Utilizing Smartwatches for Supporting the Wellbeing of Elderly People

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***Abstract* — We present a new approach for securing the wellbeing of elderly people via a smartwatch based personal health assistant. On the smartwatch, an app featuring an artificial neuronal network (ANN) analyzes the activity patterns of the smartwatch wearer. The ANN recognizes health relevant events and activities of daily living (EDLs, ADL). Especially activities associated with body care tasks are considered. From the sequence and timing of recognized EDLs, ADLs, an individual wellbeing function will be continuously calculated, summarizing the specific personal health state. If the wellbeing function value falls below a defined threshold, external alerts will be issued by the smartwatch. Such alerting will be done automatically, if the smartwatch wearer is not able to respond. It can be done autonomously via the integrated cellular radio module of the smartwatch. The system architecture of the app, the data acquisition process, the selection and design of suitable data models and the advantages of ANNs versus other recognition engines are discussed.**

Keywords* — *smartwatches; automatic recognition of activities, events of daily living (ADLs, EDLs); artificial neuronal networks (ANN); universal recognition model; wellbeing function.

I. INTRODUCTION

A self-determined and safe living of elderly people in their familiar home, as long as possible, is a desirable objective for many of us. Ambient intelligent assistance technologies safeguard such a life by regularly monitoring the wellbeing and potential health hazards. Programmable smartwatches are one of the most promising devices for such health assistance technologies, because i) they carry many of the necessary sensors for monitoring wellbeing and health parameters on board, ii) do not require expensive demolition / construction work at home and iii) can be used at home as well as outdoors. Moreover, they are available at reasonable costs. In our work, we focus on mainstream smartwatches with an integrated mobile cellular radio (like the Samsung Gear™ 3G, LG Urbane LTE™ 2 or Sport™, Huawei Watch 2™). These smartwatches allow to establish a speech connection autonomously to clarify the situation on the spot in case of a concluded emergency [1]. Moreover, relevant data (e.g., current geographic position of the smartwatch wearer, the heart rate) can be transferred directly and without the (necessary) additional utilization of a smartphone (as it is the case for the Apple Watch 2™).

Current smartwatches directly can only measure the performed steps of the smartwatch wearer and/or the heart rate, pulse. All other aspects of the wellbeing and potential health hazards for the smartwatch wearer must be concluded form condensed sensor data and suitable comparisons with data acquired, learned from the past. A common approach is to recognize - using the smartwatch sensors - those *activities of daily living* (ADLs) which are present in a healthy life of everyone and structure the days and nights. The conclusions about the wellbeing will then be based on the *presence, duration* and *intervals* between those recognized activities of daily living. Direct health hazards – like tumbles/falls, heart palpitations – need to be considered and recognized by the smartwatch sensors (as events of daily living, EDLs).

After a short description of relevant previous work in Section II we present our system architecture in Section III. This section also addresses the selection of a suitable set of EDLs, ADLs for the purposes of our app. The research questions around EDL, ADL recognition are described in Section IV. For answering the research question regarding the aptitude of a *universal recognition model,* our experiment is described in closer detail in Section V. Results of the experiment are presented in Section VI. This section also widens up the discussion on critical issues of present smartwatch technology and the inherent difficulties of recognizing (the EDL) *»tumbling«.*

II. PREVIOUS WORK

ADLs [2] have been a central issue in organizing professional nursing practice and for determining the independency status of elderly people, introduced by Sidney Katz more than 60 years ago. Automatic EDL, ADL recognition in smart homes has been a focal research point for supporting the elderly [3].

Suryadevara and Mukhopadhyvay [4] have proposed a wellbeing function w based on the components *absence* and *excess duration of ADLs.* Their approach stems on a rich instrumentation of the household by a net of wireless sensors. The wellbeing function w maps the recognized ADLs and their characteristics into $[0,1] \subset \Re$. For ideal wellbeing, the function value of w is 1; if the function value falls below a defined threshold (e.g., 0.5), a health alert is issued. In [5], we have extended the w definition for accounting a third independent wellbeing component *agility*, which measures the typically step distribution walked over the course of the day by the smartwatch wearer. The nominal values for a typical interval between the ADLs, the typical execution time of a specific ADL and the typical step sum achieved by a specific hour of the day all are individual values and specific for a certain day of the week. These nominal values have to be acquired by an initial training phase of the system with at least a one-week duration and will be further adapted by time series analysis [4] [5], taking into account also seasonal factors.

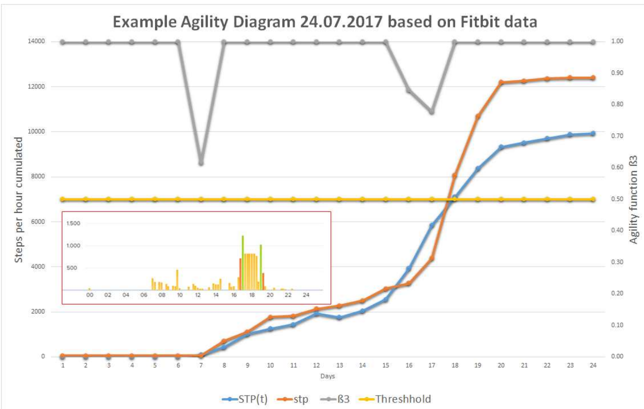

Figure 1: Typical agility for a 24-hour period.

When no recognized ADL in the household is taking place, $ß_1$, the wellbeing sub-function for *inactivity* measurement, is applied based on the definition in [4] as $ß_1(t, T) = e^{-t/2*T}$, where t is the current (time) duration of inactivity since completion of the last recognized ADL, and T is the specific average inactivity between ADLs learned from the past for the current day of the week. On the opposite, as long as a recognized ADL is ongoing, $ß_2$, the wellbeing sub-function for the measurement of *excess duration* of this specific ADLs will be applied, which has been defined in [4] to $ß_2(TN, ta) = e^{(TN - ta) / TN}$, for ta > TN; 1, otherwise where ta is the actual duration of the (ongoing) ADL and TN is the specific maximum duration of the corresponding recognized ADL in a normal situation learned from the past for the current day of the week. The agility subfunction $ß_3$ measuring the movement profile of a person at current time t is defined in [5] to

$$ß_3(t, stp, STP) = \begin{cases} e^{\frac{(stp(t) - STP(t))}{STP(t)}}, for\ stp(t) < STP(t) \wedge \neg E_1 \\ 1, for\ stp(t) \geq STP(t) \wedge \neg E_1 \\ 0, if E_1 = tumble \end{cases}$$

where stp(t) is the sum of steps performed during the current day until actual time t, F(t) is the cumulative distribution function of steps over the day, SN is the specific total number of steps learned from the past for the current day of the week and with STP(t) = SN*F(t) estimated from the nominal step sum for the current day at time t. $ß_3$ will be calculated all over the day, Figure 1 shows a typical distribution of daily steps for a 24-hour period based on an $\alpha = 0.1$ (giving heavy weights for historical values). Left scale denotes the accumulated steps (orange: actual steps of the day, blue: the estimated accumulated steps for the period, grey: the agility value $ß_3$ and yellow: the threshold for $ß_3$). The small subfigure inside denotes the step distribution on a 15 minutes basis. As can been seen the agility value is far above the threshold indicating that no agility problems are present. One exception is the period around 6pm. The decline can be explained by a later get up in the morning.

The wellbeing function w: SensoricEvents -> [0,1], $[0,1] \subset \Re$, will be formally defined as:

$$w = \min \{ß_1, ß_2, ß_3\}$$

This means that whenever the *inactivity* (missing any recognized ADL) or the *excess duration* of an ongoing activity category or the lacking *agility* gets critical and the w value falls below 0.5, a *health hazard alert* will be issued.

Lacking *agility,* which we added to the Suryadevara and Mukhopadhyvay wellbeing definition [4], is often overlooked in daily nursing activities. It is one of the symptoms of dementia, a typical indication of pain and not unusual consequence of age related complaints for elderly people [6]. In our context, we focus on the subset of basic ADLs, which

- can be recognized by the usual integrated smartwatch sensors (*3D accelerometers, and gyros, magnetometer, barometer, heart rate monitor / pulsometer, GPS for the smartwatch class chosen)* and communication technologies *(Bluetooth, Wi-Fi, 3G/4G cellular)*
- will be typically carried out each single day and by everyone, independent from culture and/or sex, ideally independent from a dominant hand (on the wrist of which the smartwatch has to be worn),
- will be carried out multiple times within a day and thus allow for a preferably equidistant partitioning and structuring of the day / night.

With respect to their eminent negative health consequence for the targeted user group, additionally the EDL »*tumbling«* needs to be considered. One third of all elderly persons of age of 65 or more tumble at least one time per year [23].

III. System Design Considerations

A. System Structure

The implemented system, smartwatch app, utilizes the Samsung Gear™ S smartwatch device for providing assistance in the four dimensions: I) *communication* (manually and automatically established speech connections to family members on duty or a home emergency call center), II) *orientation*, III) *localization* and IV) *health hazard detection.* The implemented scope of personal health assistance is described in [1] [5] in closer details, Figure 2 shows some screenshots. Figure 3 depicts a block diagram of the smartwatch personal health assistance app with its layered architecture: layer 0: smartwatch HW with sensors, I/O; layer 1: smartwatch OS; layer 2: motion analysis via ANN and location analysis via GPS monitoring – geofencing; layer 3: simultaneous health hazard recognition handling via a multitude of simultaneously running finite state machines; layer 4: health hazard presentation and dialogue control vis a blackboard based scheduler more architectural details can be found in [7] [8].

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The application architecture is based on a hierarchical structure. On the lower layer the EDL, ADL recognition via a ANN takes place (see section III). The recognized EDLs, ADLs will evoke actions in a structured description of the *health hazard handling* process executed on the upper layer. Health hazard handling is described in a declarative way via UML (finite) state machines. This declarative description is well suited for maintaining and updating the volatile, best practice *health hazard handling* knowledge [7]. The suitability and advantages of utilizing UML for modelling caregiving and medical processes is pointed out in [9].

Figure 2: Smartwatch Samsung Gear™ S

Example: In Figure 2, which shows the app displaying *communication* and *orientation* information (left), internal pre-alert (middle), indication of an external alert with data transmission and automatic speech connection (right), the health hazard handler »monitoring drinking« consists of two states. Upon (re)entering the initial state »normal health«, the timer *thirst-timer* is reset. Thus, the state machine stays in this specific state, as long as the ADL *»liquid ingestion«* occurs in sufficient frequency.

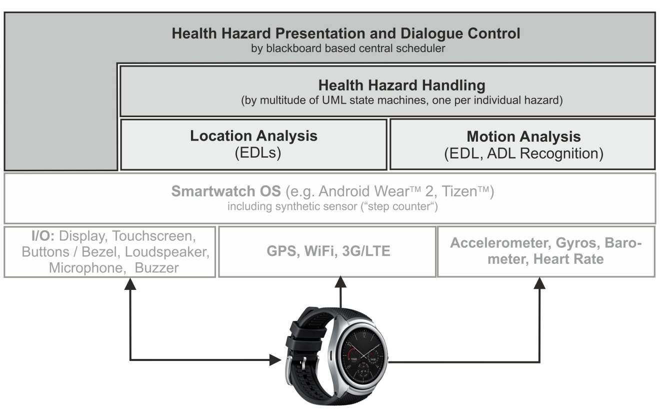

Figure 3: Block diagram of the smartwatch app

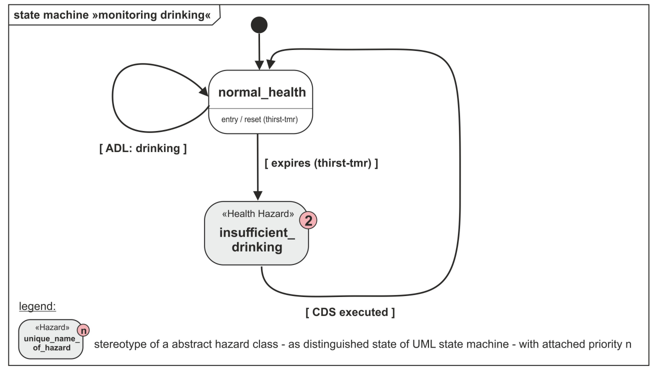

Figure 4: Simple state machine for concluding about the health hazard resulting from insufficient liquid ingestion

In Figure 4, if the *thirst-timer* expires because the time period since last recognized drinking ADL is exceeded, the state machine transfers to the new state »insufficient drinking«. This new state is of special type *critical dialogue section* and will be posted on a central blackboard (see below). Such a posting indicates an execution request with attached priority "2" for the associated internal dialogue activity flow for this state. The intended dialogue sequence with the smartwatch wearer is described in a corresponding UML activity diagram modelling the principal schema of the dialogue. This schema systematically covers all necessary dialogue steps for: a) *informing* the smartwatch wearer about the specific situation ("pre-alert"), b) *requesting a decision* from the smartwatch wearer, c) *responding* with the dialogue in case of an affirmative or rejecting user reaction, as well as a non-reaction of the user. In addition, the potential data transmission of relevant health data, which takes place in the background of the dialogue, will be covered by the schema as well as the follow-up clarification call ("external alert"). See [8] for the details of the model based dialogue management.

Isolated health hazards are typically modelled and described by a separate handler, in order to alleviate an independent representation and maintenance of the incorporated pragmatic handling knowledge. This is the case for the »monitoring drinking« state machine. But, more frequent in practice are joint hazard handlers for contextually combined *security and/or health hazards*. A state machine for jointly handling all hazards associated with the ADL *»absence from home«* is depicted in Figure 5 which handles security and health hazards resulting from an absence from home, including the health hazards for a runaway situation and an excessive absence from home. In a single state machine, only one of these hazards can be present at a time.

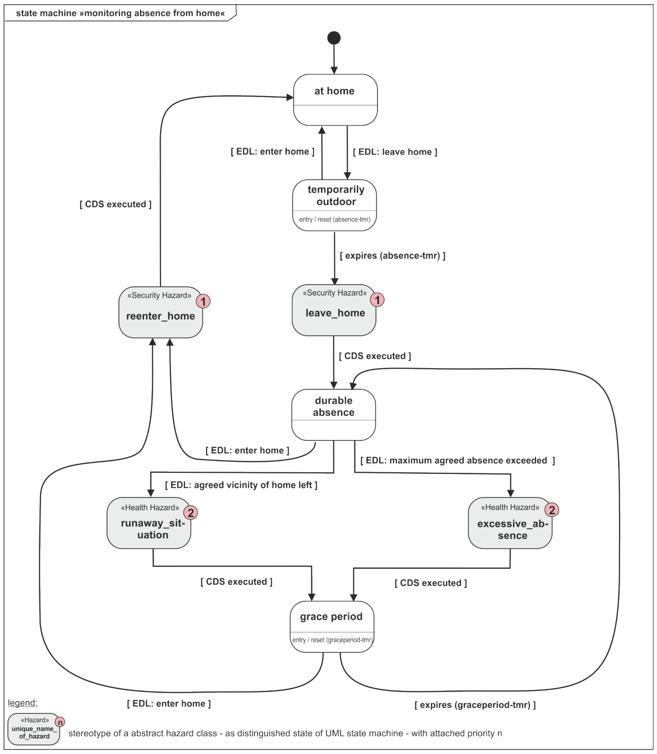

Figure 5: Complex state machine

The implemented app gains its complexity by the fact that a multitude of potential hazards have to be monitored by the smartwatch app simultaneously. This is done by executing the set of finite state machines describing all hazard handling *simultaneously*. Hazards from *insufficient drinking, absence from home, tumbles, …* may occur all at the same time. Thus, the situation may arise that more than one finite state machine or health hazard handler wants to communicate to the smartwatch wearer at the same time. This situation will be dealt with a priority – or exactly: severity – based health hazard communication management. The I/O devices of the smartwatch (touchscreen, bezel, mic, buzzer / loudspeaker) may be attached to at most one health hazard handler at time and for a short time interval. In order to realize this, we have introduced the concept of a *critical dialogue section* [8]. As soon as the smartwatch I/O resources have been granted to a selected health hazard handler, the handler will use them *exclusively* until termination of the execution of the corresponding critical dialogue section. The selection of the suitable health hazard handler for executing a dialogue sequence with the smartwatch wearer is supported via a central blackboard, on which all current communication requests are posted by the different handlers. From all current requests on the blackboard, a central scheduler selects the most appropriate health hazard handler for execution based on the medical or situational severity of the posted request and all other present requests on the blackboard (see [7] [8] for details of the scheduling algorithm).

B. Determining a Suitable Set of ADLs

A tradeoff has to be made between the plenitude of ADLs, which shall be recognized, and the reliability of the recognition results. The more ADLs the system knows and is looking for, the more fine-grained the course of the day can be partitioned into different ADLs and periods of time in between. The shorter these periods of time are, until the next ADL will typically occur, the earlier a deviant behavior influencing wellbeing and / or indicating potential health hazards can be detected. But, the more ADLs need to be discriminated by the recognition engine, the less reliable the recognition result will typically be.

Based on the aforementioned criteria, we have decided to recognize the following seven ADLs:

1. Nightly sleep
2. (midday) nap, rest
3. absence form home (for social activities/visits, strolling, shopping, etc.)
4. liquid ingestion, drinking (see [10] [11] [12] for details)
5. hand washing / drying (typically carried out after toilet activity, before eating)
6. teeth brushing
7. shaving
8. combing

ADL no. 1 »*nightly sleep« can* only be observed indirectly, in that the smartwatch is typically not worn during this period due to nightly battery recharging and usual sleeping habits. But, placing down the smartwatch when retiring to bed at night and reattaching the watch in the morning after rising can be reliably detected via movement analysis and the heart rate sensor, pulsometer.

Assuming that the smartwatch will be worn all over the day, ADL no. 2 »(*midday) nap, rest«* can be directly observed and easily detected by the smartwatch app via its characteristic non-movement pattern. Also, ADL no. 3 »*absence from home*« can be directly followed by the smartwatch app via loss of the known home Wi-Fi signal and GPS. (GPS will be further used for tracking and geofencing outdoor activities (see Figure 6 and [1] [5] for details). The process of recognizing the ADL from the delimiting EDLs »leave home*«* and »*enter home«* is described in the state machine of Figure 4.

For the recognition of ADLs no. 4 to 8, these ADLs can only be discriminated from each other by their characteristic movement pattern. This holds also for the recognition of tumbles. Based on literature research we have decided to do this recognition process via data mining and artificial neuronal networks (ANNs). Input layer of the feed forward ANN are the (condensed) specific signals from the smartwatch sensors. The ANN has one hidden layer and each ADL no. 4 to 8 will be represented by a specific output neuron, with the EDLs *»tumbling«, »heart palpitations«* as additional 6th and 7th output neuron of the ANN and a 8th output neuron for any other unclassified activity. ANNs have been chosen with respect to their favorable recognition quality and renunciation

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of additional runtime packages in comparison to logistic regression and other tested methods (see [11] for details). Another strength of ANN is their suitability for incremental training with the *backward propagation* algorithm (see [13], especially chapter 5.2).

ANN have successfully been used for detecting tumbles with quite a high precision, [16] reports an accuracy of 91%. [17] gives an overview about various sensor based implementations, most of them with an accuracy rate about 90% using various data mining techniques like multilayer perceptrons, support vector machines or naïve Bayes approaches. A good discussion about the challenges of tumble detection is given in [18], focusing not only a wearable system but also on camera bases approaches. It is important to note at least in Europe any detection techniques based on video is not accepted because of privacy concerns. Thus, only foot mat related sensor technologies which require expensive hardware investments remain as an option or any kind of wearable sensor. Lisowska et al. [19] show that Convolutional Neuronal Network (CNN) perform best for supervised learning techniques, while overall the differences to other approaches like SVM are not very high. Our work differs from those as we aim for detecting several different ADLs in one model, and not just the binary decision between tumble and not not-tumble. Weiss et al. [20] compare smartwatch based ADL detection with smartphone based detection showing that smartwatches can detect a wider variety of ADLs. Smartwatches gain their strength in tumble detection in that they are reliable worn at the wrist and will be on duty during the whole course of a day. In contrast, smartphones are typically put aside from time to time, especially during accident susceptible activities like showering.

C. Handedness and Relevance of ADLs.

ADL no. 4 »*drinking« and* no. 6 »*teeth brushing«* will be typically carried out only with the dominant hand. It turned out for the test persons that it is not a problem to wear their smartwatches on the wrist of their dominant hand (see Section IV). This is alleviated by the fact that smartwatches can rotate their display so that sideward control elements always remain at the familiar location pointing towards the hand of the wearer. *ADL* no. 4 »*drinking«* has been selected with respect to the dangerous effects of dehydration for elderly people caused by the decreasing natural thirst sensation at higher age [5].

ADL no. 5 »*hand washing / drying«* and the EDL *»tumbling«* are typically independent from the arm or wrist, on which the smartwatch will be worn. The ADL has been primarily included for technical reasons because they are typically executed several times a day and provide a good partitioning of the day into shorter time spans between those ADLs.

The importance of ADLs no. 5 »*hand washing / drying«* and 6 »*teeth brushing«* is not only given by the fact, that they have a characteristic movement pattern, which makes it suited for automatic activity recognition, but also for their social relevance. Regular teeth brushing and hand washing are significant symptom for a well-managed life. Stopping these activities typically indicate a loss of self-esteem / self-control and might be symptoms of progressing mental disorientation or dementia [14].

IV. RESEARCH QUESTIONS

A central question is whether a universal, person independent model of the ADL / EDL recognition process is sufficient or if an individually trained model will be necessary, at least for personal activities like *teeth brushing*. The additional effort for processing and building an individual model will be counter-balanced by the prospect to utilize this individual model for an authentication of the smartwatch wearer.

From this central question, several follow-up research questions have been derived:

1. Which is the best prediction model? Candidates are neuronal networks, regression models or decision trees [15].
2. Is one universal neuronal network model sufficient to recognize the relevant ADLs/EDLs based on a target recognition rate of at least 90%?
3. Are there differences in the acquired sensor data between the various smartwatch types (operating systems like Android Wear or Tizen)?
4. Are there differences based on the ADLs with regard to universal / individual model, thus while one ADL just requires a universal model, another ADL requires individual training?
5. How many training data have to be collected per person?
6. How many different persons are required to create a stable model?

In the analysis of this paper, we concentrate on research question 2 and neuronal network models. Research question 1 has been tested in [21], results show that neuronal networks perform at least as good as logistic regression, while decision trees perform much worse. To answer questions 3 to 6 the number of data currently available are not sufficient for a definite answer. First results show that at least 20 – 30 activity instances have to be collected per person for stable trainings models with a high recall and precision. Question 6 is partially answered by the results for hypothesis 2.

V. EXPERIMENT

An experiment was run over a period of one and a half year between spring 2015 and year's end 2016. The experiment included multiple test cycles of 2 to 3 weeks with different test objectives (especially ADLs to be recognized) and different sets of test persons of various ages. Between the test cycles, the smartwatch application software has been continuously improved by the authors based on prior test results. Test persons were of age between 25 and 63, predominantly males. One test group are students of one the authors, the other group are friends and family members of both authors. All test persons have been informed in advance about the capabilities of the smartwatches, especially the application software installed and the purpose of the specific tests. After being informed about the intended test objectives, the test persons agreed to the intended utilization of their collected anonymized data for research purposes. From their

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personal background, all test persons were fluent in utilizing digital devices in their daily life. In this paper, we present the results of the experiment in the area of personal health and body care, one of the most promising application area learned from our tests.

1) In a *first step,* we developed a sensor data gathering app where we collected about 2375 different activity instances starting from the above-mentioned core ADLs and EDLs like drinking, brushing, tumbling, combing, shaving, washing, etc. The data were collected using several different smartwatches running Android Wear (Sony Smartwatch 3, Samsung Gear Live) and Tizen (Samsung Gear S). For this analysis, we only used the data from the Gear S (overall 1394 activities). The Gear S based collection tool is depicted in Figure 6 and the distribution of the collected ADLs is shown in Tables I and Table II. For this analysis, ADLs, which did not fit into the category analyzed (like tumbling, walking etc.), were mapped into Other ADLs. Users are denoted by U_i, $1 \leq i \leq 5$. The user selects the ADL (Figure 5), enters a user name, pushes Collect (1) and from (2) he can start the data collection process. (3) shows a pre-countdown start, informing the user that the data collection will start in 1 second. (4) indicates that data collection has started and will last for 10 seconds. (5) indicates data collection will be finished in two seconds. (6) informs the user that now a second data collection will start. This step (6) depends on the type of activity recorded. In case of a short activity like tumbling or drinking just one ten second interval is recorded at once, in case of tooth brushing as an example of a longer activity up to five ten second interval are recorded at once.

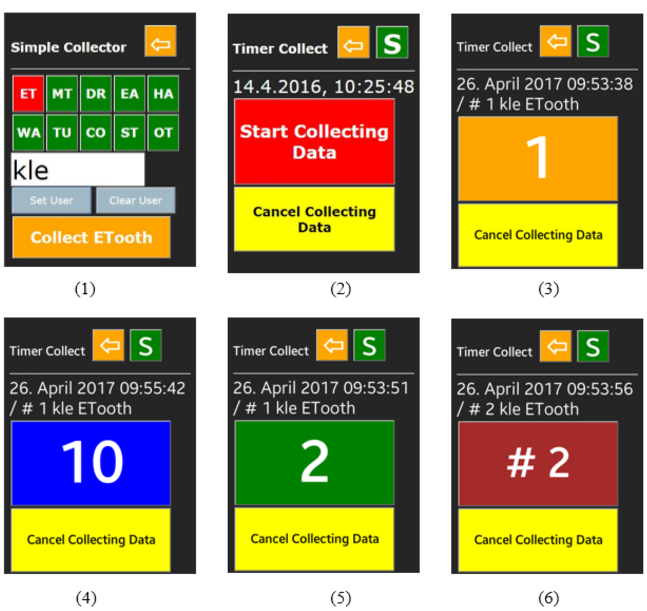

Figure 6: Samsung Gear S GUI for collecting ADLs

TABLE I: DISTRIBUTION OF FREQUENCIES OF THE COLLECTED 1394 ADLS (WITH SAMSUNG GEAR S SMARTWATCH) USED FOR THE TRAINING OF THE NEURONAL NETWORK MODEL.

ACT	U1	U2	U3	U4	U5	Sum
Other	0	0	634	78	18	**730**
Comb	0	0	39	0	0	**39**
Shave	0	0	126	0	0	**126**
Tooth	59	40	261	0	100	**460**
Wash	**0**	**0**	**15**	**0**	**24**	**39**
Sum	**59**	**40**	**1082**	**78**	**142**	**1394**

TABLE II: DISTRIBUTION OF FREQUENCIES OF THE COLLECTED 66 TEST ADLS USED FOR THE TESTING THE NEURONAL NETWORK MODEL. TEST DATA WERE GENERATED BY USER U3.

ACT TEST U3	Other	Comb	Shave	Tooth	Wash
Distribution	6	33	11	10	6

The next steps are based on a standard CRISP (Cross Industry Standard Process for Data Mining) process [22].

2) In the *second step,* the gathered sensor data are normalized:

   a) All sensor data are standardized and interpolated into a fixed time interval (20 milliseconds). This was achieved by applying some filters, e.g., a high/low pass filter.

   b) A core set of statistical attributes (39 attributes like means, standard deviations, minimum, maximum, inter quartiles…) are computed for each ADL. Dependent variable is ADL type (Activity), independent variables are the 39 statistical attributes.

   c) For each ADL (experiment) a data record is written into a new csv summary file together with the information which type of ADL is performed and the user name. This resulted in several ADL summary files depending on the hypothesis.

3) In a *third step,* the data were checked for missing values (e.g., sometimes the smartwatch did not collect gyrometer or magnetometer data for whatever reason). Those cases were ignored from the analysis.

4) In a *fourth step,* we applied several data mining techniques using R and Rapid Miner (Figure 7): multinomial logistic regression, clustering, decision trees and for the results presented in this paper neuronal networks using the normalized sensor data. For the data mining process, we grouped the ADLs in two categories: a) drinking, teeth brushing, and tumbling and b) all other activities recorded like walking, running, washing, sitting etc. into a common ADL category called other.

TABLE III: TRAINED GENERAL MODEL: RECALL AND PRECISION

ACTIVITY TRAIN	true Other	true Comb	true Shave	true Tooth	true Wash	class precision
pred. Other	**718**	0	0	6	0	99,17%
pred. Comb	1	**39**	0	0	0	97,50%
pred. Shave	2	0	**123**	4	0	95,35%
pred. Tooth	9	0	3	**450**	0	97,40%
pred. Wash	0	0	0	0	**39**	100,00%
class recall	98,36%	100,00%	97,62%	97,83%	100,00%	**1394**

TABLE IV: TEST DATA: RECALL AND PRECISION

ACTIVITY TEST U3	true Other	true Comb	true Shave	true Tooth	true Wash	class precision
pred. Other	**6**	1	0	0	0	85,71%
pred. Comb	0	**28**	0	0	1	96,55%
pred. Shave	0	0	**10**	0	0	100,00%
pred. Tooth	0	3	1	**10**	0	71,43%
pred. Wash	0	1	0	0	**5**	83,33%
class recall	100,00%	84,85%	90,91%	100,00%	83,33%	**66**

VI. RESULTS UND DISCUSSION

Our above hypothesis 2 stated that one universal model is sufficient to recognize the relevant ADLs/EDLs based on a target recognition rate of at least 90%. Considering the limited number of test persons and the specific test environment different from a real field test, our results seem to affirm this hypothesis 2.

The results of training the neuronal networks model are shown in Table III. Neuronal networks performed best compared to other data mining methods applied which is in line with the results in [10] [21]. It shows that all relevant recognition rates are above 90%. Table IV shows the results when this general model is applied to data the system has not seen before. The data were generated by user U3. User U3 was part of the training set. Combing and washing are not recognized perfectly, anyway the distinction between “hygienic ADLs” and other ADLs is nearly perfect. As one can conclude from the results, the recognition gets much better if a test person is part of the training set, which per se is not astonishing. For real world application, this could induce that before using the smartwatch as an ADL recognizing device users should be encouraged to train typical activities and use an improved neuronal network model.

A. ADL Recognition and Smartwatch System Support

Continuous monitoring of EDL, ADL recognition in the smartwatch app requires an ongoing execution and adaption of the ANN, as soon as there will be new sensor signals. This requires a reliable background operation of the smartwatch app, even when the user is not looking at the smartwatch screen and the display therefore will be shut off. Unfortunately, and for energy saving purposes, smartwatch OSs tend to hibernate the app execution in situations, were the display is shut off. Smartwatch OS like Tizen™ or Android Wear 2.0™ are featuring such (background) service operations in their most advanced versions. Reliable background operations are mandatory and of crucial importance for a wide acceptance and trust in assistance apps for the elderly.

B. EDL »Tumbling«

This EDL entails a lot of difficulties. First of all, the detection of the EDL requires a barometric sensor in the smartwatch. This sensor typically is only present in “high-end” smartwatches. Second, the training of the EDL is inherently *dangerous* for the test persons with respect to potential injuries. Trained stuntmen or young people would be no alternative because their tumbling behavior will deviate too much from tumbles of elderly people. For the same reasons, crash dummies from the automotive field also would be no alternative, in that they would remain passive and would not show the characteristic last fraction of a second active (panic) reaction against the ongoing tumble, which is typical for humans. Therefore, we used “young elderly” of about sixty years of age for our tumble tests. But, it is still an open issue whether our trained tumbles – as planned, conscious event – really are representative for the majority of everyday accidents, sudden tumbles in the household. Unfortunately, practically no video sequences are available for such real tumbles as objective illustrative evidence.

VII. CONCLUSION AND FUTURE WORK

EDL, ADL recognition based on an ANN works on today commercial smartwatches and delivers the necessary input for calculating the wellbeing of the smartwatch wearer. Continuous reliable detection of the EDL »*tumbling«, the ADLs* described requires durable background operations of the smartwatches, which only now will be supported by the most advanced smartwatch operating systems (OSs).

Universal models collected from different smartwatches, OSs and test persons are sufficient for achieving the targeted minimal 90% precision and recall rate for EDL, ADL detection. Best rates could be achieved by an individual model trained for a specific smartwatch. Such an individual model could be used even for user identification (e.g., in the scope of a benefit plan for good teeth brushing practice). But, the sensitivity of the individual model will require a substantial retraining even in cases of a smartwatch model change or even a major OS update.

A future application of the ANN based motion analysis will be dedicated to the combined analysis of the motion patterns, heart rate and blood glucose data from continuous glucose monitoring (CGM) systems. This will allow to conclude whether a change of glucose measurement data can be explained by the agility patterns of the smartwatch wearer. CGM systems like DEXCOM G5™ and Abbott’s FreeStyle Libre™ already are or will be capable to deliver these data via Bluetooth or NFC to smartwatches. The unobtrusive presence of those data on the wrist will support better self-management of the widespread diabetes mellitus type 2.

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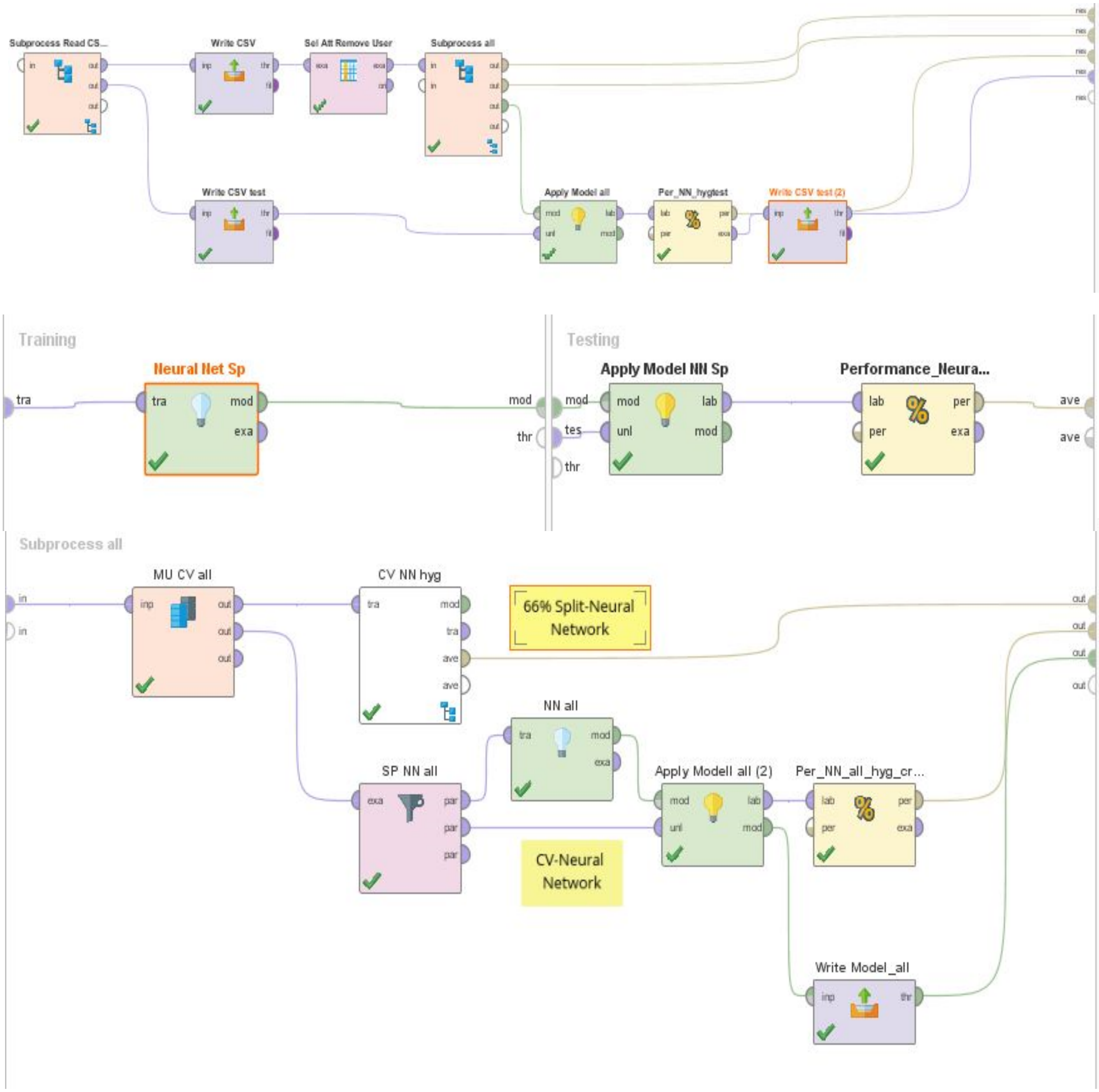

Figure 7: The Rapid Miner models used for training and testing