Real-Time Detection of Return of Spontaneous Circulation During Cardiopulmonary Resuscitation Using AI and Carotid Doppler Ultrasound

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Purpose

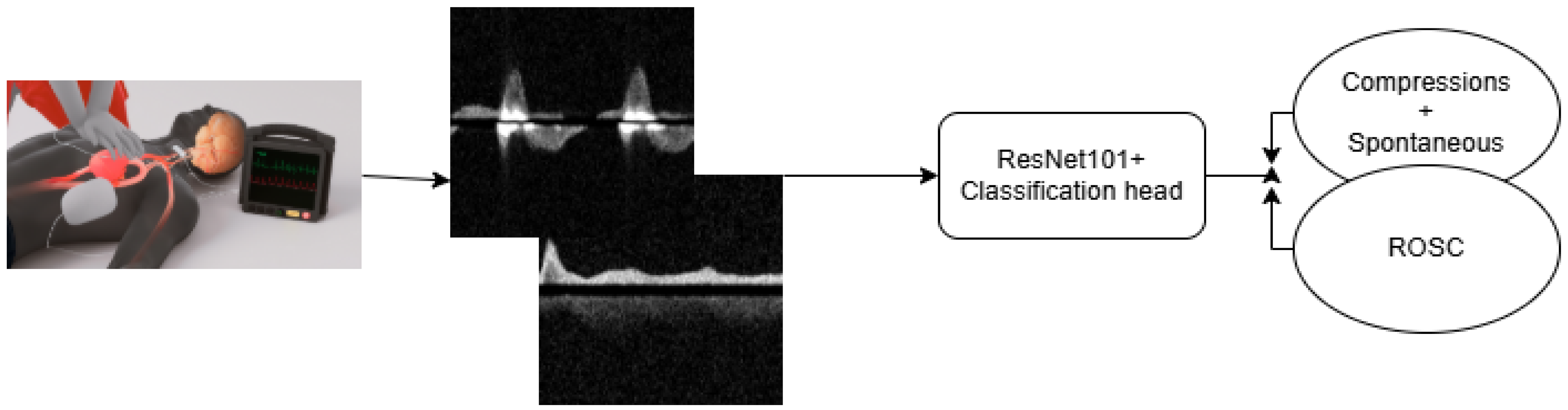
- To assist the CPR team with automatic information on carotid blood flow by leveraging deep learning techniques to automatically detect and provide real-time feedback on signs of return of spontaneous circulation (ROSC) during CPR.

Results

- Achieved mean sensitivity of 94%, specificity of 95%, positive predictive value of 95%, and negative predictive value of 93% across all folds.
- Explainable AI heatmaps (Figure 2) depicts the key features for ROSC and compressions with spontaneous circulation.

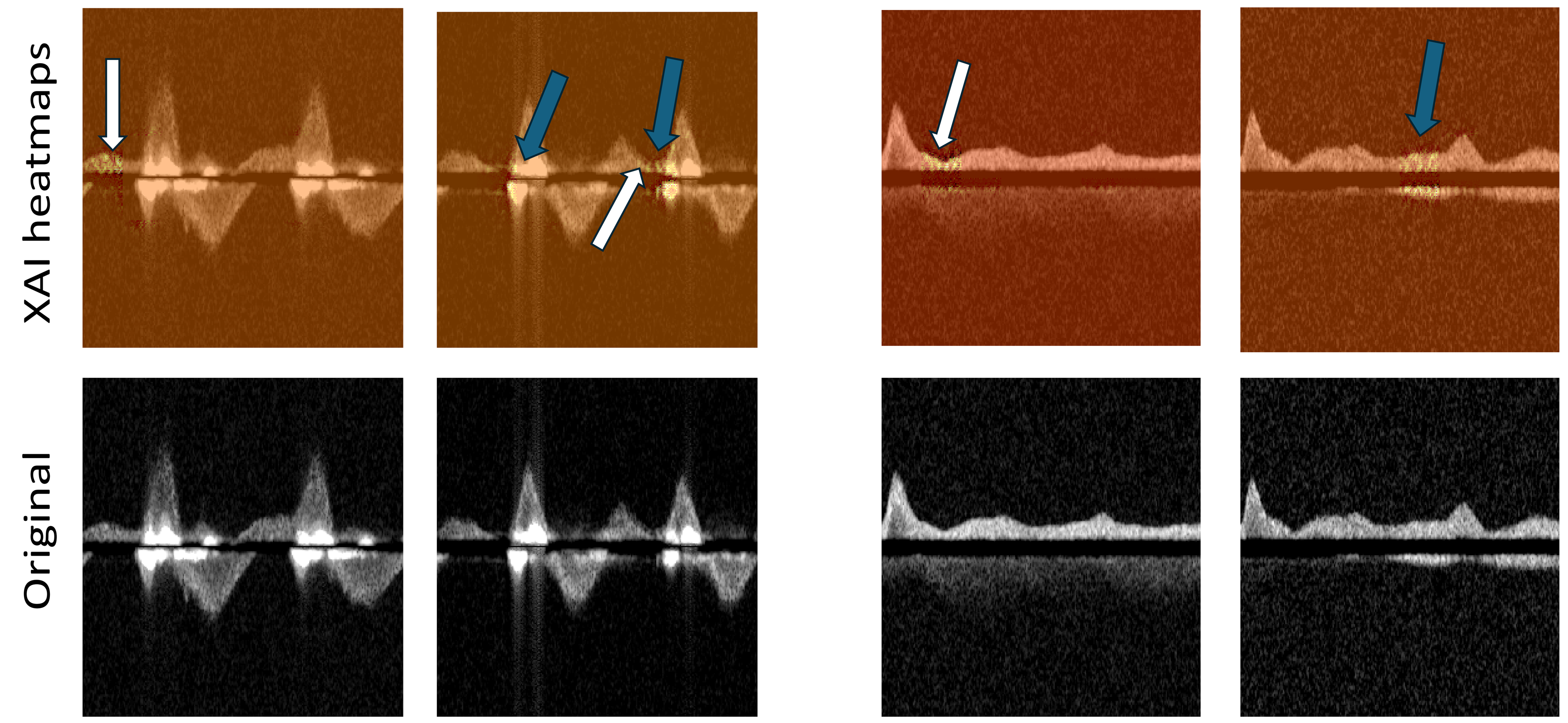
Methods

- **Data acquisition**: A continuous hands-free Carotid Doppler ultrasound probe (RescueDoppler) over the carotid artery was used in 4 men and 1 female with cardiac arrest (67 ± 11 years). The causes of arrest included cardiac etiology (n = 3), and septic shock (n = 2). Initial rhythms were pulseless electrical activity (PEA, n = 2), ventricular fibrillation (n = 2), and asystole (n = 1)
- **Annotations:** Annotated pulsed wave spectral velocity curves using an in-house annotation tool. We annotated 2608 heart cycles and labelled them as compressions with spontaneous circulation and ROSC as shown in Figure 3.
- **Dataset:** One second pulses are extracted from the recordings and are saved as grey scale images for training
- **Training:** A ResNet101 pre-trained model was used as a feature extractor with a 2-class classification head. A leave-one-subject-out approach cross-validation approach was used for testing. Only subjects exhibiting both ROSC and compressions with spontaneous circulation were included in the test set. Experimental setup is shown in Figure 1.
- **Explainable AI:** We used Grad-CAM to visualize and interpret the model's decision-making.



a. b. c.

Figure 1: Model setup for return of spontaneous circulation detection. a. RescueDoppelr probe attached over the carotid artery showing blood flow velocities on the defibrillator, b. example of images used for training, c. Model training and inference step.

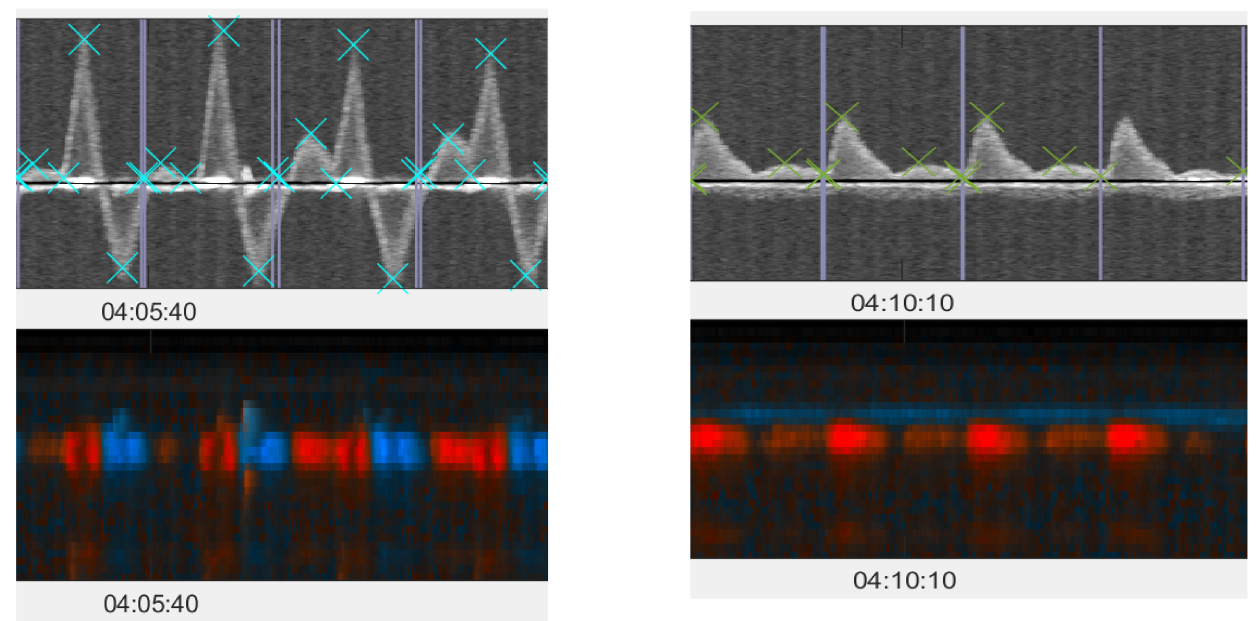


a. b.

Figure 2: Explainable AI (XAI) heatmaps (upper panel) alongside the corresponding original B-mode images (lower panel) of chest compressions with spontaneous circulation in (Figure a) and ROSC signals in (Figure b)

Conclusions

- Deep learning models integrated with Doppler ultrasound can accurately detect spontaneous circulation (intrinsic cardiac activity)during chest compressions and ROSC during CPR, achieving highly accurate results.
- Key features are diastolic flow and dicrotic notch for ROSC, and for chest compressions the systolic peak of the blood flow and noise around the baseline.



a. b.

Figure 3: The example images depict the annotations of compression with spontaneous circulation signals on left (a) and ROSC signals on right (b).

Limitations

- Dataset size is limited and needs extensive testing

Declaration of Interests

- The RescueDoppler Project has received funding from the Norwegian Research Council and the Central Norway Regional Health Authority. Charlotte Björk Ingul serves as a Medical Advisor at Cimon Medical. Hans Torp is employed by Cimon Medical. All other authors have no conflicts of interest.

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