Monthly Progress Report

NeoCare - Contactless Neonatal Health Monitoring System

October 2025

1 Individual Contributions

1.1 A.A.W.L.R.Amarasinghe 210031H

I focused on exploring and implementing data security and privacy-preserving techniques. My work initially focused on video encryption methods, including homomorphic encryption, which enables computations on encrypted data but is computationally intensive and unsuitable for training deep learning models due to its limited operation set (addition and multiplication only). I then evaluated AES (Advanced Encryption Standard), a symmetric encryption algorithm known for its strong security, achieving an encrypt-decrypt cycle of around 30 seconds for a 1.8 GB video, though it too cannot support direct machine learning processing. To address both data compression and privacy, I implemented Compressed Sensing (CS), which reconstructs signals from fewer samples than traditional methods, significantly reducing data size while preserving essential information. Using a block-based approach, I divided video frames into 32×32 blocks, applied the Discrete Cosine Transform (DCT) for sparsification, and used a Random Gaussian Measurement Matrix to compress the data to 30% of its original size. Reconstruction was performed using Orthogonal Matching Pursuit (OMP) followed by inverse DCT. Compressed sensing inherently enhanced privacy, as Random Matrix functioned as a secret key, preventing unauthorized reconstruction. A major challenge was the high memory requirement of large measurement matrices for full-frame processing; this was overcome by adopting the block-based CS method, which drastically reduced memory usage and improved computational efficiency, successfully balancing compression, privacy, and practicality.

1.2 M.K.I.G.Morawakgoda 210391J

The VideoPulse Dataset was trained using the PhysNet model; however, preprocessing challenges arose as neonatal faces were not accurately detected due to reliance on adult-optimized rPPG Toolbox methods. To overcome this, a custom neonatal face detection dataset was developed by extracting frames every 4 seconds, manually annotating 324 images with Roboflow, and augmenting them through flips and rotations to obtain 743 images, which were then trained using YOLOv11. The model achieved excellent results (mAP@0.5 = 0.995, Precision = 1.0, Recall = 1.0) and demonstrated robust generalization across unseen videos from VideoPulse and NBHR datasets. The same approach was extended to region-of-interest (ROI) detection by annotating cheeks, forehead, and chin as a single region and training YOLOv11 with additional augmentations such as brightness, contrast, and exposure adjustments to improve generalization under varying lighting conditions. The trained ROI model showed effective convergence and achieved comparable performance. Although the model performed well in detecting ROIs across frames, real-time processing was slow when analyzing every frame. To optimize performance, three approaches were tested: YOLOv11's built-in video tracking, interval-based detection, and strict motion freeze. The built-in tracker could not process frames faster than the video frame rate, while interval-based detection improved processing time but suffered from accuracy loss during high-motion scenes. Therefore, the strict motion freeze method was selected for its balance between accuracy and speed. To further enhance reliability, motion analysis was restricted to the detected regions (with padding), minimizing false triggers from unrelated movements such as caregivers' or baby hands.

1.3 S.M.S.M.B.Abeyrathna 210005H

The feasibility of estimating blood oxygen saturation from the PPG (Photoplethysmogram) signal was explored, aiming to utilize the same signal processing pipeline currently applied for heart rate estimation. SpO_2 estimation requires extraction of AC and DC components for both red and infrared (IR) LED readings from the pulse oximeter. The AC component represents pulsatile changes due to arterial blood flow, while the DC component represents the baseline intensity. Filtering techniques were applied to the oximeter output to isolate these components, and the ratio of ratios (R) method was used for SpO_2 calculation. Initially, it was assumed that the CSV file output from the oximeter contained the raw red and IR LED readings. Using these values, SpO_2 estimates were calculated and compared with reference readings. Some test samples showed promising results, but most exhibited significant deviations. Further investigation revealed that the CSV file did not contain the raw LED intensities, but rather processed values unsuitable for direct SpO_2 estimation. As a result, it was concluded that accurate SpO_2 estimation cannot be achieved using the available PPG data from the oximeter. Consequently, the rPPG (remote Photoplethysmography) approach will be used for SpO_2 estimation, aligning with the project's goal of non-contact neonatal vital signs monitoring. The rPPG method allows estimation of SpO_2, heart rate, and respiratory rate directly from camera recordings, ensuring a contactless solution suitable for neonatal care. Following the SpO_2 investigation, the mobile application interface was developed using React, enabling users to record videos and capture images through the mobile camera. These recordings are transmitted to the backend for processing. To validate the data flow, a demo jaundice detection model was integrated into the backend. The model successfully received video input from the app, processed it, and returned the estimated jaundice outcome to the interface, confirming the proper functioning of the end-to-end system.

1.4 U.M.Y.B.Alahakoon 210027C

I focused on synchronizing pulse oximeter readings with the mobile camera video and improving jaundice detection accuracy. I began by retrieving and testing the previous group's synchronization code, which aligned pulse oximeter data and video frames using global and relative timestamps. After resolving connection issues, I successfully received real-time data from the oximeter, which transmits 5-byte packets. Based on earlier work, the third byte was used as the PPG signal value, allowing synchronization between the sensor data and video feed for aligned temporal analysis. Next, I implemented skin segmentation using "Skinny," a lightweight U-Net model adapted for infant skin detection. The model produced reasonable results, though some regions were under- or over-segmented due to lighting and skin tone variations. To enhance jaundice detection, I created a segmented dataset using YOLOv8 to isolate baby regions and retrained the classifier. The segmented dataset improved accuracy and reduced background noise, demonstrating better focus on relevant skin areas. However, performance on unseen images still showed some variation. Future work includes applying color normalization, data augmentation, and testing newer models like YOLOv9 to further improve generalization and robustness.

2 Overall Progress Summary

During this month, we made significant advancements across all core components of the NEOCARE system. Data security and privacy were strengthened through the implementation of a block-based Compressed Sensing approach, effectively balancing compression, privacy, and efficiency. The computer vision pipeline achieved major progress with the successful training of YOLOv11 models for neonatal face and ROI detection, reaching near-perfect accuracy and improved real-time performance using a motion-freeze optimization method. Efforts to estimate SpO from oximeter data revealed limitations in available signals, leading to a transition toward rPPG-based estimation in line with the project's non-contact objective. The mobile application was also integrated and validated with backend processing, confirming end-to-end system functionality. Additionally, pulse oximeter-video synchronization was re-established, and improvements in jaundice detection were achieved through segmentation-based preprocessing and dataset refinement. Overall, the system has progressed toward a more integrated, accurate, and privacy-preserving neonatal monitoring solution.

Declaration

We certify that the information provided in this report is true and accurate to the best of our knowledge.

Student: A.A.W.L.R.Amarasinghe **Signature:** ....

Student: M.K.I.G.Morawakgoda **Signature:** ....

Student: S.M.S.M.B.Abeyrathna **Signature:** ....

Student: U.M.Y.B.Alahakoon **Signature:** ....

Approval

Approval of project supervisors.

Supervisor: Dr. Sampath K. Perera **Signature:** ....