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ORIGINAL ARTICLE

A machine learning model to detect falls mimicking cardiac arrest-related collapse based on wrist-derived accelerometry: the DETECT-2 study

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Aims

In wearable-based automated cardiac arrest detection technology, photoplethysmography (PPG) is the most commonly used sensor to detect the absence of pulsations. To minimize false-positive cardiac arrest alerts, accelerometry signals are often used for the detection of ongoing movement. We conducted the DETECT-2 study to develop an accelerometer-based machine learning model for the detection of cardiac arrest-related collapse, which is often a first manifestation of cardiac arrest.

Methods and results

Healthy volunteers simulated cardiac arrest-related collapses through sudden and soft falls without subsequent movement. Accelerometer signals were collected using the CardioWatch wristband; video recordings were made as a reference. An accelerometer-based gradient boosting model (GBM) for fall detection was trained (70%) and tested (30%). The primary endpoint was the sensitivity for the detection of falls; secondary endpoints were false-positive fall alerts. Nineteen participants performed 567 falls. In the training set (n =13; 388 falls), the sensitivity of the GBM was 99.2% (95% confidence interval [CI] 98–100%], with four false positives. In the test set (n = 6; 179 falls), sensitivity was 96.1% (95% CI 92–98%), with two false positives. For sudden falls (n = 120) and soft falls (n = 59), sensitivities were 100% (95% CI 96–100%) and 88.1% (95% CI 76–95%) in the test set ($P < 0.001$), respectively.

Conclusion

Using accelerometry data from the CardioWatch, sudden and soft falls that mimic cardiac arrest-related collapse can be accurately detected. The next step in the development of automated cardiac arrest detection is the integration of accelerometer signals into the existing PPG-based model, with the aim of reducing false positives and increasing sensitivity in everyday use.

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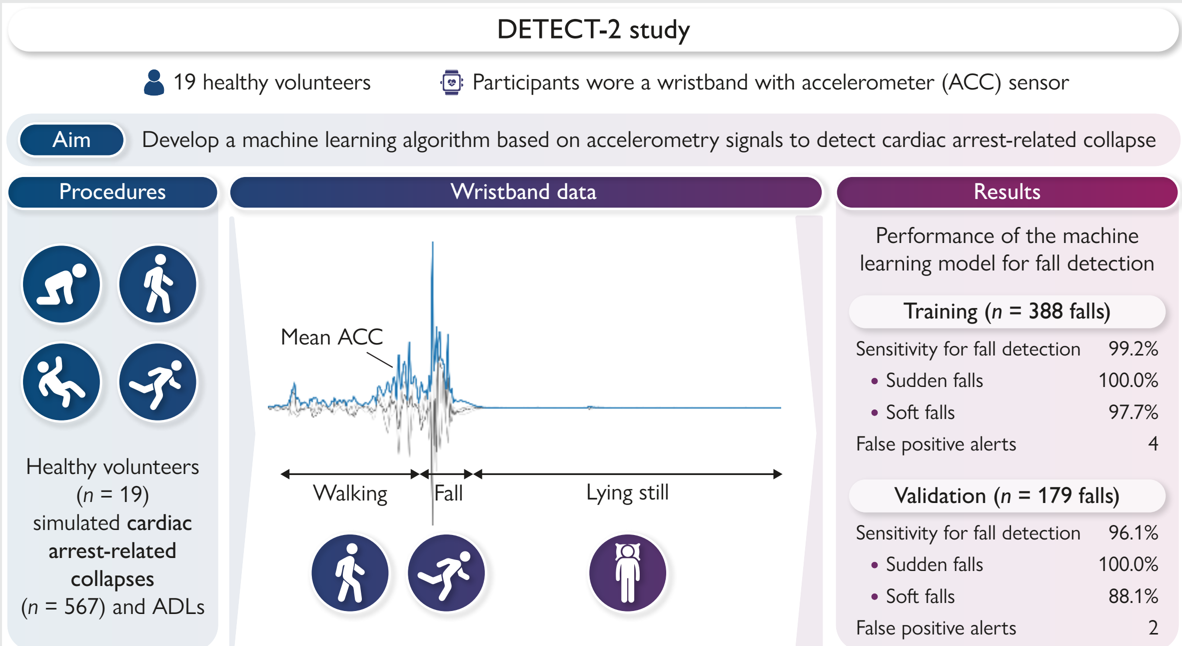
Graphical Abstract



Keywords Out-of-hospital cardiac arrest • Early detection • Wearable • Cardiac arrest-related collapse • Accelerometry

Introduction

Unwitnessed out-of-hospital cardiac arrest (OHCA) is associated with dismal survival chances, since bystander help is too late in most cases.[1–3] Wearable devices with the functionality to automatically detect cardiac arrest and alert medical rescuers could provide a technological solution to facilitate early assistance for these cardiac arrest victims.[4] Widespread use of such devices has a high potential impact on survival after unwitnessed OHCA.[5]

Initiatives have recently been launched to develop smartwatches capable of automatically detecting cardiac arrest using biosensor technology.[6–10] Among these, the DETECT-1 study demonstrated excellent sensitivity for detecting induced circulatory arrest events based on wrist-derived photoplethysmography (PPG).[11] A potential downside of using PPG as a single parameter to detect cardiac arrest is a high number of false positives caused by artifacts in the signal during daily life use. Artifacts are often introduced by human movement, which can be registered by an accelerometer sensor worn on the wrist. Therefore, incorporating accelerometry data in a cardiac arrest detection model has the potential to enhance its performance in two ways. First, it could help reduce false positives by ruling out cardiac arrest in the presence of ongoing movement.[9] Second, accelerometer input could assist in the detection of cardiac arrest by recognizing a physical collapse, which is often the first manifestation of cardiac arrest in individuals in an upright position.

The feasibility of detecting falls using wrist-derived accelerometry data has been demonstrated in studies involving older adults who frequently fall.[12–16] Although it demonstrated to be challenging related to frequent hand movement during activities of daily living (ADLs), accuracies of 90% have been reported.[12] Based on these findings and the characteristic pattern of a sudden fall followed by absence of movement in the setting of a cardiac arrest, we hypothesized that wrist-derived accelerometry can accurately detect cardiac arrest-related falls. If proved, this could be incorporated into a cardiac arrest detection model, thereby not only reducing false positive alerts but also help detect cardiac arrest.

In the current DETECT-2 study, we aimed to develop a machine learning algorithm based on accelerometry signals only to detect deliberate falls performed by healthy individuals, mimicking cardiac arrest-related collapses.

Methods

Study design and participants

DETECT-2 was a prospective study in adult healthy volunteers. Recruitment was performed at universities and sports clubs and focused on volunteers with a background in sports and without known comorbidities. Exclusion criteria were as follows: (physically) unable or unwilling to perform the (fall-)motions, and medical issues that interfere with wearing the wristband or physical exercise. The study was conducted at the judo dojo of the SportQube (Nijmegen, The Netherlands) in August 2023. The study was set up by research consortium DETECT, consisting of Radboud University Medical Center (Nijmegen, the Netherlands), Erasmus University Medical Center (Rotterdam, the Netherlands), Reinier de Graaf hospital (Delft, the Netherlands), and Corsano Health (The Hague, The Netherlands). The study protocol was approved by the Medical Research Ethics Committee of East Netherlands. Written informed consent was obtained prior to inclusion.

Data collection

Study participation lasted about 2 h during which participants wore a wristband equipped with accelerometer sensors (CardioWatch 287-2, Corsano Health B.V., The Hague, The Netherlands, manufactured by MMT, Geneva, Switzerland). Computerized web-based 1:1 randomization (Castor EDC, randomization block size 2, 4) was used to determine whether the wristband was worn at the right or the left wrist. Accelerometry signals (three-axis [X, Y, Z]; sample frequency 32 Hz) were recorded and sent by a Bluetooth-connected smartphone (Samsung Galaxy A40, Android OS, Samsung Electronics) to a protected cloud. Video recordings served as the reference standard, with two cameras recording the entire study area, and two additional cameras dedicated to capturing the falls from two angles. Time synchronization between the video recordings and the accelerometer signals was performed by one camera dedicated to recording the clock of each smartphone that was connected to a wristband. Collected baseline parameters include demographics, medical history, history of sports, skin type (Fitzpatrick scale), and arm hair density.[17,18]

Study procedures: simulation of cardiac arrest-related collapse

To simulate cardiac arrest-related physical collapse, participants were instructed to perform sudden falls and soft falls and lie still afterwards. Sudden falls were based on previous research analysing videotaped sudden cardiac arrests and included falls forward from a standing position or while jogging, falls sideways (*Figure 1*), and falls backwards.[19–21] Soft falls included falls not directly to the ground, including sliding off a chair or against a wall. Each type of fall was performed five times per study participant, resulting in 30 falls per participant. After each fall, participants were instructed (J.H./A.G.) to lay still for 20 s and avoid placing the lower arm on the abdomen or chest, in order to minimize the impact of breathing on the accelerometer recordings. They were not instructed to hold their breath. A physiotherapist (D.M.), experienced in fall protection and prevention, provided instruction and a short training to ensure safe falls. The falls were performed on fall mats to minimize the risk of injury. Additionally, participants were instructed to perform a prespecified series of ADLs. *Table 1* provides an overview of the performed falls and ADLs; video recordings of the different types of falls can be found in the Supplement.

Model development

The three-axis (x, y, and z) accelerometer signals were used for the fall detection algorithm. The dataset was randomly divided into a 70% training set and 30% test set. The performed falls were analysed as individual fall events, but participants were split individually to prevent overfitting. The falls and ADLs were annotated from video recordings (R.E.), with the annotator blinded to the accelerometer signals. The algorithm developer (K.E.), who had access to the accelerometer signals, was blinded to the fall annotations of the test set.

First, the data were converted from acceleration values into units of gravity (g = ∼9.8 m/s). The total acceleration was calculated by taking the square root of the sum of the squared three signals. For model training and testing, we used all collected accelerometry signals without applying filtering (see Supplement 2, lines 107–111 and 11–15). A peak in the acceleration, which entails a possible fall event, is detected when the acceleration is larger than 3 g.[22] The time of this acceleration is noted as *peak time*. To verify the peak, the algorithm determines the *impact start* and *impact end*. The *impact start* denotes the last time the total acceleration was above 1.5 g before *peak time*. *Impact end* is the first time the total acceleration was below 1.5 g after the *peak time*.[22] If the *impact start* and *impact end* meet the criteria to be flagged as a possible fall event, seven features will be determined based on the *peak time*, *impact start*, and *impact end*. If the impact start and impact end do not meet the criteria, the peak will be discarded. For every peak, the following features are determined: Average Absolute Acceleration Magnitude Variation, Maximum Peak Index, Minimum Valley Index, Peak Duration Index, Activity Ratio Index, Free Fall Index,

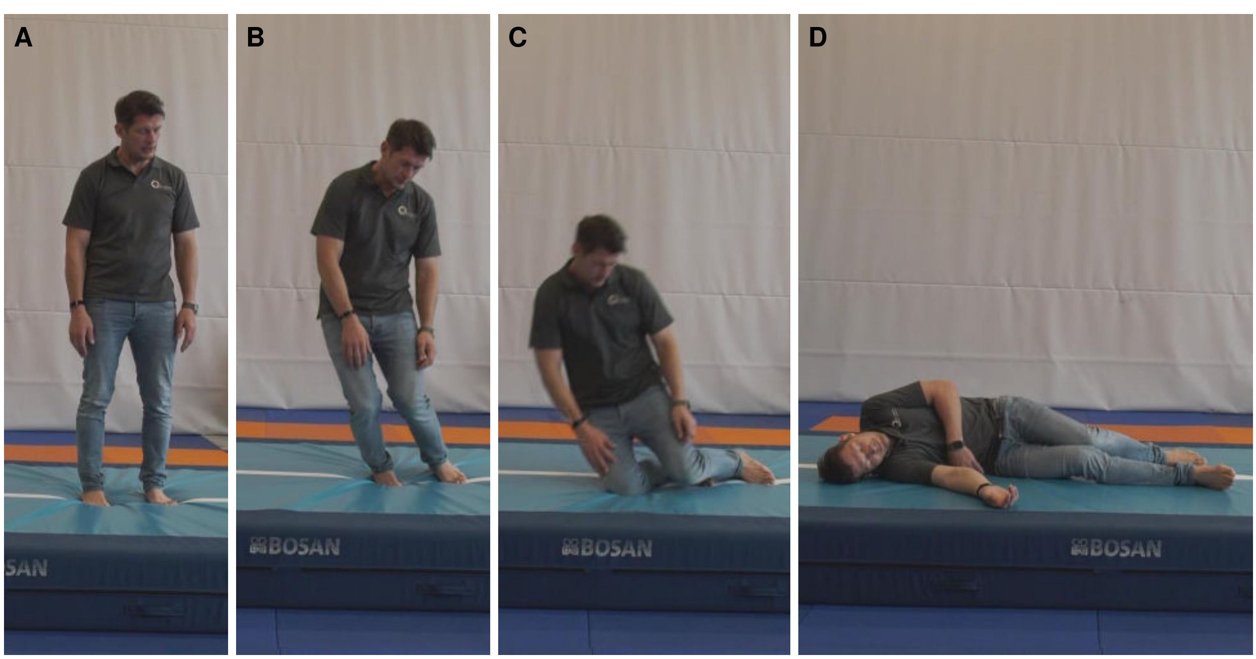


Figure 1 Video screenshots of the instructor demonstrating the fall sideways, which is one of the sudden falls. The CardioWatch was worn on the right wrist. *A*) starting position, *B*) initiation of the fall to the right, *C*) fall to the right, and *D*) after the fall, the subject lay still for 20 s.

Table 1 Overview of the performed falls and ADL movements

Falls	Activities of daily living (ADLs)
Sudden falls	Standing
Fall forward, from standing still	Walking
Fall forward, from walking	Running
Fall backward	Clapping*
Fall sideways	Jumping*
Soft falls	Picking up an object*
Sliding off a chair	Bump to the wristband*
Fall via a wall	Sitting
	Standing → sitting*

After each fall, the participant lay still on the mat for 20 s. Every fall was performed five times, resulting in 30 (sudden + soft) falls per participant. ADLs were performed for 1 min or *10 repetitions. Start- and end times were annotated by the researchers. ADL, activity of daily living.

and Step Count Index (Supplementary material).[22,23] To train the fall detection model, we used a dataset with the seven features of all detected peaks, which are annotated as a fall or no fall. The same thresholds were used for sudden and for soft fall detection. The obtained dataset was used to train and hypertune a gradient boosting model. The gradient boosting model was chosen, as it generally performs well on relatively small, structured datasets.[24] It combines the predictions of several weak learners to adjust the model weights of the overall model.

First, the model was trained to detect the falls (sudden and soft falls combined) as described above. Then, an additional feature was added to the fall detection algorithm: the standard deviation of the acceleration magnitude over a period of 10 s after a potential fall was detected. This feature measured movement variability and provided the model with post-fall movement patterns. If motion was detected within these 10 s, defined as a mean standard deviation ≥0.1 g, the fall alert was cancelled; otherwise, it was triggered. During model development, the 70% training set was further split 75%/25% for algorithm tuning (e.g. hyperparameter optimization and assessment of feature contribution). The 30% test set remained untouched until the final evaluation. Data analyses and model development were performed in Python, using packages scikit-learn and xgboost (version 3.11.9, Anaconda Software Distribution, Anaconda Inc.; 2021).

Endpoints

The primary endpoint is the sensitivity for detecting simulated cardiac arrest-related collapses, defined as falls followed by the absence of movement for 10 s. Secondary endpoints include false-positive fall alarms and the sensitivity for detecting sudden or soft falls separately. Additionally, we also report sensitivity for detecting sudden and soft falls alone, that is, without considering the absence of the movement period.

Statistical analysis

Baseline characteristics were presented as means ± standard deviations or medians with interquartile ranges (IQR), whichever was appropriate. Categorical variables were reported as frequencies with percentages. Continuous variables were compared between the training and test sets using the independent *t*-test or Mann–Whitney U test, depending on the normality of the distribution. Categorical variables were compared between the training and test sets using the χ^2 test or Fisher's exact test. A two-sided *P*-value lower than 0.05 was considered significant. Sensitivities with 95% CI were calculated for the training and test sets. Sensitivity was defined as the percentage of falls correctly classified as a fall. The z-test for proportions was used to analyse the differences in sensitivity between the sudden and soft falls. Confidence intervals for proportions were calculated using the Wilson score method with continuity correction. The specificity was reported based on one-minute intervals during which the accelerometer signal was correctly identified as no fall. Additionally, a subanalysis was performed to correct the sensitivities for intra-individual clustering using a generalized linear mixed model. Statistical analyses were performed using SPSS (IBM Corp. Released 2020. IBM SPSS Statistics for Windows, Version 29.0. Armonk, NY: IBM Corp).

Results

Baseline characteristics

A total of 19 healthy individuals were enrolled in the study, of which 9 (47%) were females, 9 (47%) were males, and 1 (5%) was nonbinary. The median age was 23 years old (21–25), and the median body mass index was 22.8 (21.3–25.7). Baseline characteristics did not differ between the training and the test sets (*Table 2*).

Training

The training set consisted of 13 study participants, who performed 260 sudden falls and 128 soft falls in 23.5 h of accelerometry data. The sensitivity for detection of a fall followed by absence of movement was 99.2% (95% CI 98–100%). Four false-positive alarms occurred, resulting in a positive predictive value of 99.0% (95% CI 98–100%). The sensitivities for detecting a sudden or soft fall followed by absence of movement were, respectively, 100% (95% CI 98–100%) and 97.7% (95% CI 93–99%). The sensitivity for detecting a fall alone (not taking into account the absence of movement period) was 96.7% (94–98%) with 18 false-positive alarms, resulting in a positive predictive value 95.4% (95% CI 93–97%). All performance metrics can be found in *Table 3*. An example of accelerometry data from a sudden and soft fall is presented in *Figure 2*.

Test

The test set consisted of six study participants, including 120 sudden falls and 59 soft falls in 9.5 h of accelerometry data. The sensitivity for detection of a fall followed by the absence of movement was 96.1% (95% CI 92–98%). Two false-positive alarms occurred, resulting in a positive predictive value of 98.9% (95% CI 95–99.8%). The sensitivities for detection of a sudden and soft fall followed by the absence of movement were, respectively, 100% (96–100%) and 88.1% (95% CI 76–95%) ($P < 0.001$).

The sensitivity for the detection of a fall alone (not taking into account the absence of movement period) was 94.4% (95% CI 90–97%) with 10 false-positive alarms, resulting in a positive predictive value of 94.4% (95% CI 90–97%). Sensitivity for the detection of the sudden falls alone was 98.3% (95% CI 94–99.7%) and for soft falls 86.4% (95%CI 74–94%) ($P = 0.001$). All performance metrics can be found in *Table 3*. The sensitivities from the training and test set adjusted for clustering are reported in Supplement 3.1.

Discussion

A physical collapse is often a first manifestation of cardiac arrest and can be accurately detected using wrist-derived accelerometry data in a controlled setting in healthy individuals. The fall detection model performed better in detecting sudden falls than

Table 2 Baseline characteristics

	All participants (*n* = 19)	Training (*n* = 13)	Test (*n* = 6)
Gender			
Male	9 (47%)	6 (46%)	3 (50%)
Female	9 (47%)	6 (46%)	3 (50%)
X	1 (5%)	1 (8%)	0
Age (years)	23 (21–25)	23 (22–25)	22 (20–25)
BMI (kg/m^2)	22.8 (21.3–25.7)	22.8 (21.1–26.0)	22.3 (21.3–24.9)
BSA (m^2)	1.88 (1.76–1.93)	1.89 (1.74–1.95)	1.88 (1.81–1.90)
Baseline systolic blood pressure (mmHg)	122 (114–131)	122 (113–133)	122 (114–132)
Baseline diastolic blood pressure (mmHg)	75 (70–81)	75 (70–81)	73 (68–85)
Participation in sports	16 (84%)	11 (85%)	5 (83%)
Judo athlete	4 (21%)	2 (15%)	2 (33%)
CardioWatch on the left arm	9 (47%)	7 (54%)	2 (33%)
Wrist circumference (cm)	16.0 (15.5–16.5)	16.0 (14.8–16.4)	16.0 (15.5–16.6)
Fitzpatrick skin color type			
I—White	0	0	0
II—Fair	10 (53%)	6 (46%)	4 (67%)
III—Medium	8 (42%)	7 (54%)	1 (17%)
IV—Olive	1 (5%)	0	1 (17%)
V—Brown	0	0	0
VI—Very dark brown	0	0	0
Arm hair density			
Nil	4 (21%)	3 (23%)	1 (17%)
Sparse	8 (42%)	5 (39%)	3 (50%)
Moderate	7 (37%)	5 (39%)	2 (33%)
Dense	0	0	0

Variables are presented as median (interquartile range) or as number (percentage). There are no significant differences in baseline characteristics between the training and test sets. Gender was self-reported. Baseline systolic and diastolic blood pressure are the mean of two blood pressure cuff measurements. BMI, body mass index; BSA, body surface area.

soft falls, presumably due to the direct impact on the ground producing a stronger accelerometer signal (Supplement 3.2). Our findings have important implications for the development of cardiac arrest detection models in wearable devices, where accelerometry data may further enhance model performance. The next step towards wearable-based automated cardiac arrest detection involves integration of the accelerometer sensor into PPG-based models.

Studies on wristband-based fall detection, not specifically related to cardiac arrest, reported sensitivities ranging from moderate to excellent (60–96%).[13–16] However, distinguishing falls from other movements appeared to be challenging due to the frequent hand use in ADLs, and false-positive alerts remained a concern.[12,16] In DETECT-2, the false-positive alarms in the test set all occurred during hand clapping. When the motionless period following a fall was incorporated into the model, the number of false positives decreased. Thus, combining detection of the fall with the absence of subsequent movement, which is typical for cardiac arrest, created a more robust model for detecting falls related to cardiac arrest. This DETECT-2 study is the first to separately describe a fall detection algorithm for the application in an automated cardiac arrest detection model.

By adding accelerometry data to the cardiac arrest detection model, we aim to enhance its performance in two ways. First, the most obvious way is that it could reduce false positives in cases where ongoing user movements contradict a presumed cardiac arrest based on PPG analysis.[9] Second, the cardiac arrest detection model could also be triggered by detecting the characteristic pattern of a fall without subsequent movement. In this case, the PPG signal should be closely monitored to detect pulsations. This could be crucial for detecting cardiac arrest during movement, as the PPG signal may be affected by noise. The latter is important since the sensitivity for cardiac arrest detection in a simulation setting with motion was only 31–53% in the recently published 'loss of pulse' detection model.[9] Concluding, with accelerometry we aim to both preserve excellent sensitivity for cardiac arrest detection while also lowering the false-positive alarm rate.

To closely mimic real-world scenarios, the falls performed in this study were based on previous studies analysing sudden cardiac arrest in athletes. Their collapses most often occurred during low-intensity exercise and presented as a forward or backward fall.[19–21] In a home setting, less is known about the presence of a collapse prior to a cardiac arrest event. Victims may suffer a cardiac arrest not only during physical activity but also while sleeping or sitting. To better simulate the home setting, softer falls (sliding off a chair and a fall via a wall) were also included. The performance of the model for soft fall detection was slightly lower but remained acceptable when

Table 3 Performance of the fall detection model

	Fall detection	Fall detection + 10 s absence of motion
Training (n = 388)		
True-positive alarms	375	385
False-negative alarms	13	3
False-positive fall alarms	18	4
Sensitivity for fall detection		
All falls (*n* = 388)	96.7% (94–98%)*	99.2% (98–100%)*
Sudden falls (*n* = 260)	99.6% (98–100%)	100% (98–100%)
Soft falls (*n* = 128)	90.6% (84–95%)**	97.7% (93–99%)**
Positive predictive value	95.4% (93–97%)	99.0% (98–100%)
Specificity	99.3% (98.6–99.7%)	99.8% (99.4–100%)
Test (n = 179)		
True-positive fall alarms	169	172
False-negative fall alarms	10	7
False-positive fall alarms	10	2
Sensitivity for fall detection		
All falls (*n* = 179)	94.4% (90–97%)	96.1% (92–98%)
Sudden falls (*n* = 120)	98.3% (94–99.7%)+	100% (96–100%)‡
Soft falls (*n* = 59)	86.4% (74–94%)+	88.1% (76–95%)‡
Positive predictive value	94.4% (90–97%)	98.9% (95–99.8%)
Specificity	99.0% (97.6–99.6%)	99.8% (98.7–100%)

Data are presented as *n* or value (95% CI). Three study participants performed four repetitions of the soft fall, 'sliding off a chair,' instead of five repetitions. *$P = 0.023$. **$P = 0.017$. +$P = 0.001$. ‡$P < 0.001$. No predictors of false-positive or false-negative alarms could be identified in both the training and the test set. The specificity for the detection of no falls in the accelerometer recording was reported based on 1-min intervals correctly identified as 'no fall'.

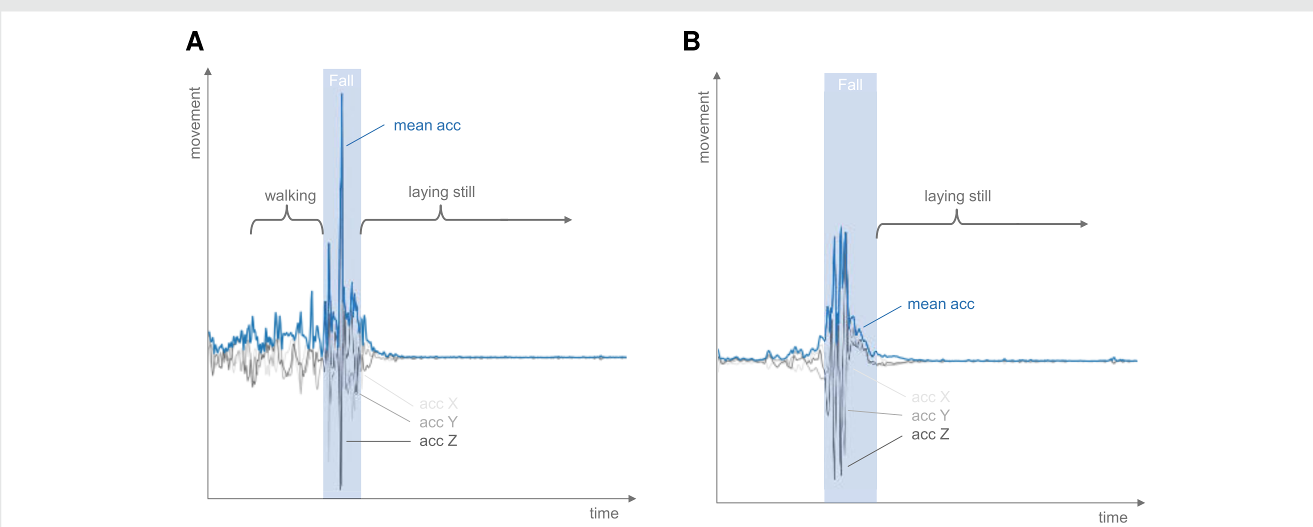


Figure 2 Accelerometer signals of two types of falls. The grey signals are the X, Y, and Z of the accelerometer sensor. The blue signal (mean acc) is the square root of the sum of the squared three signals. *A*) Accelerometry data from a sudden fall forward preceded by walking. On the left, the subject is walking. In the blue frame, the subject falls forward and then lies still. *B*) Accelerometry data from a soft fall. In the blue frame, the subject slides off a chair and then lies still. The sudden fall creates a stronger accelerometer signal than the soft fall.

comparing it to previous studies.[12,14–16] However, the model requires validation in real-life and target populations.

This study is part of the DETECT program, which aims to develop a wristband for automated cardiac arrest detection and alerting. In an earlier study, we developed a PPG algorithm for cardiac arrest detection, yielding an excellent sensitivity but an anticipated relatively high false-positive alarm rate.[11] It is important not to rely solely on PPG for the detection of cardiac arrest, because although sensitivity is essential in devices intended for patients, frequent false-positive cardiac arrest alarms would be a major concern. False alarms result in unnecessary activation of the emergency medical services and may undermine the credibility of the technology. Therefore, in the follow-up DETECT-3 study, we will study false-positive cardiac arrest alerts in healthy volunteers and patients who wear the wristband during daily life. Among others, we will study the added value of accelerometry in reducing false positive cardiac arrest alarms. Other initiatives also integrate accelerometer signals in their multisensory cardiac arrest detection systems.[6,7] The use of accelerometry could enhance sensitivity, particularly in daily life, where cardiac arrests are not uncommon during physical activity. Further studies will be performed to confirm this hypothesis.

A strength of this DETECT-2 study includes the realistic simulated cardiac arrest-related collapses, inspired by video footage of actual collapses related to sudden cardiac death. Additionally, the model's robustness was trained on challenging non-fall data, including activities that have similarities with fall movements. Limitations include the relatively small sample size, although it involved a substantial number of falls ($n = 567$), and the controlled setting with a soft surface, which differs from real-life collapses on a hard surface. Accelerometry data were not filtered, which limits comparability with studies that applied filtering. Moreover, the study population is not a representative sample of the intended target groups, especially regarding the young age. This study setup was a deliberate choice to minimize the risk of injury. Finally, the real-world distribution of types of cardiac arrest-related falls is unknown. Therefore, the performance of the algorithm in daily life may differ compared to this controlled setting.

Conclusion

Accelerometer-based detection of sudden and soft falls mimicking cardiac arrest-related collapses shows excellent sensitivity and low false positives. Further research is needed to evaluate the model's performance in real-life settings and target populations. The next step towards wearable-based automated cardiac arrest detection involves integration of the accelerometer sensor into the existing PPG-based model, which has the potential to reduce false positives and enhance accuracy during everyday use.

Supplementary material

Supplementary material is available at *European Heart Journal – Digital Health*.

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Author contributions

Roos Edgar (Conceptualization, Formal analysis, Investigation, Methodology, Validation [equal], Data curation, Visualization, Writing—original draft [lead]), Kambiz Ebrahimkheil (Data curation, Methodology, Resources [supporting], Formal analysis, Software, Writing—review & editing [equal]), Danny Meeuwsen (Investigation, Methodology, Writing—review & editing [supporting], Resources [equal]), Maud De Jong (Data curation, Investigation, Writing—review & editing [supporting], Methodology [equal]), Job Herrmann (Data curation, Investigation [supporting], Writing—review & editing [equal]), Alexander Griffioen (Data curation, Investigation [supporting], Writing—review & editing [equal]), Niels Scholte (Conceptualization, Funding acquisition [supporting], Writing—review & editing [equal]), Marc Brouwer (Conceptualization, Funding acquisition [supporting], Writing—review & editing [equal]), Rypko Beukema (Conceptualization, Funding acquisition [supporting], Writing—review & editing [equal]), Eelko Ronner (Conceptualization, Funding acquisition [supporting], Writing—review & editing [equal]), Eric Boersma (Conceptualization [supporting], Funding acquisition, Writing—review & editing [equal]), Aysun Cetinyurek-Yavuz [Methodology, Writing—review & editing (supporting)], Peter Stas (Funding acquisition, Resources, Software [equal], Methodology, Writing—review & editing [supporting]), Claudine Lamoth (Conceptualization, Methodology [supporting], Writing—review & editing [equal]), Niels Van Royen (Conceptualization, Project administration, Writing—review & editing [equal], Funding acquisition, Supervision [lead], Methodology, Validation [supporting]), and Judith Bonnes (Conceptualization [lead], Formal analysis, Investigation, Writing—original draft [supporting], Funding acquisition, Methodology, Project administration, Validation [equal])

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Data availability

The data underlying this article will be shared on reasonable request to the corresponding author.

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