# WashSpot: Real-Time Spotting and Detection of Enacted Compulsive Hand Washing with Wearable Devices

Robin Burchard
robin.burchard@uni-siegen.de
Ubiquitous Computing,
University of Siegen
Siegen, Germany

Philipp M. Scholl
pscholl@informatik.uni-freiburg.de
Embedded Systems,
University of Freiburg
Freiburg, Germany

Roselind Lieb
lieb@unibas.ch
Dept. of Psychology,
University of Basel
Basel, Switzerland

Kristof Van Laerhoven
kvl@eti.uni-siegen.de
Ubiquitous Computing,
University of Siegen
Siegen, Germany

Karina Wahl
wahl@unibas.ch
Dept. of Psychology,
University of Basel
Basel, Switzerland

## ABSTRACT

The automatic detection of hand washing has numerous applications in work and medical environments. Checking the compliance with hygiene standard in hospitals, or personal hygiene support are examples thereof. However, hand-washing can also become pathological and is a symptom of the obsessive-compulsive disorder (OCD) spectrum. Individuals suffering from OCD are compelled to wash their hands often to the extent of harming themselves. Automatically spotting *compulsive* hand-washing throughout the day can assist therapeutic interventions by augmenting the on-going monitoring of compulsions. Based on this the therapist can gauge the efficacy of the chosen interventions. We present WashSpot, a neural-network based method to spot (*compulsive*) hand-washing on commercially available Smartwatches using inertial motion sensor data.

## CCS CONCEPTS

• **Computing methodologies** → *Neural networks*; • **Applied computing** → *Health informatics*; • **Human-centered computing** → *Ubiquitous and mobile computing*.

## KEYWORDS

Obsessive Compulsive Disorder; Hand Washing; Real-Time Detection

**ACM Reference Format:**
Robin Burchard, Philipp M. Scholl, Roselind Lieb, Kristof Van Laerhoven, and Karina Wahl. 2022. WashSpot: Real-Time Spotting and Detection of Enacted Compulsive Hand Washing with Wearable Devices. In *2022 International Symposium on Wearable Computers (ISWC '22), September 11–15, 2022, Atlanta, USA and Cambridge, UK*. ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3544793.3563428


*ISWC '22, September 11–15, 2022, Atlanta, USA and Cambridge, UK*

ACM ISBN 978-1-4503-XXXX-X/18/06…$15.00
https://doi.org/10.1145/3544793.3563428

## 1 INTRODUCTION

Obsessive compulsive disorder (OCD) is a mental disorder that affects about 1-3% of humans during their life [17, 5]. OCD shows itself in the form of intrusive thoughts that can lead to obsession and the carrying out of compulsive behavior. There are multiple subgroups of obsessions and compulsions, including contamination concerns, symmetry and precision concerns, saving concerns and more [15]. These concerns lead to respective compulsive behavior: Symmetry and precision concerns lead to arranging and ordering, saving concerns lead to hoarding and contamination concerns can lead to excessive washing, bathing and showering, including compulsive hand washing. By spotting those automatically diary-like entries for later revision with a therapist could be created or even simple interventions (e.g. issuing a warning, vibration or sound) could be provided, if the detection delay is small.

Previously published methods for the detection of hand washing or its steps rely on a multitude of different machine learning algorithms. One study was able to recognize 13 steps of a hand washing procedure on wrist motion data with an accuracy of 85 % with a sliding window feature-based hidden markov model (HMM) and running a continuous recognition [8]. Sensor wristbands can be used to assess the user's compliance with given hand washing hygiene guidelines by detecting different steps of a scripted hand washing routine[19]. By using an LSTM-based neural network, this approach can be extended to prompting the user, if they confuse the order of the steps or forget one of the steps [4]. The hand washing step detection technology can also be used to support elderly patients with dementia. More complicated hybrid network architectures can be used to improve single step detection or to rate the quality of hand washing procedures [20, 12]. An approach for separating hand-washing from possibly confounding activities, for example brushing one's teeth, is out-of-distribution detection [13].

Our approach is based on the application of neural networks for human activity recognition (HAR). Frequently used architectures reach from fully connected networks [13] over convolutional neural networks (CNNs) [21], long short term memory (LSTM) with or without attention [22] to a combination of CNN and LSTM layers, DeepConvLSTM with one or two LSTM layers [9, 3]. Recently, DeepConvLSTM combined with an attention mechanism

(DeepConvLSTM-A) was shown to perform better than plain DeepConvLSTM on some data sets [14].

Related work is mostly concerned with WHO-compliant hand-washing, however enacted compulsive and non-compulsive hand-washing can be separated [18] with F1 score from 0.65-0.87. We extend this approach by showing that (enacted compulsive) hand-washing can be successfully spotted in all-day wrist motion recordings, and that compulsive and non-compulsive hand-washing can be separated. WashSpot spots (enacted compulsive) hand washing in inertial sensor data typically found in Smartwatches. It provides an online detection of hand washing to supplement therapy for patients suffering from cleanliness OCD. We contribute:

(1) a method to spot and distinguish enacted compulsive and non-compulsive hand-washing in all-day inertial wrist motion recordings.
(2) a deep learning architecture which can be executed on resource-constrained devices like commercial Smartwatches.
(3) an outline of how to use online-detection of hand-washing for semi-automatic labeling of real-world data.

## 2 SPOTTING HAND-WASHING

We compared six artificial neural network architectures: Fully Connected (FC), convolutional neural network (CNN), Long-Short-Term-Memory (LSTM), LSTM with attention (LSTM-A), DeepConvLSTM, and DeepConvLSTM with attention (DeepConvLSTM-A). The respective architectures are displayed in Fig. 1, and are similar to the architectures used in other papers [13, 21, 22, 9, 3, 14]. All neural networks use ReLU as activation function and were trained with ADAM [6] in PyTorch [10], using early-stopping with a validation set consisting of 15 % of the training data.

In order to spot hand washing in real-world activity, a neural network was then exported into a smart watch application which is able to run on any recent Android-based Smartwatch. The watch continuously records the data from the integrated inertial measurement unit (IMU) at 50Hz. To filter out the most basic idle case of "no movement" a threshold $v_{idle}$ is applied to all sensor values. The neural network is only run when this threshold is exceeded. Then, a forward pass of the neural network model is done with the data of the window. This thresholding ensures that the energy consumption of the application is kept as low as possible, as even a forward pass is computationally expensive. If the Smartwatch detects a hand washing activity in multiple consecutive windows (3s), a notification is sent. The Smartwatch only sends this notification if the mean of the last 20 predictions is higher than an empirically set threshold $t_{notify}$. This ensures that single outliers do not trigger user notifications. The user is then prompted to confirm the correctness of the classification (*"Did you just wash your hands?"*) and subsequently also queried about the type of hand wash, i.e. whether it was compulsive or not and to rate their current stress level. The application can thus collect new data for future research with semi-automatic and interactive labeling. Fig. 2 shows the execution flow of the classification loop that is continuously running on the Smartwatch.

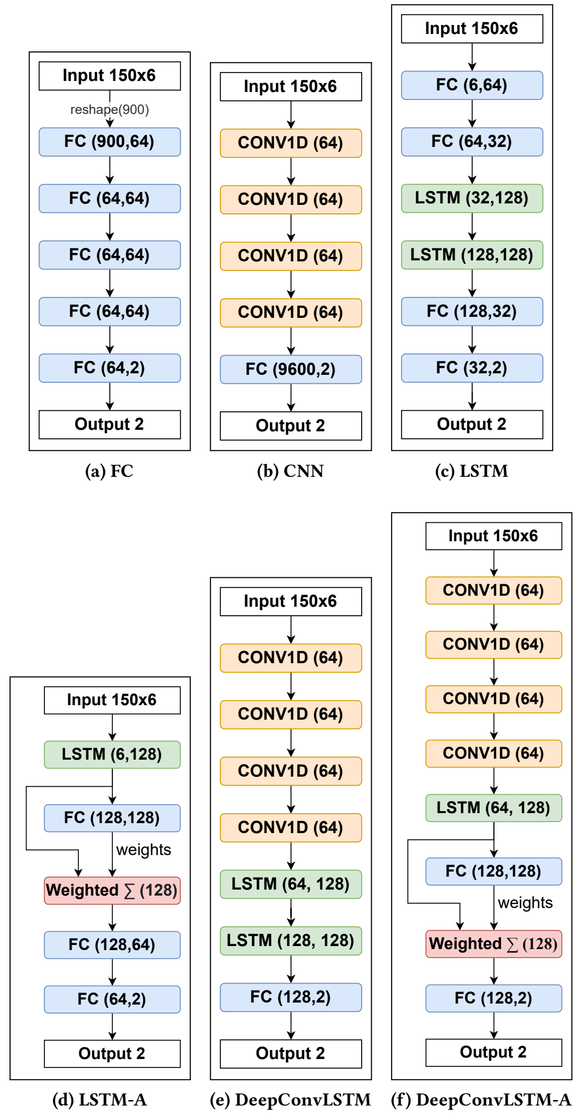


**Figure 1: Network Architectures. DeepConvLSTM and DeepConvLSTM-A are amongst the best performing models currently used in other HAR tasks.**

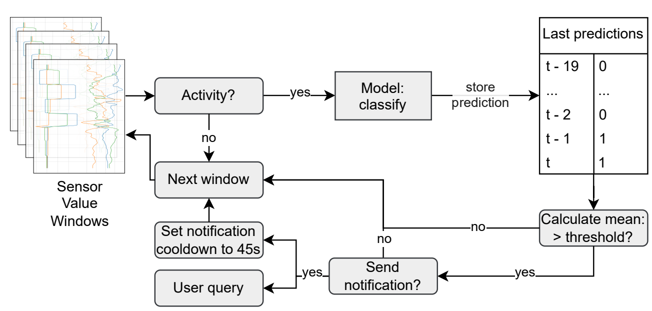


**Figure 2: Flow diagram of the smart watch classification loop. A notification is only sent, if the notification cooldown is 0.**

**Table 1: Data sets and activities contained in our combined data set. The first three data sets stem from our group's collection, the rest are external publicly available data sets. The collected data contains routine hand washing (HW), enacted compulsive hand washing (HW-C) and other activities (Null).**

| Dataset name | Contained activities | |
|---|---|---|
| OCDEnact | (compulsive) hand washing | 50Hz |
| ConfoundWash | confounding and washing | 50Hz |
| All-Day | activities of daily living | 50Hz |
| WISDM [7] | movement | 20Hz |
| RealWorld [16] | movement | 50Hz |
| REALDISP [2] | movement & exercising | 50Hz |
| PAMAP2 [11] | movement, sports, household chores, desk work | 100Hz |
| **Activity** | **Amount of windows (3s)** | **Share** |
| Null | 178480 | 91.9 % |
| HW | 5513 | 2.8 % |
| HW-C | 10251 | 5.3 % |

## 3 EVALUATION

In order to train the artificial neural network models, a collection of data sets was created. For handwashing we used data from [18]. This includes data collected under ethical approval of the University of Basel with data from enacted OCD hand-washes, of confounding activities (brushing teeth, peeling carrots, and dish washing), and all-day recordings of daily activities. For enacted compulsive handwashing, participants were asked to follow a pre-defined protocol stemming from the observational experiences of clinically treated patients. In total five differents hand-washing protocols were executed by 21 participants (cf. [18]). Added to those data sets, we used publicly available data sets of human activities such as activities of daily living and sports. All collected data sets were re-sampled to 50Hz, if necessary. Only data from wrist worn IMUs was used, namely the accelerometer and gyroscope data (both 3-axes). The description of the used data sets is shown in Table 1.

The final, combined, data set used to train WashSpot contains a total of 14.4 million 6-dimensional data points. With these 14.4 million data points we created windows, each of length 150 samples (3s) with 50% overlap. This left us with 194,000 windows. Out of those windows, 15,750 (8, 2%) contained hand washing, 178,500 (91, 8%) were other activities or idle (Null). Out of the 15,750 hand washing windows, 10,250 (65%) were enacted compulsive hand washing windows (HW-C), 5500 (35%) were non compulsive washing (HW).

To avoid a bias towards the more frequent classes, we used a class-weighted version of the cross-entropy loss function. The weights passed to PyTorch's implementation of the cross-entropy loss were calculated as follows:

$$w_{class} = \frac{n_{total}}{n_{classes} \cdot n_{class}} \tag{1}$$

Here, $n_{total}$ is the total amount of sample windows in the training set, $n_{classes} = 3$ and $n_{class}$ is the amount of windows of each specific class. Multiplying the loss of each forward pass with the weight of its true label's class weight balances each classes' influence on the model parameter update. The formulated classification problem is to spot hand washing (HW) and enacted compulsive hand washing (HW-C) separately and distinguish both from other activities (Null). The data was split into a train set (85% of recordings) and a test set (15% of recordings). Additionally we made sure that no participant appeared in both training and test data. This ensures that the model generalizes independently of personal motion patterns.

To evaluate the trained models, they were applied to the test set and evaluated with different metrics. The harmonic mean of recall and precision, i.e. the F1 score is commonly used to evaluate binary prediction tasks. For our three-class classification problem we therefore report the *F1 score multi* [22]. F1 score multi is calculated by taking the mean over all classes $\mathbf{C}$, of the F1 scores if we treat the class $\mathbf{C}_i, i \in [0, 1, 2]$ as the positive class, and the remaining classes as the negative class: $F_1\ score\ multi = \frac{1}{3} \cdot \sum_{i=0}^{2} F_1\ score(\mathbf{C}_i)$. We also report the mean diagonal value (MDV) of the confusion matrix. Both these scores indicate the probability of spotting both enacted compulsive and non-compulsive hand-washing.

The best model (DeepConv-LSTM-A) was converted to ONNX [1] runtime (ORT) format using *torch.onnx* for execution on a smart watch, namely an Android-based TicWatch. The ORT model is around 1 $MB$ in size and no further measures were required in order to run it with ONNX's Android runtime. It was able to run in real-time, to predict hand washing and to notify the user of the detection. The user was subsequently queried whether detection was correct. The battery of the smart watch lasted through an entire day of recording and only had to be charged at night.

## 4 RESULTS

The different model architectures were executed on the test set which contains recordings from unseen participants. The performance of the models was then assessed by comparing the respective F1 scores and the confusion matrices. All models tested reached a performance level in the range of 0.62 to 0.69 (F1 score multi) and 0.624 to 0.712 (mean diagonal value (MDV)), as reported in Table 2. In line with results found in literature, the DeepConvLSTM variants performed best with an F1 score of 0.692 and MDV of 0.712 for the model with the self-attention mechanism and an F1 score of 0.676 and MDV of 0.701 for the model without it. The attention mechanism also leads to improved performance for the LSTM based network without convolutional layers.

The confusion matrices for each classifier are shown in Fig. 3. The highest accuracies could be reached for the HW-C class, with values ranging from 0.72 % (CNN) up to 0.88 % (LSTM). Similarly, the accuracies achieved for the HW class were high (from 70 % (FC) up to 79 % (DeepConvLSTM)) with exception of the CNN (51 %). However, the accuracy for the Null class was low, ranging from 33 % (LSTM) to 64 % (CNN). We found that most incorrect predictions made for Null samples were attributed to the HW class by the models (around 30 %) versus only around 20 % for HW-C. The reason for this may be that some of the activities in the null class were designed to be confounding, i.e. washing a cup, peeling a carrot or brushing ones teeth. The HW samples were most confused with HW-C samples (around 18 %) versus 10 % for the Null class. HW-C samples were misclassified into the Null class (10 %), although the

**Table 2: Scores of (Enacted Compulsive) Hand Washing Detection. F1 score is for combined hand-washing detection, mean diagonal value (MDV) refers to the mean of the diagonal of the confusion matrix. The deep convolutional LSTM with attention performs best.**

| modelclass | F1 score multi | MDV |
|---|---|---|
| FC | 0.647 | 0.664 |
| CNN | 0.621 | 0.624 |
| LSTM | 0.629 | 0.665 |
| LSTM-A | 0.665 | 0.679 |
| DeepConvLSTM | 0.676 | 0.701 |
| **DeepConvLSTM-A** | **0.692** | **0.712** |

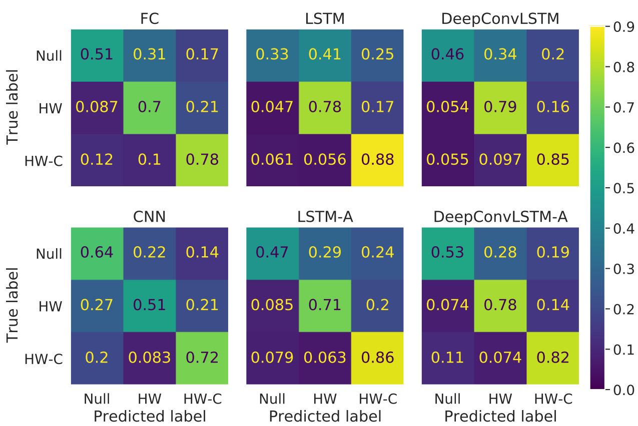


**Figure 3: Confusion Matrices for (Enacted Compulsive) Hand Washing Classification. DeepConvLSTM-A performs best, followed by DeepConvLSTM. The HW and HW-C classes were predicted with high accuracy. The Null class was most confused with routine hand washing.**

difference to HW (8 %) was smaller. These trends were observed for the majority of models. Overall this means that hand washing and enacted compulsive hand washing were detected with a high sensitivity. However, lower scores for the Null class indicate a lower specificity than desired.

Based on the reported performance measures, DeepConvLSTM-A was selected to be used in the WashSpot smart watch application. For our online detection of hand washing we combined the HW-C and HW classes into a new positive class HW-ALL, leaving the Null class untouched. The spotting of activities from any of the categories of hand washing can be done with the same 3-class pretrained model, by assigning the HW and HW-C class predictions to HW-ALL. A slightly better performance could likely be achieved by directly training a binary classification model instead.

## 5 DISCUSSION

We propose WashSpot, a system to detect (compulsive) hand washing from inertial sensors typically found in current smartwatches. Our system can be installed on current Android smart watches to execute real-time detection of hand washing. We explain the relevance of the proposition as a supplement in the therapy for patients suffering from cleanliness OCD. Besides the main goal of spotting hand washing for therapeutic purposes, the system can aid at collecting new inertial measurement data for further increasing the performance of future models.

Our system's reported prediction accuracy is lower than in hand washing (step) detection work in literature. However, we argue that the problem it tackles is harder: Instead of detecting a step out of a fixed script, or detecting hand washing conducted in a constrained style, we try to detect all kinds of hand washing and distinguish it from all kinds of activities that can be found in other data sets for HAR. The Null class of irrelevant activities also contained confounding activities, which increases the difficulty further. To improve the performance on the Null class, even more data of confounding activities that are similar to hand washing could be used to train the model. Improvements of the real world perceived performance are also likely achieved by the thresholding on past prediction values. By only sending a notification if a consecutive window of 10s was classified mostly as hand washing, the false positive rate is reduced.

Unlike other systems to spot hand washing, WashSpot does not rely on external cues to spot a hand washing procedure conducted by the user. While external cues such as proximity to a Bluetooth beacon or a camera mounted to a sink could improve the performance, they also limit the applicability of the respective solutions to the spaces in which such systems are present. As the compulsive hand washing can be conducted anywhere, it is critical that our system abstains from dependencies to external cues.

Future work in this area should focus on obtaining sensor data of real-world compulsive hand washing patterns by conducting a study with patients suffering from cleanliness OCD. WashSpot together with models trained on the then collected data will likely be able to supplement the treatment of the patients, which would need to be evaluated in a clinical study.

## 6 CONCLUSION

We presented WashSpot, a system to spot compulsive and non-compulsive hand-washing on commercially available Smartwatches. The system was tested on enacted compulsive hand-washes combined with a dataset of all-day recordings, a dataset of possibly confounding activities and several publicly available wrist-motion datasets, which cover a total of 80h, of which ∼ 7h were hand-washing. We estimated the prediction performance by testing on 15 % of this data, on which the DeepConvLSTM-A model achieves an F1-score 69.2 % for spotting (compulsive) hand-washes. Running this model on a commercial Smartwatch (TicWatch E2, 310mA h) results in a runtime of 8h. As such the proposed smart watch application can supplement therapy of patients suffering from OCD by spotting hand washing activities.

## ACKNOWLEDGMENTS

*We would like to thank all participants. This work was partially funded by EUCOR - The European Campus - Seed Money. The funding body had no involvement in study design; collection, analysis nor interpretation of data.*

# REFERENCES


[1] Junjie Bai, Fang Lu, Ke Zhang, et al. 2019. Onnx: open neural network exchange. https://github.com/onnx/onnx. (2019).

[2] Oresti Baños, Miguel Damas, Héctor Pomares, Ignacio Rojas, Máté Attila Tóth, and Oliver Amft. 2012. A benchmark dataset to evaluate sensor displacement in activity recognition. In *Proceedings of the 2012 ACM Conference on Ubiquitous Computing* (UbiComp '12). Association for Computing Machinery, New York, NY, USA, (Sept. 5, 2012), 1026–1035. ISBN: 978-1-4503-1224-0. DOI: 10.1145/2370216.2370437.

[3] Marius Bock, Alexander Hölzemann, Michael Moeller, and Kristof Van Laerhoven. 2021. Improving deep learning for HAR with shallow LSTMs. In *2021 International Symposium on Wearable Computers*. UbiComp '21: The 2021 ACM International Joint Conference on Pervasive and Ubiquitous Computing. ACM, Virtual USA, (Sept. 21, 2021), 7–12. ISBN: 978-1-4503-8462-9. DOI: 10.1145/3460421.3480419.

[4] Yetong Cao, Huijie Chen, Fan Li, Song Yang, and Yu Wang. 2021. AWash: handwashing assistance for the elderly with dementia via wearables. In *IEEE INFOCOM 2021 - IEEE Conference on Computer Communications*. IEEE INFOCOM 2021 - IEEE Conference on Computer Communications. ISSN: 2641-9874. (May 2021), 1–10. DOI: 10.1109/INFOCOM42981.2021.9488688.

[5] Emily J. Fawcett, Hilary Power, and Jonathan M. Fawcett. 2020. Women are at greater risk of OCD than men: a meta-analytic review of OCD prevalence worldwide. *The Journal of Clinical Psychiatry*, 81, 4, (June 23, 2020), 0–0. Publisher: Physicians Postgraduate Press, Inc. DOI: 10.4088/JCP.19r13085.

[6] Diederik P. Kingma and Jimmy Ba. 2017. Adam: a method for stochastic optimization. *arXiv:1412.6980 [cs]*, (Jan. 29, 2017). Retrieved Oct. 18, 2021 from http://arxiv.org/abs/1412.6980 arXiv: 1412.6980.

[7] Jennifer R. Kwapisz, Gary M. Weiss, and Samuel A. Moore. 2011. Activity recognition using cell phone accelerometers. *ACM SIGKDD Explorations Newsletter*, 12, 2, (Mar. 31, 2011), 74–82. DOI: 10.1145/1964897.1964918.

[8] Hong Li, Shishir Chawla, Richard Li, Sumeet Jain, Gregory D. Abowd, Thad Starner, Cheng Zhang, and Thomas Plotz. 2018. WristWash: towards automatic handwashing assessment using a wrist-worn device. *Proceedings - International Symposium on Wearable Computers, ISWC*, 132–139. ISBN: 9781450359672. DOI: 10.1145/3267242.3267247.

[9] Francisco Ordóñez and Daniel Roggen. 2016. Deep convolutional and LSTM recurrent neural networks for multimodal wearable activity recognition. *Sensors*, 16, 1, (Jan. 18, 2016), 115. DOI: 10.3390/s16010115.

[10] Adam Paszke et al. 2019. PyTorch: an imperative style, high-performance deep learning library. In *Advances in Neural Information Processing Systems*. Vol. 32. Curran Associates, Inc. Retrieved Oct. 7, 2021 from https://proceedings.neurips.cc/paper/2019/hash/bdbca288fee7f92f2bfa9f7012727740-Abstract.html.

[11] Attila Reiss and Didier Stricker. 2012. Introducing a new benchmarked dataset for activity monitoring. In *2012 16th International Symposium on Wearable Computers*. 2012 16th International Symposium on Wearable Computers. ISSN: 2376-8541. (June 2012), 108–109. DOI: 10.1109/ISWC.2012.13.

[12] Sirat Samyoun, Sudipta Saha Shubha, Md Abu Sayeed Mondol, and John A. Stankovic. 2021. iWash: a smartwatch handwashing quality assessment and reminder system with real-time feedback in the context of infectious disease. *Smart Health (Amsterdam, Netherlands)*, 19, (Mar. 2021), 100171. DOI: 10.1016/j.smhl.2020.100171.

[13] Md Abu Sayeed Mondol and John A. Stankovic. 2020. HAWAD: hand washing detection using wrist wearable inertial sensors. In *2020 16th International Conference on Distributed Computing in Sensor Systems (DCOSS)*. 2020 16th International Conference on Distributed Computing in Sensor Systems (DCOSS). IEEE, Marina del Rey, CA, USA, (May 2020), 11–18. ISBN: 978-1-72814-351-4. DOI: 10.1109/DCOSS49796.2020.00016.

[14] Satya P. Singh, Aimé Lay-Ekuakille, Deepak Gangwar, Madan Kumar Sharma, and Sukrit Gupta. 2021. Deep ConvLSTM with self-attention for human activity decoding using wearables. *IEEE Sensors Journal*, 21, 6, (Mar. 15, 2021), 8575–8582. arXiv: 2005.00698. DOI: 10.1109/JSEN.2020.3045135.

[15] Dan J Stein. 2002. Obsessive-compulsive disorder. *The Lancet*, 360, 9330, (Aug. 3, 2002), 397–405. DOI: 10.1016/S0140-6736(02)09620-4.

[16] Timo Sztyler and Heiner Stuckenschmidt. 2016. On-body localization of wearable devices: an investigation of position-aware activity recognition. In *2016 IEEE International Conference on Pervasive Computing and Communications (PerCom)*. 2016 IEEE International Conference on Pervasive Computing and Communications (PerCom). (Mar. 2016), 1–9. DOI: 10.1109/PERCOM.2016.7456521.

[17] LAURA A. Valleni-basile, CAROL Z. Garrison, KIRBY L. Jackson, JENNIFER L. Waller, ROBERT E. McKEOWN, CHERYL L Addy, and STEVEN P. Cuffe. 1994. Frequency of obsessive-compulsive disorder in a community sample of young adolescents. *Journal of the American Academy of Child & Adolescent Psychiatry*, 33, 6, (July 1, 1994), 782–791. DOI: 10.1097/00004583-199407000-00002.

[18] Karina Wahl, Philipp Marcel Scholl, Silvan Wirth, Marcel Miché, Jeannine Häni, Pia Schülin, and Roselind Lieb. 2022. On the automatic detection of enacted compulsive hand washing using commercially available wearable devices. *Computers in Biology and Medicine*, 143, (Apr. 2022), 105280. DOI: 10.1016/j.compbiomed.2022.105280.

[19] Chaofan Wang, Zhanna Sarsenbayeva, Xiuge Chen, Tilman Dingler, Jorge Goncalves, and Vassilis Kostakos. 2020. Accurate measurement of handwash quality using sensor armbands: instrument validation study. *JMIR mHealth and uHealth*, 8, 3, (Mar. 26, 2020), e17001. DOI: 10.2196/17001.

[20] Fei Wang, Xilei Wu, Xin Wang, Jianlei Chi, Jingang Shi, and Dong Huang. 2021. You can wash better: daily handwashing assessment with smartwatches. (Dec. 9, 2021). Retrieved July 12, 2022 from http://arxiv.org/abs/2112.06657 arXiv: 2112.06657[cs,eess].

[21] Jian Bo Yang, Minh Nhut Nguyen, Phyo Phyo San, Xiao Li Li, and Shonali Krishnaswamy. 2015. Deep convolutional neural networks on multichannel time series for human activity recognition. *Proceedings of the 24th International Joint Conference on Artificial Intelligence (IJCAI)*, (July 25, 2015), pp. 3995–4001.

[22] Ming Zeng, Haoxiang Gao, Tong Yu, Ole J. Mengshoel, Helge Langseth, Ian Lane, and Xiaobing Liu. 2018. Understanding and improving recurrent networks for human activity recognition by continuous attention. In *Proceedings of the 2018 ACM International Symposium on Wearable Computers*. UbiComp '18: The 2018 ACM International Joint Conference on Pervasive and Ubiquitous Computing. ACM, Singapore Singapore, (Oct. 8, 2018), 56–63. ISBN: 978-1-4503-5967-2. DOI: 10.1145/3267242.3267286.