Recognition Models for Distribution and Out-of-Distribution of Human Activities

Sergio Staab
RheinMain University of Applied Sciences
Wiesbaden, Germany
Sergio.Staab@hs-rm.de

Simon Krissel
RheinMain University of Applied Sciences
Wiesbaden, Germany
Simon.Krissel@student.hs-rm.de

Johannes Luderschmidt
RheinMain University of Applied Sciences
Wiesbaden, Germany
Johannes.Luderschmidt@hs-rm.de

Ludger Martin
RheinMain University of Applied Sciences
Wiesbaden, Germany
Ludger.Martin@hs-rm.de

***Abstract*—By monitoring movements and activities, the progression of neurological diseases can be detected. The implementation of such monitoring requires a high level of documentation, which is hardly possible in view of the ever-increasing shortage of nursing staff.**

In cooperation with two dementia residential communities, we are trying to gradually relieve the burden on nursing staff by developing an approach to automated documentation.

In the attempt to recognise activities in the dementia environment, everyday activities can be well recognised using smartwatch sensor technology and machine learning, as shown in previous results from this research group.

However, the literature lags behind (can hardly be found in the literature) on how to distinguish an activity from a non-activity, as a person does not perform an activity to be classified at all times. This paper explores a model to solve this problem, taking several approaches:

Approach 1: First step classification to distinguish activity $<->$ non-activity. Second step activity detection using LSTM if activity was detected in step 1. Approach 2: First step differentiation of activity $<->$ non-activity directly with LSTM. Second step activity detection with LSTM if activity was detected in step 1.

Approach 3: Direct distinction of activity $<->$ non-activity and activity detection with an LSTM.

We show the advantages of the respective smartwatch sensor technology, compare the different approaches of our models to the prediction accuracy of the classification of different activities.

***Index Terms*—Human Motion Analysis, Machine Learning, LSTM Model, Dementia**

I. INTRODUCTION

The decline in the birth rate and the associated aging of society are leading to a massive increase in the number of people in need of care. In outpatient care alone, there will be a shortage of more than 66,000 skilled workers over the next 15 years. The shortage of care workers will lead to a loss of value added and total losses of 35 billion euros due to unfilled positions by 2030, according to the Federal Statistical Office [1].

With the aim of relieving the burden on caregivers, we have been cooperating with two self-managed dementia residential communities for four years. Several different care teams work in the residential communities and monitor the persons suffering from dementia. This monitoring refers to the documentation of daily activities over three shifts per day. The documentation is intended to help understand what stage of the disease the patients are in.

In the first step, we digitized the documentation that was previously only available in analog form, cf. Staab et al [2] and section III. Now, activities of the ill persons can be represented in a matrix per nursing shift. The activities range from helping with cooking and handicrafts to training in daily living skills.

After completion of the software documentation named INFODOQ (compare section III), it was examined several times by means of empirical and analytical usability tests, cf. Staab et al. [3]. It turns out that documentation gains significantly in speed and efficiency compared to analog processing, but it still represents a significant amount of work, according to Staab et al. [4]. In addition, there is a possibility that staff may not perform certain activities due to the heavy workload.

The need for a seamless system led to the development of advanced sensor technology from wearables. After consulting with different care teams, it became apparent that a smartwatch offered the opportunity to integrate sensor technology into a patient's daily routine without disturbing them, as many patients wear watches anyway. Nadal et al. [5] support this statement, saying that interaction with smartwatches reduces the perceived shame of monitoring because monitoring occurs unconsciously. Liu [6] and Guo [7] also argue that wearable health monitoring provides an opportunity to achieve effective collaboration among hospitals, communities, families, and individuals. Smartwatch-generated health data are seen by the majority of clinical staff as a way to reduce workload, according to Alpert et al. [8].

In previous work, the possibility of recognizing everyday activities was elaborated. We approached the problem with a first prototype for arm position recognition based on a wide variety of sensors from the Apple Watch 6 in interaction with machine classification algorithms, cf. [9]. We then considered different arm motion patterns ([10]) and based on this, we examined the motion patterns of similar to almost identical activities, cf. [11].

Recently, we have been able to test this approach in the field with several activities, compare Staab et al. [12] and Hassemer et al. [13].

However, since our focus is now away from the first prototypes towards a realistic application, we have to take

978-1-6654-6975-3/22/$31.00 ©2022 IEEE

into account the fact that a realistic application only works if recognized movements do not only consist of the previously defined activities. There must be a handling between undefined movements and movements that could belong to an activity. The consideration of this idea is missing in various similar works and now we try with this work to find a first model to solve the problem.

Within this framework, this elaboration makes the following contributions:

- Approach for recognition of very similar activities with smartwatches
- Model for classification between undefined movement patterns
- Model for aggregation of single activities over a time distance

This paper is structured as follows: section 2 presents related work in the field of health information technologies, human activity recognition, and classification algorithms. section 3 describes the INFODOQ project. section 4 includes the project setup - including the watchOS application, sensor data aggregation, and the machine model. section 5 details the activity recognition process, shows the results of the tracking process and the visualization of the recognized activities. section 6 summarizes the paper and concludes with a look into the future.

II. Related Work

There is a growing demand for health information technologies, particularly in the medical field, according to Lau et al. [14]. Although the availability and affordability of portable devices such as smartphones and smartwatches are increasing, these devices are often developed without collaboration with clinical staff and thus provide little value to clinical staff. According to Malu and Findlater [15], smart devices and their sensors can greatly ease the lives of people with mobility impairments, providing them, and therefore caregivers, with relief in their daily lives.

Various works of the last years deal with the field of Human Activity Recognition (HAR). Thereby, different approaches for the acquisition of motion data as well as for the classification of these data are used. Smartphones and smartwatches are particularly suitable for capturing sensor data. These can be purchased and used comparatively inexpensively, and the wearer can continue to use the devices normally in addition to collecting sensor data. Weiss et al. [16] compare the classification accuracy of different activities when using smartwatches and smartphones. They use an LG G Watch smartwatch and a Samsung Galaxy S4 smartphone, each of which records 18 activities of 17 users at 20 Hz. This shows that the classification using the acceleration sensor of the smartwatch offers an average accuracy of up to 93.3 % for the classification using a random forest. However, the acceleration sensor of the smartphone achieves a comparatively low average accuracy of 75.5 %.

These results show that smartwatches are particularly well suited for recognizing activities. It should also be noted that activities based only on hand movements can only be detected with the help of smartwatches. Silva and Galeazzo [17] use an EZ-430 Chronos smartwatch to capture eight activities from six users at a sampling rate of 33 Hz. They were able to achieve up to 93.47 % accuracy using Support Vector Machines (SVM).

In the work of Mekruksavanich and Jitpattanakul [18], the authors use a Hybrid LSTM, which consists of the combination of an LSTM and a Convolutional Neural Network (CNN). Here, despite the high number of activities, the authors achieve an average accuracy of 96.2 %, in detecting 18 activities from the WISDM dataset. This includes activity data from 51 participants recorded with an LG G Watch at a sampling rate of 20 Hz. All of this work in the area of activity recognition using smartwatches and smartphones is nevertheless difficult to transfer to the real world, as a person's daily life does not consist of a small set of predefined activities, but people also perform unknown and/or uninteresting activities for classification. These activities, unknown to the classification algorithm or deep learning approach, can result in incorrect classification or low classification accuracy.

According to Boyer et al. [19], classification algorithms in particular provide better results in distinguishing between in-distribution (IIN) and out-of-distribution (OOD) of sensor data. Using a smartwatch accelerometer, gyroscope and magnetometer, measurements of 20 participants were recorded for six activities each as in-distribution, and a minimum of 3 hours each for out-of-distribution. Here it is shown that traditional classification algorithms provide a particularly high Area Under the Receiver Operating Characteristic curve (AUROC). In particular, K-nearest-neighbors (KNN) was able to discriminate with an AUROC of up to 0.982, with deep-learning approaches consistently providing worse results.

In order to be able to use the high classification accuracy in classifying known activities by deep-learning approaches, as well as the better results in distinguishing between in-distribution and out-of-distribution, respectively, by traditional classification algorithms, we decided in this work to combine both approaches in a multi-level classification system.

III. Infodoq

INFODOQ [20] is a web-based information platform for use in outpatient residential care groups. The system was developed in response to the desire for a transparent information, coordination, and communication platform for various dementia residential communities to optimize day-to-day care and nursing. A decisive factor for the digitalization of the documentation, which until now has only been available in analog form, is the enormous increase in performance. In addition to the reduction of redundant or incorrectly addressed information and communication channels and the simultaneous reduction of bureaucratic and administrative effort, the system ensures effective and efficient care and maintenance. Furthermore, the information platform offers a transparent way for the mobile use of information as well as for the coordination and scheduling of relatives, nurses and assistants.

The functionality of nursing documentation are displayed in a matrix of all activities of the patients in a shift. The activities range from helping with cooking and handicraft lessons to training of everyday skills and day structures. A day in the shared flats consists of three shifts, each with different nursing staff. Fig. 1 even at the beginning of a sentence. Shows an activity matrix in which nurses enter the respective activities as a binary decision with their name abbreviation. The header contains information about the respective shift.

Figure 1. Overview of a nursing service as a matrix: activities vertically and patients horizontally as table structure

Below that the patients are shown visually and by name. This is followed by the nursing documentation matrix in which activities are assigned to residents.

According to an initial study, the effort required to perform analog documentation averages 16 seconds per activity; extrapolated, this amounts to 79.2 minutes of documentation work per day (0.16 seconds * 11 residents * 15 activities * 3 shifts).

Documentation via an activity matrix averages ten seconds per activity, resulting in 49.5 minutes of documentation work per day.

Documentation via a drop-down menu (mobile version) averages 15 seconds per activity, resulting in 74.25 minutes of documentation work per day.

Add to this the average error rate as well as breaks and shift changes. In subsequent work [4], we investigated the errors of poor usability and were able to increase efficiency again by restructuring the controls. However, based on the daily starting time (79.2 minutes), the results still leave significant room for improvement.

The next step is to build up the project in the direction of automated documentation.

IV. Project Structure

Based on the research to date, the question arises as to how monitoring can be further supported. This section is devoted to data generation and classification, with a view to making monitoring as digital as possible.

As described before, smartwatches can be easily integrated into everyday life and at the same time they bring a variety of sensor technology. Therefore, a watchOS application was implemented to aggregate and provide motion and health data through one interface. The Apple Watch Series 6 is used, which is equipped with the latest sensor technology. The application includes methods for retrieving motion and health data, a temporary backup in the smartwatch memory, methods for tagging data, and an interface for exchanging sensor data with a web server via a WebSocket. Data transfer from smartwatch to web server is done using TCP/IP over Wireless Local Area Network or Long-Term Evolution.

Figure 2 gives an overview of the work of data generation, data handling and data storage.

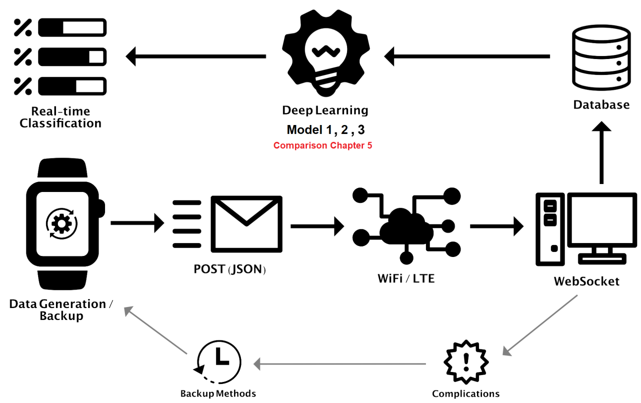

Figure 2. Overview of data generation and data handling

A. Sensors

The sensor system consists of an accelerometer, gyroscope, magnetometer, position sensor and heart rate sensor. The various sensor systems are described below.

Accelerometers are electromechanical devices that detect physically induced accelerations and convert them into electrical signals for further processing, according to Hering and Schönfelder [21]. They are used to measure instantaneous acceleration in multidimensional space [22], which describes the rate of change of velocity over time [23].

In the case of the Apple Watch Series 6, a triaxial sensor is installed, which, according to Apple Developer Documentation [24], provides acceleration values in three dimensions and thus in each direction of the orthogonal axes X, Y, and Z. The unit of the values is g. The unit of the values is g, where 1 g represents the gravitational acceleration caused by the Earth's gravitational field, normalized to 9.81 m/s^2 in one direction on the Earth's surface. According to Hering and Schoenfelder [21], gyroscopes are angular rate sensors that measure the rotational velocities of a body. Rotational velocity is measured as an angle in radians per second, rad/s, about a corresponding axis by the gyroscope, which, like the Apple Watch's accelerometer, measures rotational values in three dimensions [25].

A magnetometer is a meter that measures magnetic flux density in T (Tesla) and is measured from 10^{-15} T to 10 [26]. It is assumed that in the Apple Watch, the magnetometer, accelerometer, and gyroscope contribute to the mathematical calculation of the device's position.

Although accelerometer data already seems promising, the data base is to be significantly expanded in the present project. In addition to accelerometer and gyroscope data, the processed data object also provides combined device orientation data, also called attitude, according to the Apple Developer Documentation [27]. This is the aggregated values of Pitch, Roll, and Yaw as specific attitude angles to describe the orientation of a device in three-dimensional space. Thus, the three values above reflect the position of a smartwatch in space relative to a defined reference frame. The rotation values are given in radians rad and range from $-\pi$ to π about a given axis.

Consequently, while the gyroscope data describes an instantaneous angular velocity, the attitude values represent the steady orientation of the device relative to a specific reference frame. For this reason, attitude is considered promising for the present work, as it provides meaningful values independent of active arm movements of a user and thus allows for constant position determination in space. Consequently, this may serve a more fine-grained detection of arm movements. To the best of our knowledge, Apple does not disclose details about the so-called adjustment. However, a commonly used method to compute it is sensor fusion. Wu et al. [28] describe a corresponding method for determining the attitude by combining multiple sensors and applying mathematical methods such as Kalman or complementary filters. Here, accelerometer, gyroscope, and magnetometer contribute to the mathematical calculation of the device attitude.

Gravity acceleration can be used to determine where „is below“, and magnetic field vectors can be used to determine where north is from the instrument's point of view. Gyroscope rotation values are integrated to estimate the deviation from the previous position. The combination of multiple sensors is thus used to calculate the location, using the strengths of each sensor to compensate for or minimize the weaknesses of each sensor, according to Wu et al. [28].

It is important to mention that a number of other sensors such as the altimeter, air pressure sensor, GPS sensor, pedometer, heart sensor and blood oxygen sensor have also been implemented. However, these are not crucial for the pure detection of movements for our model and will only become relevant in the course of later work.

B. Data Structure

The goal of data generation is a continuous data stream. All motion data captured by the realized application is first stored as arrays in an appropriately predefined structure and then encoded as JSON and thus prepared for data exchange.

The data from the four motion-dependent sensors, Acceleration, Attitude, Gyroscope, and Gravity, which were collected according to previous work (Staab et al. [4]) are chosen as the database for this work, have three-dimensional x, y, and z axes respectively. The data is output as decimal numbers from 10^1 to 10^{-23} from the sensor system and stored accordingly in the database.

The pulse is processed as an integer from 0 to 300. Thus, in addition to the meta-data, an object per hertz of 14 data records is created. A data rate of 20 Hz has proven itself; accordingly, 260 (13*20) sensor data enter the system per second.

Continuous polling of motion data takes place at an individually adjustable time interval, the frequency. The maximum frequency is 100 Hz when using an Apple Watch Series 6 [29]. Thus, a maximum of 100 motion data objects can be generated per second. At this point, it must be questioned which frequency of the query meets the requirements of this work. If more objects are generated than required, this leads not only to redundancies but also to a noticeable increase in the load on the CPU and battery due to the increased number of queries. Therefore, in this work, a default frequency of 20 Hz is initially set, especially since, according to Dadafshar [30], a human's natural movements do not exceed 12 to 20 Hz. The following is a description of the data Characteristics.

V. Activity Recognition

The methodology described above has been applied to three models in a series of experiments. The idea is to filter the movements that do not correspond to any activity beforehand by a separate classifier.

A. Activitys

Four subjects were included, each generating 60 labels for the activities. Figure 3 shows different arm position sequences of the nearly identical motion sequences (drinking, eating, writing, and nose blowing).

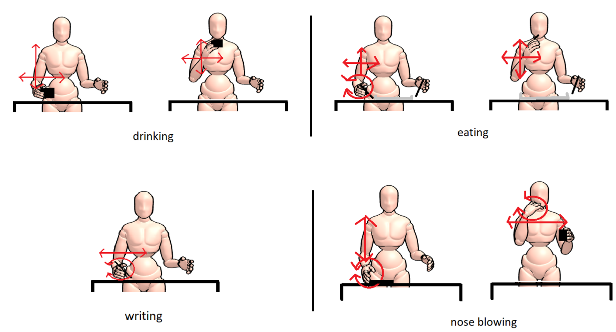

Figure 3. The motion sequences of the activities studied and labeled in the present work, which are very similar, making it more difficult to classify them.

Each of the activities writing, drinking, eating and blowing the nose follows a clear sequence. The red arrows indicate the range of motion of the arm and wrist. In writing, the arm is rigid while the wrist moves with the pen. At the same time, the arm moves from right to left. In contrast, the movements during drinking, eating and blowing the nose are very similar: the arm moves towards the head, the wrist is rather stiff.

Figure 4 shows the characteristics of the motion sequences using the gravity sensor.

Drinking (from a cup) starts with picking up the cup, a steady movement of the arm to the mouth and a brief pause in front of the face. During the drinking movement, the hand moves more and more slightly toward the face, from almost 90 degrees at the beginning to 150 degrees when the cup is empty.

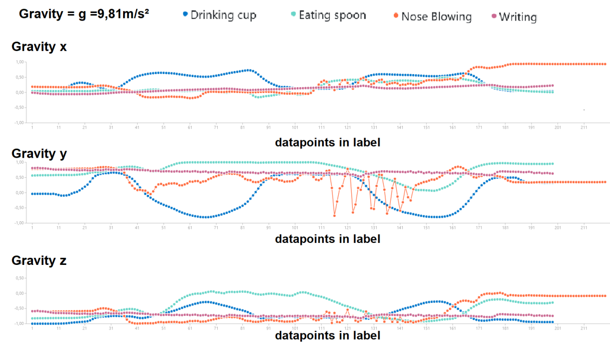

Figure 4. Illustration of the movement pattern of the gravity sensor during the execution of the four activities (drinking, eating, writing, and nose blowing)

The movement ends as it began, with a possibly now faster movement toward the table. There is a clear shift in gravity can be seen as soon as the cup has to be tilted. Blowing the nose also follows a similar pattern. The paper handkerchief is taken from the table and then shaken with the dominant hand to which the sensory system is attached. Then follows the movement towards the head. The blowing is done only by holding the paper in front of the nose and making one or two short movements are made in the direction of the nose. In our scenario, the handkerchief is not put down again. After a calm phase e, the movement of shaking the handkerchief is noticeable, followed by a quiet movement of the wrist in all directions. Especially with the similar movement of blowing the nose, it becomes clear that a movement is easier to classify the more unique it is. When writing, the arm is rigid while the wrist moves with the pen. At the same time, the arm moves from right to left. This can be recognized by a simultaneous oscillating movement.

B. Model Training

The raw sensor data is divided into the classes in-distribution (IIN) and out-of-distribution (OOD) in preparation for training. Out-of-distribution refers to data that is not interesting for the activity documentation, i.e., data that does not belong to any activity (in the following also default Label or Data). With in-distribution data is marked, which must be classified more exactly, thus data which belong to an activity. All data points with the labels Drinking Cup, Eating, Writing and Nose Blowing get the categorization IIN, and all data points with the label Default get the category OOD. Next, the data is divided into training as well as test data sets. The separation takes place on the basis of the users according to the leave-one-out procedure. Thus, the measured values of 3 users are used as training data. The fourth user is used for testing.

C. Classification

The first classification model **model I** is based on a two-stage approach and is shown graphically in figure 5. In the first stage, a classification algorithm distinguishes between IIN and OOD using different feature combinations. In the second stage, all data classified as IIN by the classification algorithm are classified by an LSTM, which has been trained only with the four activities, i.e., not with the label Default. Data classified with OOD are discarded.

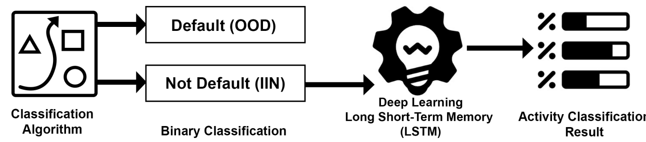

Figure 5. Model I:Structure of the two-stage classification algorithm utilizing a classification algorithm for the distinction between OOD and IIN and a LSTM for the activity classification.

The results, i.e. the product of OOD and activity recognition of the first classification model, are shown in the table I.

Table I

MODEL I: PREDICTION ACCURACY IN PERCENT - COMPARISON OF THE ACCURACY OF THE CLASSIFICATION ALGORIHMS LOGISTIC REGRESSION, SUPPORT VECTOR MACHINE, K-NEAREST-NEIGHBOR AND RANDOM FOREST WITH DIFFERENT FEATURE COMBINATION AND SUBSEQUENT ACTIVITY CLASSIFICATION VIA A LSTM. THE BEST VALUE OF EACH ALGORITHM IS MARKED IN RED

Sensor Combination	L. R.	SVC	KNN	R. F.
Acceleration	52.19%	52.79%	55.56%	53.43%
Attitude	**55.77%**	50.94%	52.26%	45.77%
Gyro	51.62%	52.97%	51.82%	51.65%
Gravity	43.76%	41.87%	44.15%	39.59%
Acceleration,Attitude	55.72%	50.74%	60.44%	**53.54%**
Acceleration,Gravity	44.28%	42.16%	49.87%	42.94%
Acceleration,Gyro	52.18%	**54.12%**	52.43%	53.53%
Attitude,Gyro	55.64%	48.55%	**65.1%**	45.69%
Attitude,Gravity	43.5%	46.11%	50.51%	44.64%
Gyro,Gravity	43.54%	42.6%	46.71%	41.93%
Accel., Attitude,Gyro	55.48%	49.14%	63.93%	48.91%
Accel., Attitude,Gravity	44.16%	47.01%	55.65%	44.36%
Accel.,Gyro,Gravity	44.1%	43.67%	46.69%	42.96%
Attitude,Gyro,Gravity	43.43%	45.75%	62.36%	43.49%
All four sensors	43.84%	47.58%	61.78%	44.22%

The values represent the accuracy of both levels. If the accuracy of the first level is comparatively low, the LSTM will receive many data points with the label Default, although it has not been trained with this label and therefore cannot classify them.

It can be seen that all algorithms perform best with different combinations of features. The K-Nearest Neighbor (KNN) algorithm performs comparatively well with most combinations of features.

The second model **model II** uses an LSTM to distinguish between OOD and IIN and is shown in Figure 6.

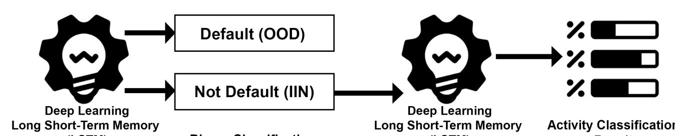

Figure 6. Model II:Structure of the two-stage classification algorithm. This model uses a LSTM both for distinction between OOD and IIN and the activity classification.

This performs the binary decision between OOD and IIN analogously to the classification algorithms, where the training dataset was split into training data and validation data using the leave-one-out method to train the LSTM.

The performance (i.e. the product of OOD and activity recognition) of model two is shown in the table II. Again, the values represent the accuracy of the combination of both levels. This model performs best in the classification of the features Acceleration, Gyroscope, and Gravity, although the values of the features Acceleration, Attitude, and Gyroscope also give good results.

Table II
MODEL II: TWO STAGED LSTM CLASSIFICATION ACCURACY WHEN USED WITH DIFFERENT FEATURE COMBINATIONS. RED MARKS THE BEST COMBINATION OF SENSOR TECHNOLOGY.

Sensor Combination	LSTM Accuracy
Acceleration	51.01 %
Attitude	63.17 %
Gyro	51.59 %
Gravity	53.06 %
Acceleration,Attitude	57.5 %
Acceleration,Gravity	23.05 %
Acceleration,Gyro	51.43 %
Attitude,Gyro	62.87 %
Attitude,Gravity	54.12 %
Gyro,Gravity	74.73 %
Acceleration,Attitude,Gyro	78.17 %
Acceleration,Attitude,Gravity	58.48 %
Acceleration,Gyro,Gravity	**79.81 %**
Attitude,Gyro,Gravity	68.69 %
All four sensors	69.01 %

The third model **model III**, unlike **model I** and **model II**, consists of a single LSTM. This is trained with the same division of data into training, validation, and test data sets as **model II**. The idea behind this is an evaluation of our basic idea to filter the data which do not belong to any activity first. Since this model does not remove any second stage OOD data, it is classified as a separate activity.

The structure of this model is shown in Figure 7.

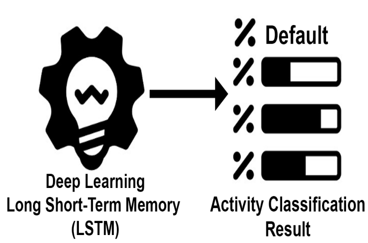

Figure 7. Model III: Classification of all sensor values by a single LSTM. Checking whether it makes sense to switch two models in series or whether one model is sufficient

Table III shows the performance (i.e. the product of OOD and activity recognition) of this model.

It can be seen that the accuracy of the model increases with the number of features. All four sensors together have the best accuracy.

Table III
MODEL III:COMPARISON OF THE ACCURACY OF DIFFERENT LEARNING ALGORITHMS AND FEATURE COMBINATIONS. RED MARKS THE BEST COMBINATION OF SENSOR TECHNOLOGY.

Sensor Combination	LSTM Accuracy
Acceleration	36.82 %
Attitude	51.04 %
Gyro	35.52 %
Gravity	50.6 %
Acceleration,Attitude	49.69 %
Acceleration,Gravity	50.23 %
Acceleration,Gyro	39.75 %
Attitude,Gyro	52.96 %
Attitude,Gravity	53.57 %
Gyro,Gravity	42.21 %
Acceleration,Attitude,Gyro	50.48 %
Acceleration,Attitude,Gravity	57.11 %
Acceleration,Gyro,Gravity	38.9 %
Attitude,Gyro,Gravity	51.96 %
All four sensors	**60.10 %**

VI. RESULTS AND OUTLOOK

In this work we have addressed the problem of activity recognition including the question of how to distinguish an activity from a non-activity. We have modeled and tested several sensor systems with different classification algorithms.

Approach 1: First step was classification to distinguish activity versus non-activity. Second step was activity detection using LSTM if activity was detected in the first step.

Approach 2: First step was activity versus non-activity discrimination directly using LSTM. Second step was also activity detection using LSTM if activity was detected in the first step.

Approach 3: This approach consisted of discriminating activity versus non-activity directly with LSTM + activity detection.

The test series show how the best predictions perform with all three models in combination different sensors (cf. table I, table II, table III). Thereby the different predictive powers are given in percentages to the respective sensor. It should be noted that the Attitude sensor axes (Attitude - X, Y and Z) perform best as the sole sensor. The test series further show that Model II performs best with 79.81 %. Thus, the combination of Acceleration, Gyro, Gravity using two LSTMs connected in series is the strongest. This is followed by the same model with Acceleration, Attitude, Gyro 78.17 %.

Model I performs better on average than Model III, which makes a simple direct classification of activities and non-activities. It can therefore be confirmed that the basic idea of first distinguishing activities from non-activities and only then classifying them makes sense.

In the future, based on these results, this work contributes to automate the documentation of dementia patients as much as possible, providing opportunities for development to preventively improve the disease progression of patients.

In the next step, based on this work, the trained model is applied to the INFODOQ software. Subjects wear the watch, which actively measures at 20 Hz. The classifications are then visually provided to the nursing staff in the nursing documentation to facilitate the selection.

The best accuracy of the three approaches is 79.81 %, the choice of algorithm should only be provided as an option to the nurses. However, this extension will then make the work of the nursing staff easier and will significantly improve the performance of the nursing documentation.

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