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Neurological observation assistant in healthcare (NOAH): Classifying postures and estimating disability of neurology in-patients using wearable inertial sensors

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Introduction

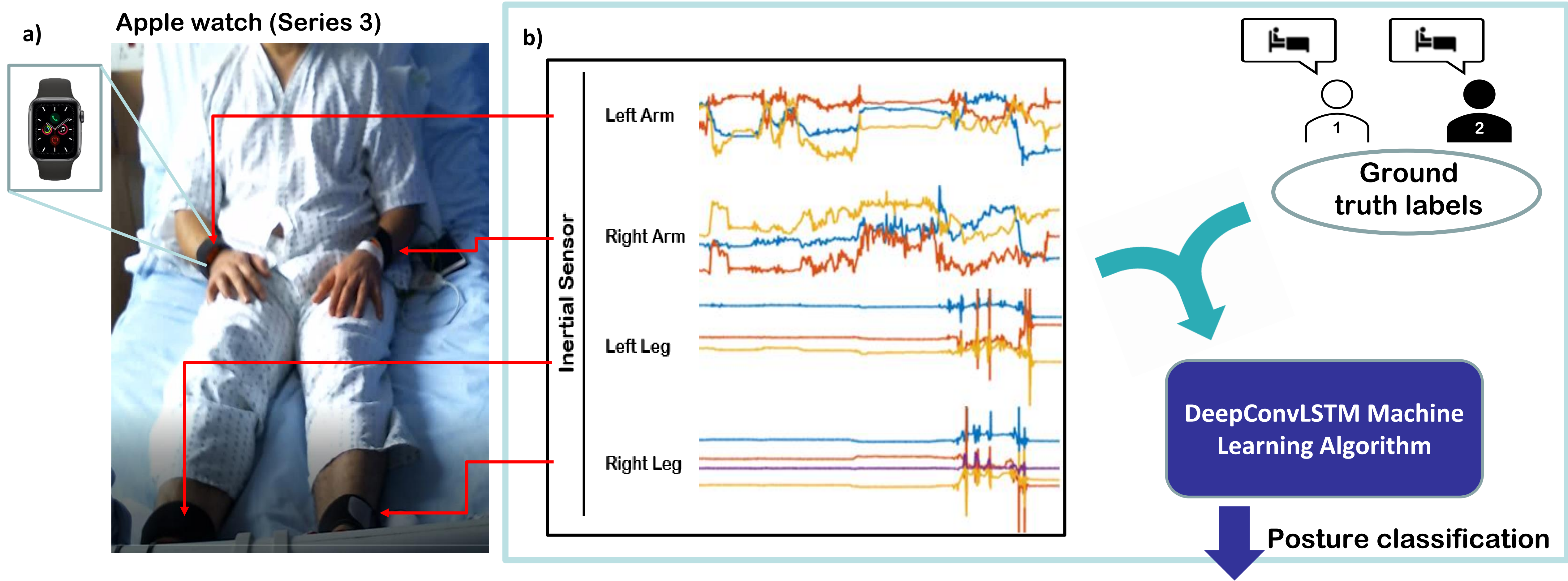
In-patient behavioural monitoring provides key insights about their cognitive and motor functional performance.[1-3] Current behavioural observations rely on intermittent and labour-intensive assessments conducted by healthcare professionals and sometimes patient self-reports.[4,5] The assessments suffer from inter-rater variability, and are subject to recall bias. Using standard wearable consumer smartwatches, our team developed an automated method to record clinical behaviours. Our project aims to address the challenges faced by gold-standard optical motion tracking and research-grade inertial sensors, such as cost, practicality, usability, and patient privacy.

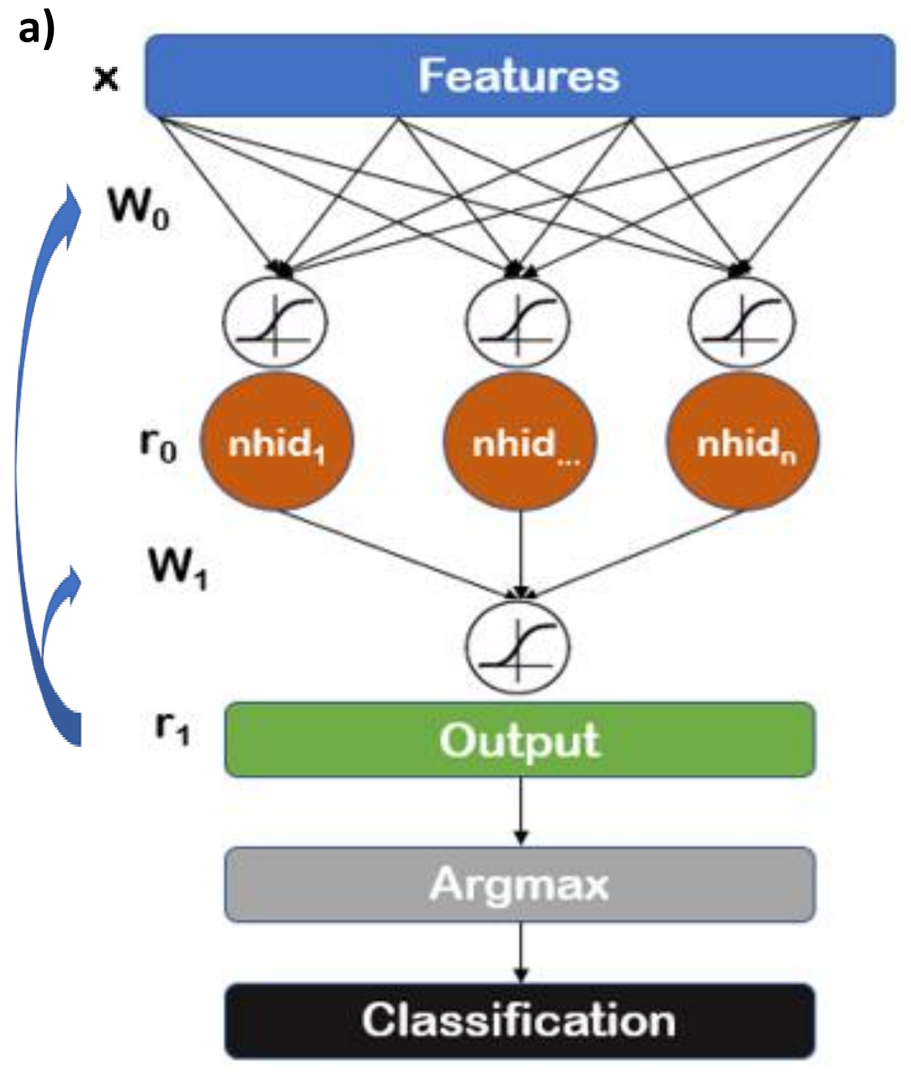
Goals:
- Continuous monitoring
- 'In-wild' behaviour with external validity
- Automatic & objective classification
- Minimal invasion to patient privacy

Methods

We recruited 44 patients (male: 23, female: 21) admitted to Charing Cross Hospital stroke unit with capacity to consent and full cognitive function. Participants wore smartwatches on their four limbs for an 'in-wild' (free-living, non-instructed) activity recording **(Fig. 1)**. Video ground truth was used to generate behaviour labels. We used this data to train a deep convolutional long-short term memory (DeepConvLSTM) model to classify whether the in-patient is **in bed, sitting in chair, standing, and walking.**[6]

Subsequently, we used the predicted percentage time spent in each posture from the model, as well as patient's anthropometric data (age, weight, and height) to train a logistic regression model for predicting 1) functional disability (modified Rankin Score ≥ 3), and 2) clinical deterioration within two weeks of the inertial sensor recording **(Fig. 2)**. All models are tested using leave-one-out cross-validation for each subject in turn, and the average performance across all subjects was calculated.





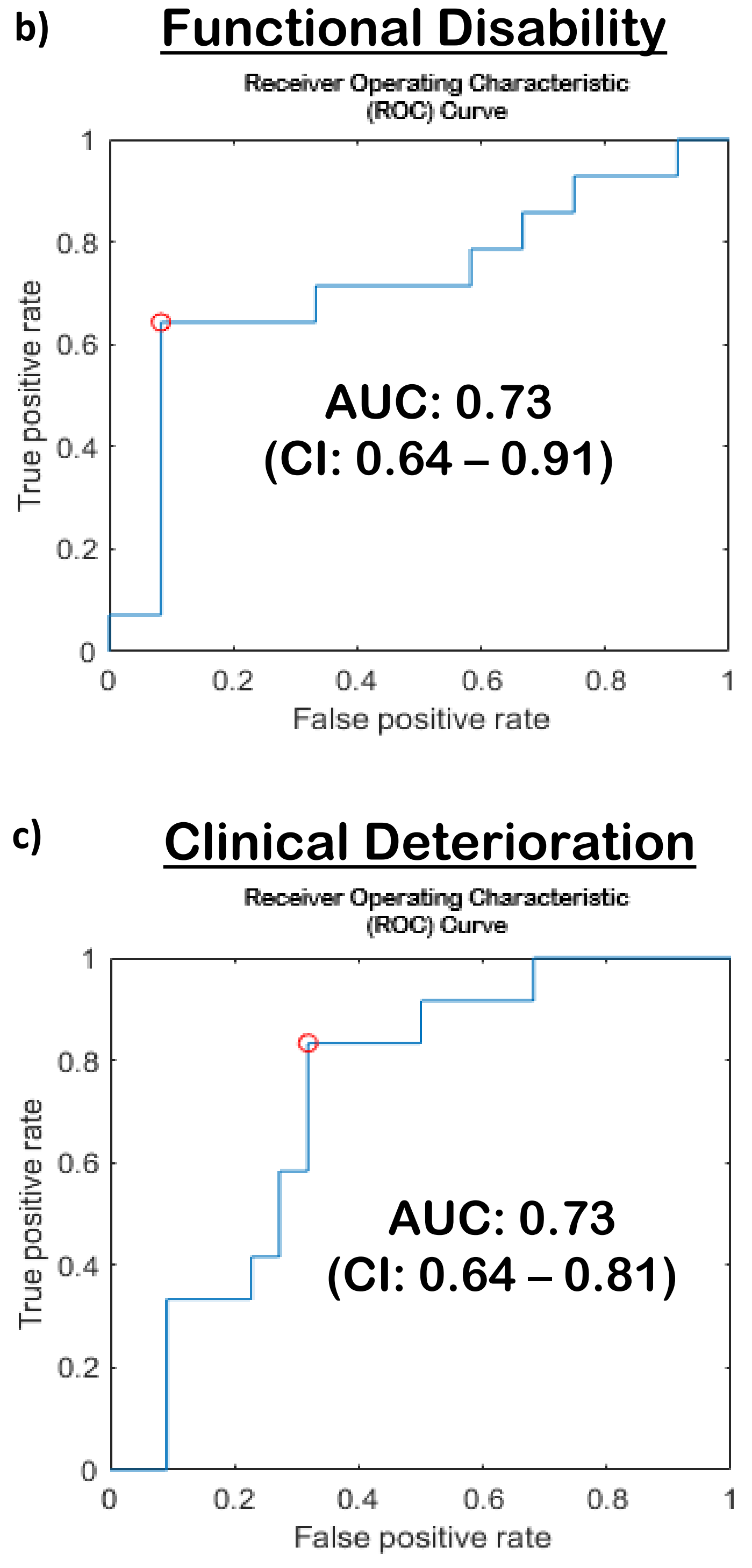
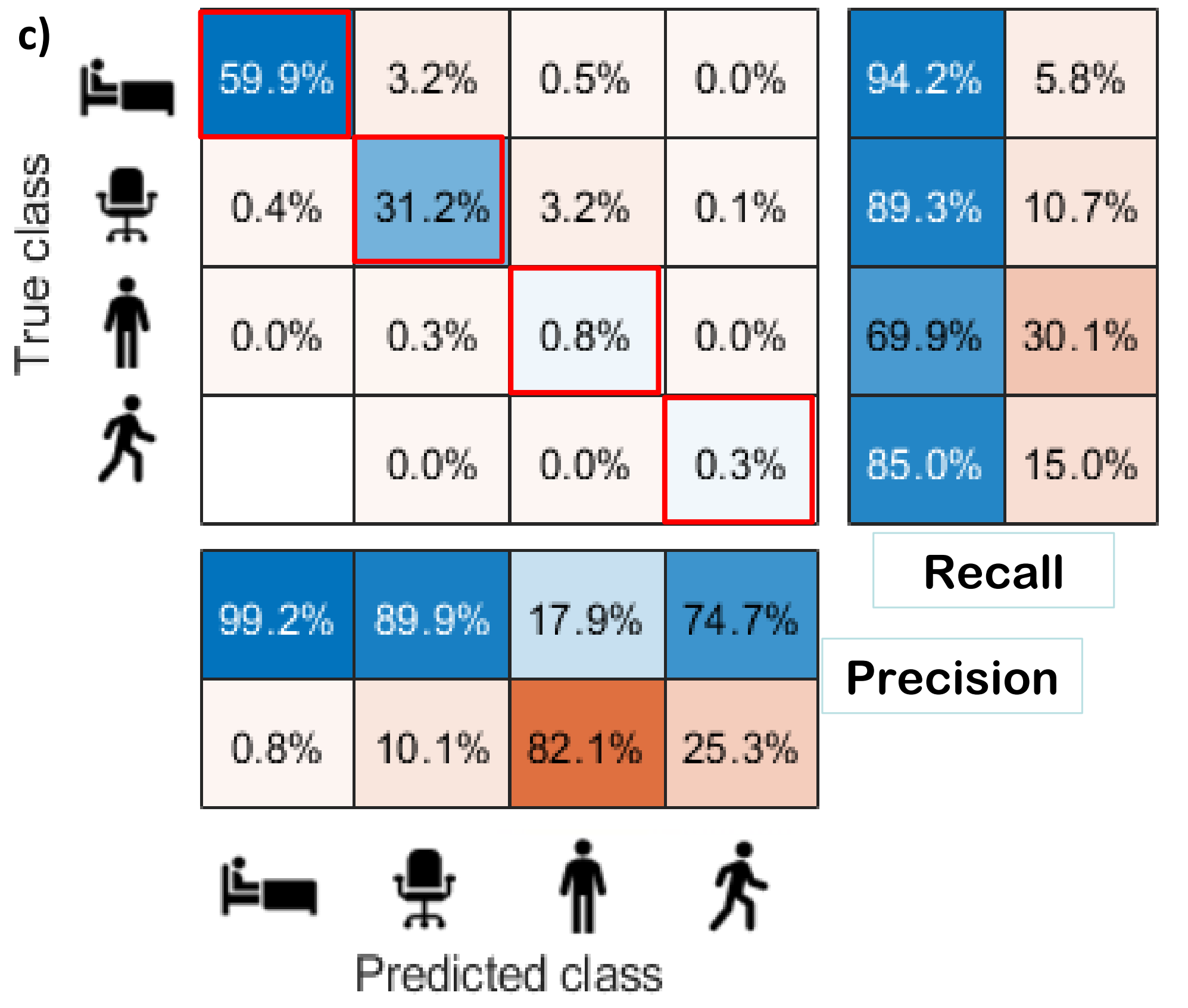


Figure 2. **a)** Two-layer Logistic Regression architecture used for the two clinical prediction models. Features includes age, height, weight, and percentage time spent in each posture from the DeepConvLSTM model. **b)** Functional disability model (modified Rankin Score ≥ 3) achieved AUC of 0.73 (CI: 0.64 – 0.91). **c)** Clinical deterioration (examples below) model achieved an AUC of 0.73 (CI: 0.64 – 0.81).



59.9%	3.2%	0.5%	0.0%	94.2%	5.8%
0.4%	31.2%	3.2%	0.1%	89.3%	10.7%
0.0%	0.3%	0.8%	0.0%	69.9%	30.1%
	0.0%	0.0%	0.3%	85.0%	15.0%
99.2%	89.9%	17.9%	74.7%		
0.8%	10.1%	82.1%	25.3%		

Figure 1. Flow chart of the posture classification process. **a)** A neurology in-patient with consumer-grade smartwatches worn on both wrists and ankles. **b)** Raw triaxial accelerometer (x, y, z axis) movement data (± 8 g) recorded from the four Apple watch (Series 3) at 100 Hertz were labelled by ground truth raters and fed into the DeepConvLSTM model. **c)** The confusion matrix demonstrating the overall prediction results, the DeepConvLSTM model achieved a weighted F1-score of 0.93 ± 0.02.

Examples of clinical deterioration
- atrial fibrillation
- crohn's disease flare
- delirium and septicemia
- symptomatic hypokalemia
- new stroke
- symptomatic UTI
- pulmonary embolism
- renal function deterioration

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Discussion

DeepConvLSTM model for 'in-wild' human activity recognition

Demonstrated posture classification in a representative in-patient population
- Inertial data collected from **free-living neurology in-patients**
- **Continuous** and **objective** classification using machine-learned features, with **minimal invasion to patient privacy**

Two-layer Logistic Regression model for Clinical Prediction

- **Functional disability model** provides a less intrusive & costly alternative to assess patient performance with similar performance to a recent study utilizing CT brain scans.[7]
- A comprehensive **clinical deterioration model** that accounts for non-neurological worsening (examples in Fig. 2), as compared to earlier literature focusing primarily on neurological deterioration.[8]

Conclusion

NOAH aims to alleviate healthcare professionals' workload by enabling continuous, objective assessments of neurological in-patient's functional performance using consumer wearable smartwatches and machine learning algorithms.

Ongoing studies are developing models to classify more complex every-day functional behaviours, such as gesticulating, eating and drinking. We hypothesize that these additional behavioural insights will serve to improve predictions of functional disability and clinical deterioration.

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