. 4176–4186.

[6] Z. Yu, X. Li, P. Wang, and G. Zhao, "TransRPPG: Remote photoplethysmography transformer for 3D mask face presentation attack detection," *IEEE Signal Process. Lett.*, vol. 28, pp. 1290–1294, 2021.

[7] X. Liu, B. L. Hill, Z. Jiang, S. Patel, and D. McDuff, "EfficientPhys: Enabling simple, fast and accurate camera-based vitals measurement," *arXiv preprint* arXiv:2110.04447, 2021. [Online]. Available: https://arxiv.org/abs/2110.04447

[8] J. Speth, N. Vance, P. Flynn, and A. Czajka, "Non-contrastive unsupervised learning of physiological signals from video," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2023, pp. 14464–14474.

[9] C. H. Cheng, Z. Yuen, S. Chen, K. L. Wong, J. W. Chin, T. T. Chan, and R. So, "Contactless blood oxygen saturation estimation from facial videos using deep learning," *Bioengineering*, vol. 11, no. 3, p. 251, 2024.

[10] B. Huang, W. Chen, C. L. Lin, C. F. Juang, Y. Xing, Y. Wang, and J. Wang, "A neonatal dataset and benchmark for non-contact neonatal heart rate monitoring based on spatio-temporal neural networks," *Eng. Appl. Artif. Intell.*, vol. 106, p. 104447, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0952197621002955

[11] R. D. Riley *et al.*, "Calculating the sample size required for developing a clinical prediction model," *BMJ*, vol. 368, Mar. 2020, doi: 10.1136/bmj.m441.

[12] “The Best Baby Monitors,” *The New York Times*, 2024. [Online]. Available: https://www.nytimes.com/wirecutter/reviews/best-baby-monitor/

[13] S. Brahnam *et al.*, “Neonatal pain detection in videos using the iCOPEvid dataset and an ensemble of descriptors extracted from Gaussian of local descriptors,” *Appl. Comput. Informat.*, Jul. 2020, doi: 10.1016/j.aci.2019.05.003.

[14] Dialzara, “Privacy-preserving AI: Techniques and frameworks,” *Dialzara Blog*. [Online]. Available: https://dialzara.com/blog/privacy-preserving-ai-techniques-and-frameworks

[15] U. Abiha, D. S. Banerjee, and S. Mandal, “Demystifying non-invasive approaches for screening jaundice in low resource settings: a review,” *Front. Pediatr.*, vol. 11, Art. no. 1292678, Nov. 2023, doi: 10.3389/fped.2023.1292678.

[16] A. Saxena, S. Shukla, and N. Gupta, “Neonatal jaundice diagnosis using a smartphone camera based on eye, skin, and fused features with transfer learning,” *Sensors*, vol. 21, no. 21, Art. no. 7038, Oct. 2021, doi: 10.3390/s21217038.

[17] A. Y. Al-Naji, S. L. Mohammed, and J. Chahl, “Real-time jaundice detection in neonates based on machine learning models,” *BioMedInformatics*, vol. 4, no. 1, pp. 623–637, 2024.

[18] A. Aydin *et al.*, “Artificial intelligence-based non-invasive bilirubin prediction for neonatal jaundice,” *Sci. Rep.*, 2025.

[19] T. M. Bahr, E. Henry, R. D. Christensen, S. D. Minton, and V. K. Bhutani, “A new hour-specific serum bilirubin nomogram for neonates 35 weeks of gestation,” *J. Pediatr.*, vol. 236, pp. 28–33.e1, 2021.

[20] X. Liu, G. Narayanswamy, A. Paruchuri, X. Zhang, J. Tang, Y. Zhang, R. Sengupta, S. Patel, Y. Wang, and D. McDuff, “rPPG-Toolbox: Deep remote PPG toolbox,” in *Advances in Neural Information Processing Systems*, vol. 36, pp. 68485–68510, 2023.

[21] W. Wang, A. C. den Brinker, S. Stuijk, and G. de Haan, “Algorithmic principles of remote PPG,” *IEEE Trans. Biomed. Eng.*, vol. 64, no. 7, pp. 1479–1491, 2017.

[22] A. Gu and T. Dao, “Mamba: Linear-time sequence modeling with selective state spaces,” 2024. [Online]. Available: https://openreview.net/forum?id=AL1fq05o7H

[23] C. Hu, K.-Y. Zhang, T. Yao, S. Ding, J. Li, F. Huang, and L. Ma, “An end-to-end efficient framework for remote physiological signal sensing,” in *Proc. IEEE/CVF Int. Conf. on Comput. Vis. Workshops (ICCVW)*, 2021, pp. 2378–2384.

[24] B. Huang, W. Chen, C.-L. Lin, C.-F. Juang, Y. Xing, Y. Wang, and J. Wang, “A neonatal dataset and benchmark for non-contact neonatal heart rate monitoring based on spatio-temporal neural networks,” *Eng. Appl. Artif. Intell.*, vol. 106, p. 104447, 2021, doi: 10.1016/j.engappai.2021.104447.

[25] Z. Yu, Y. Shen, J. Shi, H. Zhao, P. H. S. Torr, and G. Zhao, “PhysFormer: Facial video-based physiological measurement with temporal difference transformer,” in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2022, pp. 4186–4196.

[26] C. H. Cheng, Z. Yuen, S. Chen, K.-L. Wong, J.-W. Chin, T.-T. Chan, and R. So, "Contactless blood oxygen saturation estimation from facial videos using deep learning," *Bioengineering*, vol. 11, no. 3, p. 251, 2024.

[27] F. O. Salami, M. Muzammel, Y. Mourchid, and A. Othmani, "Artificial intelligence non-invasive methods for neonatal jaundice detection: A review," *Artif. Intell. Med.*, vol. 162, p. 103088, Apr. 2025, doi: 10.1016/j.artmed.2025.103088.