SN Computer Science (2022) 3:230
https://doi.org/10.1007/s42979-022-01091-3

ORIGINAL RESEARCH

CNN for Elderly Wandering Prediction in Indoor Scenarios

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Received: 13 October 2021 / Accepted: 12 March 2022 / Published online: 20 April 2022

Abstract

This work proposes a way to detect the wandering movement of Alzheimer's patients from path data collected from non-intrusive indoor sensors around the house. Due to the lack of adequate data, we have manually generated a dataset of 220 paths using our developed application. Wandering patterns in the literature are normally identified by visual features (such as loops or random movement), thus our dataset was transformed into images and augmented. Convolutional layers were used on the neural network model since they tend to have good results in finding patterns mainly on images. The Convolutional Neural Network model was trained with the generated data representing the hourly analysis and achieved an F1 score (relation between precision and recall) of 75%, recall of 60%, and precision of 100% on the validation slice. For comparative purposes, we have also trained the model with a 30-min interval of analysis and achieved an F1 score of 57.14%, a recall of 80% and a precision of 44.44%.

Keywords Machine learning · Health · Alzheimer · IoT

Introduction

Alzheimer's is a type of dementia characterized as a neurodegenerative disease that affects especially memory and behaviour. Alzheimer's patients should be monitored at home to prevent accidents and moderate changes in the patient's behaviour, such as agitation, aggression and wandering behaviour [6].

Family members or contracted professionals usually do this task. In particular, the family caregiver is more susceptible to several pathologies due to the impact that this task has on the deprivation of time and its activities [33]. According to [7], the lockdown restrictions in the COVID-19 pandemic has increased even more the necessity to monitor Alzheimer patients because in confinement, they eventually suffer from anxiety and even increased health risks. Which, in turn, contributes to the caregiver burden.

Wandering is one of the most common behavioural problems of Alzheimer's patients, as seen in [39]. Since wandering behaviour is most times coupled with agitation in Alzheimer patients [6], a system that automatically and correctly detects wandering behaviour in a smart home can take actions to alleviate the agitation of the elderly or trigger events to inform the caregiver that the elderly is wandering. There are a variety of interventions to reduce agitation in elderly people with Alzheimer. Some of them can be automated inside a smart home scenario. Such as aroma, music, and lights [28]. Thus, by utilizing a smart home to identify wandering behaviour and perform tasks to reduce agitation, a system can alleviate some of the caregiver burdens.

By observing the difficulties caregivers face in monitoring Alzheimer patients, the necessity of continuous supervision was noticed and highlighting the importance of this work. Using the Internet of Things (IoT) [19], we could obtain the movement data of the elderly, however, due to the massive quantity of data, it is hard to identify wandering patterns.

In Figs. 1 and 2 we have six different patterns of movements between point A and point B. It was identified that

This article is part of the topical collection "Biomedical Engineering Systems and Technologies" guest edited by Hugo Gamboa and Ana Fred.

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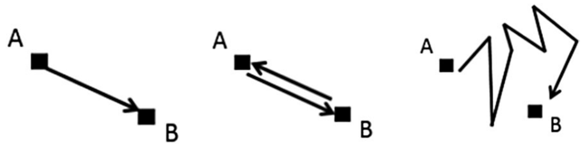

Fig. 1 Wandering and non-wandering movement patterns [11]

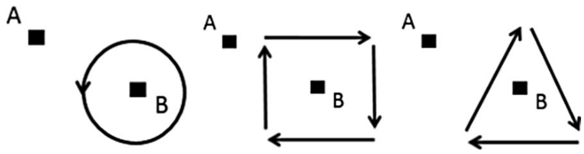

Fig. 2 Wandering and non-wandering movement patterns [11]

some of these patterns are associated with wandering movement [11, 25]. In Fig. 1 the first pattern is present in both wandering and non-wandering movements, but mostly in non-wandering activities. So it was not associated with a wandering movement. The other two patterns of the figure, pacing, and random are associated with wandering movement. Figure 2 shows the most likely patterns of wandering movements called lapping, where the movement turns on a loop around a point.

Due to the lack of data of normal and wandering movement in the same scenario, we have reproduced manually the likely wandering patterns represented in Figs. 1 and 2 to create the anomalous activity data and also normal data mainly composed of direct movements.

This work presents an intelligent smart home environment to assist the family caregiver's task with the elderly with Alzheimer's. The objective of the environment is to use sensors to identify the movement of the elderly and build a path of movement. A neural network model analyzes this path to infer if the patient's movement is wandering or normal movement. With this information, the smart home environment can act in trying to mitigate its negative effects. It is hoped that this can be an important tool to help caregivers and relatives of Alzheimer's patients.

The work presented here extends the initial approach presented in [27] by redesigning and generalizing the integration of the proposed CNN with the IoT architecture. We also greatly improved the IoT architecture and proposed a new method of filtering and aggregating the data to enhance the analysis. The synthetic dataset generation tool was also improved to conceive the new experiments. A new method of filtering and aggregating the data was proposed. Moreover, experiments were added to evaluate the impact of the selection of the dataset characteristic.

A prerequisite to such a system is to detect a wandering behaviour correctly. In this sense, this work focuses mainly on data collection and machine learning techniques for identifying wandering patterns in indoor scenarios. For those purposes, our contributions are (i) a proposal of IoT architecture and data collection; (ii) a data filtering to prevent false activation of the sensors; (iii) a synthetic dataset generation tool; and (iv) neural network architecture to identify wandering behaviour.

This work is organized as follows, the proposed smart home architecture is shown in "Proposed Smart Home Architecture". Related work of IoT monitoring and the use of machine learning will be shown in "Related Work". "Proposed Data Filtering and Collection Method" presents the Data collection method to prevent false activation. "Dataset Generation" overviews the application developed for the data generation and the composition of the dataset used in our learning structure. "Implementation" approaches the data pre-processing and the construction of our neural network model. In "Results", we discuss the performance of our model and experiments. Finally, in "Conclusions" we show future applications and conclude our work.

Proposed Smart Home Architecture

Even though this work reaches especially the machine learning part of the project, it is crucial to overview of the entire system's architecture. The system's architecture represented in Fig. 3 is divided into seven components. Each one is part of the flow from the client to data capturing. The client is the interface of access and the system configuration. The REST API [26] is a double way to communicate with other components. With that, the client can request the API data from the machine learning engine and NoSQL Database [18].

The data can be captured through ultrasonic, presence, and pressure sensors. In our work, we call this sensing method non-intrusive, as there are no devices in direct contact with the patient (e.g., wristbands). Also, some devices hamper the perceived privacy of the patient (e.g., with cameras). That is, a patient should not feel that they are constantly being monitored, as this may increase the risk of rejection of the [10] technology. For the scope of this paper, we assume that the data collection is performed by ultrasonic sensors distributed across the home. Each sensor is fixed on a location in the home. Every time the elderly move through a sensor, it is identified as a movement point (i.e., data point). This work also proposes a method to prevent the system to interpret any activation of the sensors as a movement from the elderly (i.e., false positives). This process is explained in more detail in "Proposed Data Filtering and Collection Method".

The communication protocol between devices is done with the Message Queuing Telemetry Transport (MQTT) interface [22]. The data collected from the sensors are sent to the controller. The controller analyzes the raw activation

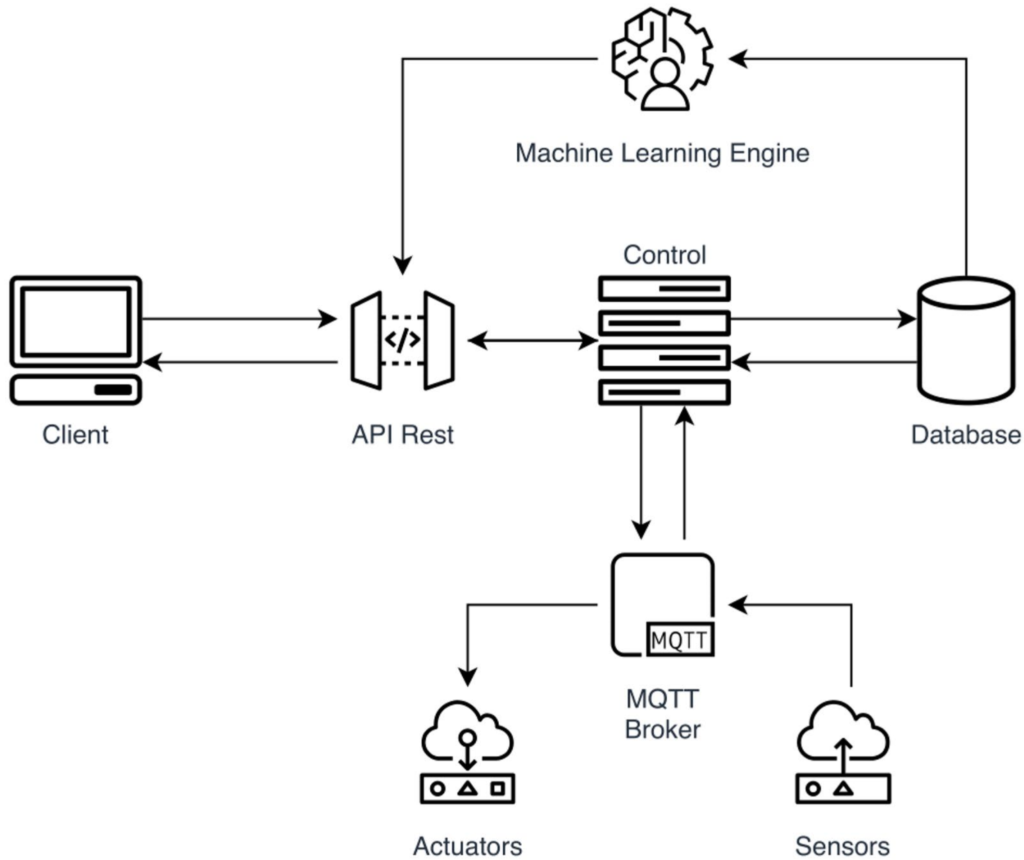

Fig. 3 Architecture of the system [27]

of simple sensors around the house and, with data aggregation, generates the path of the elderly that will be used to identify the movement. Raw and treated data are stored in the database. Temporal data from the database are analyzed and used to create a predictive model that can infer stress activities in Machine Learning Engine, which is the one that was approached in more depth by this work.

Related Work

As stated in [30], human activity recognition (HAR) is based on the assumption that specific body movements translate into characteristic sensor signal patterns, which can be sensed and classified. This classification can be performed with machine learning techniques such as in the work of [2]. In this work, the authors used data from a wristband sensor and trained neural networks to learn the users' sleep patterns to turn off the lights after they fall asleep. And as well in [29], IoT data are used to train an artificial neural network model that, given the information of the arm and body pose of the patient, can track activities such as the walking movement or even predict if the user was sitting down.

[20] surveys and compare the literature about agitation and aggression detection. The tracking modalities presented in the works selected by this survey were wearable devices and cameras. The survey also raises the possibility of using movement data from wearable sensors to identify agitation in dementia patients. Relating this overview of previous papers to our work, we focus on the patient's well-being by assuming that the ambient only employs non-intrusive sensor-tracking. The elderly do not need to wear a device or feel the hostility of a camera watching them.

There is plenty of work in image classification to detect human conditions, such as diseases or behaviours. In [3, 4], machine learning is used to detect brain tumours. [3] uses CNN (Convolutional neural networks) and [4] autoencoders to approach the problem. They were trained and evaluated using BRATS challenges databases and had good results compared to the literature. Concerning our work, we similarly have an image classification problem. However, in the work of [3], the CNN has 14 layers, whereas our networks have only four layers. Similarly, the work of [40] uses CNN to help the diagnosis of leukaemia. Using images of blood smears, complemented with the application of transfer learning and data augmentation techniques, it reached a result of

Table 1 Overview of related implementations

Author	Scope	Type of DNN
Ordóñez and Roggen [30]	Activity recognition	CNN/RNN
Akbar et al. [2]	Recommendation system	ANN
Oniga and Sütő [29]	Activity recognition	ANN
Amin et al. [3]	Stroke lesion detection	CNN
Vogado et al. [40]	Leukemia diagnosis	CNN
Amin et al. [4]	Brain tumor detection	CNN

98.28% of accuracy. Compared to our work, we use CNNs to detect anomalies in images and data augmentation to generate more data.

[12] proposes a system to monitor patients with dementia using non-intrusive sensors to track their activities. The way used to detect wandering was by counting repeated movement patterns such as sitting down, moving to the chair, opening and closing drawers. The authors then calculated a score based on if these events were repeated within 5 min. The advantage of the Machine Learning approach proposed in our work is the easy adaptability to the patient. Our method is based not only on repetitions but on any movement throughout the environment. It counts on the advantage of adapting to new patterns if needed.

In Table 1 below, the related work were divided according to their scope and types of neural networks used (e.g., Recurrent Neural Networks, Convolutional Neural Networks). Some referenced implementations did not specify the type of network used. Thus, the ANN (Artificial Neural Networks) nomenclature was then used to refer to generic neural networks due to this lack of detail.

The main contrast to related work is that our method focuses on predicting wandering using information collected by non-intrusive sensors. In this sense, our work is similar to [12] but coupled with a machine learning approach similar to the one in [3]. Furthermore, our work aims to detect known patterns of wandering in the literature and also be able to be extended and trained to detect other movement patterns that indicate wandering. On top of this, our CNN architecture is lightweight, capable of running on an IoT device.

Similarly to the work of [12], we employ only non-intrusive sensors. However, a problem of the work in [12] and similar works is that this method is prone to detect false information. In the following section, we will present a solution for our architecture to reduce the probability of incorrect information.

However, it is essential to note that we could not implement the data collection architecture in this work. Mainly due to the COVID-19 pandemic and lockdown restrictions, data collection in real home environments became unfeasible. Since the data collection is essential to the implementation of this wandering detection solution, in "Dataset Generation" we present our solution to generate artificial data that was used for the neural network model training.

Proposed Data Filtering and Collection Method

As mentioned in in "Proposed Smart Home Architecture", the data collection is done in a non-intrusive way with proximity sensors. Figure 4 illustrate this method. In the figure, the ultrasound sensors are represented as arrows and the points of detection are represented as dots with a yellow colour. The process works as follows. When the sensor is activated, a data point is marked on the database. This process repeats itself each time a sensor is activated in the home, leading to the construction of a path. However, as pointed out in [31, 36], there are limitations in this exclusive monitoring with ultrasonic sensors. False positives can misidentify the patient's position, and blind spots in the sensing can hamper the detection.

We can take the following examples to illustrate the limitations mentioned above. How to know that activation in an ultrasonic sensor is really due to the movement of a patient and not an animal in the house? How to detect if the patient was moving between rooms but stopped somewhere? How to identify if the patient passed an ultrasonic sensor but are still moving in the room? Therefore, it is necessary to use other types of sensing to solve these limitations and complement the system's reliability in identifying movements in the environment.

The use of sounds to monitor movement is a possible non-invasive solution for the environment in question [21]. Using sound detection and audio classification, we can take advantage of a different range of ambient sounds to identify different behaviours in the environment. Therefore, we propose to detect the footsteps in the environment to complement ultrasound detection and improve the identification of movement in the environment. As seen in [32] the use of CNNs for audio classification shows good performance

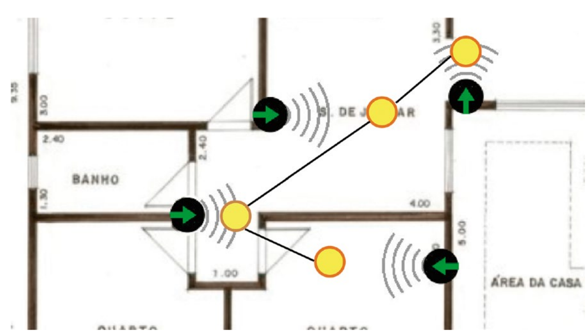

Fig. 4 Illustration of a detection and path creation using ultrasound sensors

in comparison with the state of the art models for sound classification. Through the implantation of microphones, movement sounds will be captured, and a CNN was trained to identify footstep sounds. It is important to note that this detection through sounds is limited to motion capture. Not being used to identify the patient's position, for this, the ultrasonic sensors are still necessary.

Figure 5 illustrates this process. In the figure, if a proximity sensor detects, the audio is captured by a microphone for 5 s. The sound is converted into audio features and sent to a neural network to detect if there is a footstep sound at the moment of the sensor activation. If the CNN identifies the footstep, the data point will be added to the database to build the path. If the footstep sound is not present, the data point is discarded, thus filtering the misleading activations.

A CNN was chosen as the method to infer the footsteps from the audio data. The CNN was trained on data from Google Audioset [14] to identify patterns of human footsteps. The output of the model is a value representing the probability of the sound to be footsteps. In our experiments, an accuracy of 82.65% was achieved in the training dataset and 79.83% in the validation dataset. Both were removed from the Google Audioset. It indicates that this application can predict with an accuracy of more than 80%. This application is available at https://github.com/Unilasalle-SmartCare/smartcare-cnn-footstep.

It is important to note that the filtering method in question is located in the control module of the architecture in Fig. 3. Thus the filtering process occurs before insertion of the data into the database. This means that this inference is performed in real-time, and it is not necessary to store any audio data on the database. Only 5 s after the ultrasonic sensor detection.

The results obtained with this filtering method can be used to improve the effectiveness of wandering detection in the environment and alleviate the problems raised by [36].

Dataset Generation

Due to the lack of indoor datasets containing normal and anomalous activity, the data generation strategy was adopted similar to the one presented in [5]. Therefore, an application to simulate these paths was developed. With our tool, the user can manually insert, annotate and visualize movement data point-by-point, without the need of an actual patient. With this tool, we generated movement patterns of wandering and normal movement.

To make the work of data generation easier, we have created a web application, as shown in Fig. 6. The application, can upload a floor plan image and set the points in the ground floor plan. Every point represents a sensor reading indicating the position of the patient. In this application, we have defined the interval of analysis of every path created to be hourly. Since a path is a group of points with this delimiter, we can classify the entire hour path as wandering or normal movement. It is important to note that, although the generated data of the datasets were synthetic and do not represent the real world, they were generated to simulate the real-world scenario. Since the architecture of the neural network is simple and robust, it is expected that it generalizes in the real world with real data in a similar manner as the work of [5] does.

As seen in Fig. 6, on the left, we have the ground floor plan. On the right, the statistics were created to help to monitor the data balance, such as the number of hours with

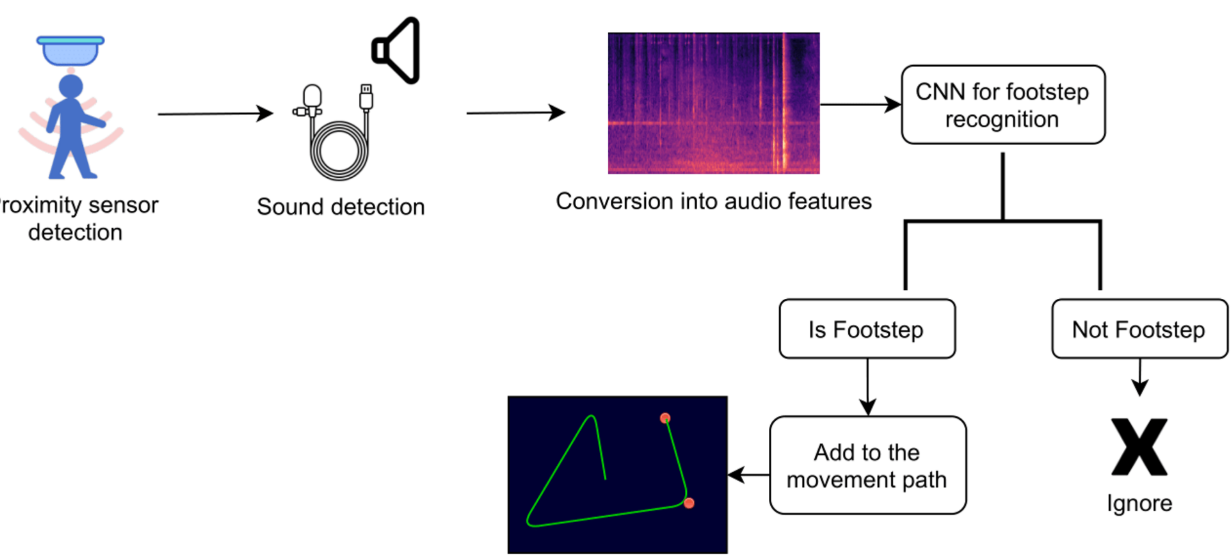

Fig. 5 Diagram of the data filtering architecture

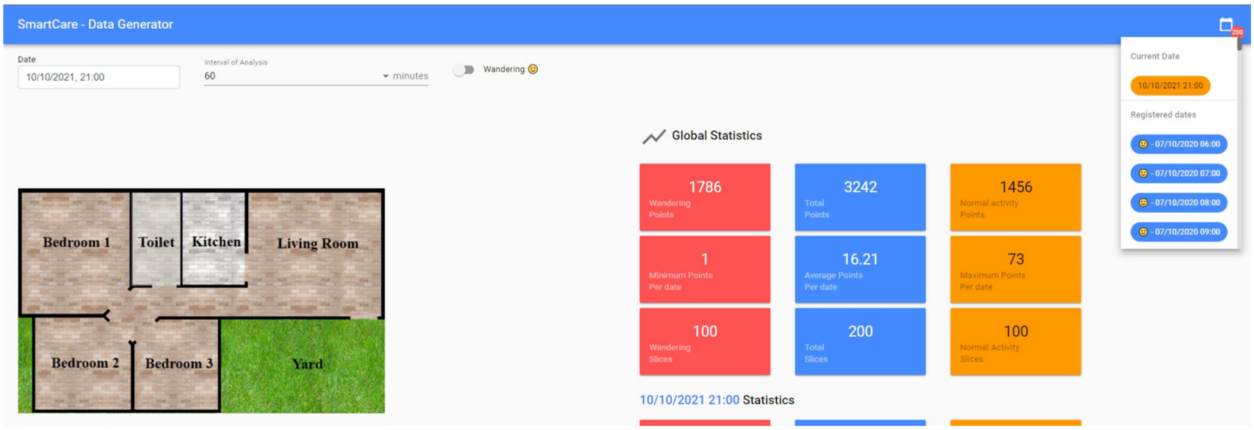

Fig. 6 Developed application for data generation. The user interacts with the floor-plant to place movement points. The right side of the page shows the statistics created to visualize the generated data. In the upper right, there is a menu that shows all the registered movement dates and hours

wandering and normal movement. The visual part of the application was developed using Vue.js, Vue Material, and bootstrap libraries. The ground floor plan and the points mechanism P5.js library was used, which simplifies the JavaScript canvas. The application is available at https://github.com/Unilasalle-SmartCare/smartcare-frontend.

The created data using our application were exported in JavaScript Object Notation (JSON) [34] format. The file structure is based on an array of objects, where each object represents a location point in the environment. Each point consists of four attributes. 'x' and 'y' represent its respective coordinates in the ground floor plan image, starting from the upper left. The 'date' attribute shows the point date and hour. Each point has the attribute stress that indicates if the elderly is wandering. Even though each point has the attribute 'stress', the application considers a time interval to account for a wandering movement. It is not able to have two points in the same time interval with different stress values. To know where the movement starts and ends, the points of the same data and interval are inserted in the order of the elderly movement. The JSON points coordinates were plotted into pixels using the naive line drawing algorithm [35], turning the dataset into images for a later CNN approach.

With the application, we developed two datasets. The first is a train/test dataset, and the second is a validation dataset. The generated train/test dataset consists of a total of 200 h, being 100 h of normal movement, and 100 h of stress. As seen in Table 2, they are sliced into training and test parts, respectively 75% and 25%. The validation dataset to be used in the evaluation of our machine learning model consisted of 20 h, being 50% anomalous activity and the other 50% normal movement. The composition can be seen in more depth in Table 3.

For the purpose of generating consistent anomalous data, patterns present in [11, 25] were reproduced manually using our developed data generation application. We assumed normal movement as being not anomalous or random. The patterns classified as anomalous are Lapping and Pacing, seen in [25]. Random patterns are described by [25] as a roundabout or haphazard travel to many locations within an area without repetition and is mostly composed of direct movements.

Table 2 Distribution of the train/test dataset

Movement type	# Samples
Lapping	59
Random	11
Pacing	30
Normal	100

Table 3 Distribution of the validation dataset

Movement type	# Samples
Lapping	7
Random	2
Pacing	1
Normal	10

Implementation

Data Processing

With the generated dataset, it is still needed to do some processing to use our artificial neural network model. First, all the points were grouped by their date and hour. Then, the points were converted to grayscale images. To create such images, each point is converted and placed in the corresponding location on the image and a straight line is plotted between two adjacent points. As seen in Fig. 7, the resulting image shows a stroke where the patient moved in each hour.

Each pixel of an image consists of a value between 0 and 255. To make the values smaller and faster for our model, we normalized the pixels to be between 0 and 1, maintaining the distribution and ratio of the data. Since the images have the resolution of the ground floor plan, it would be a waste of resources to give big images to the model with very small features, which would impair the generalization of the model. To account for the aforementioned problems, the images were rescaled to 128 × 128 resolution.

Data Augmentation

Even with the generated dataset, we do not have much data. To prevent overfitting and help the model generalization, we used data augmentation techniques. As seen in Fig. 8, each training image generates more training images.

Differently from [40] where zoom and shearing were applied to the new images, we only rotated each image to a maximum interval of 3 degrees and randomly flipped vertically and horizontally.

Artificial Neural Network Model

Using path images, we saw that the Convolutional Neural Network (CNN) approach could be an interesting idea since

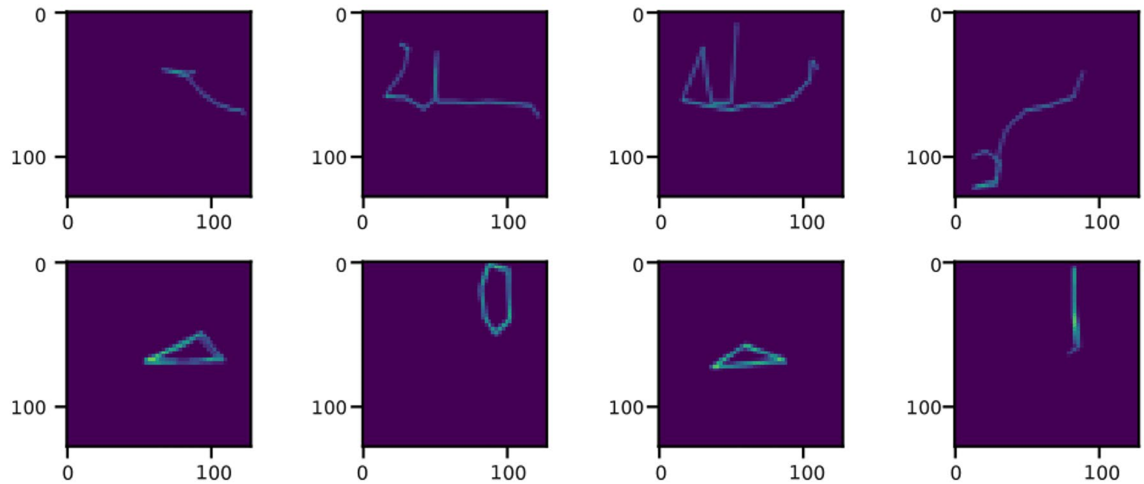

Fig. 7 Samples of the path data plotted as images after rescaling [27]

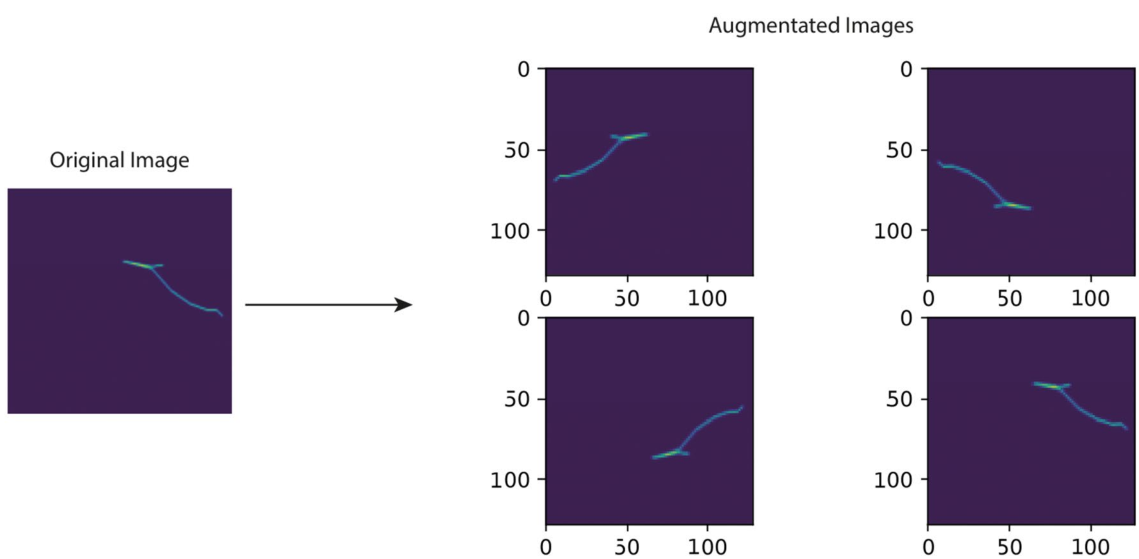

Fig. 8 Data augmentation technique applied in the images [27]

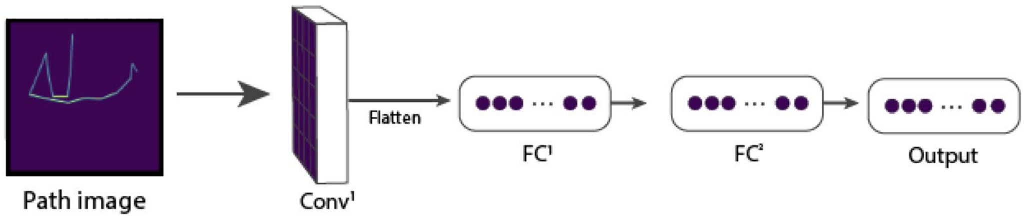

Fig. 9 Architecture of our neural network model [27]

it could identify the anomalous movement activities by learning the shapes and pixel distribution of the paths based on the patterns shown in Figs. 1 and 2. The CNN architecture is presented in Fig. 9. In the figure, the processed image is given as input and goes into a convolutional layer (conv^1) with a filter size of 32. Filtering is used to highlight features of the input. Max pooling is applied to reduce the dimensionality and make the neural network training faster, and then the output is flattened into an array. After that, we have three fully connected layers (FC^1, FC^2, and FC^3). Being the last one, the output of our network, a number between 0 and 1, represents whether the input path is predicted as wandering or not. To avoid overfitting, we randomly dropped 25% of the hidden units between the fully connected layers (FC^1 and FC^2) [37].

For the prediction, the backpropagation algorithm is used for training, a process where the network is fed with training data to learn. The algorithm constantly passes on each layer and by calculating predictions and measuring errors, it adjusts the weights of the neurons to reduce errors [17]. From the convolutional to the fully connected layers, we opted to use the Rectifier activation function (ReLU) in all of them, since it reduces the probability of vanishing gradient problem [38]. The loss function was binary cross-entropy, which is efficient with binary classification problems.

The architecture was implemented using Keras [9] with TensorFlow [1] as the backend. To train the network, we used 150 epochs and trained in mini-batches of 64 samples with a learning rate of 0.001. The model and dataset will be available at https://github.com/Unilasalle-SmartCare/smartcare-machinelearning. We have used a Ryzen 9 5900HX with a GeForce RTX 3080 Laptop GPU to execute our method. To collect the inference runtime on a sample of the validation set, we used the TensorFlow profiler and obtained an average inference runtime of approximately 12.3 ms.

Results

The accuracy of the model, which represents the model performance on the train/test data, is presented in Fig. 10. The loss, that is the distance between the true target and the prediction, is presented in Fig. 11. The model was

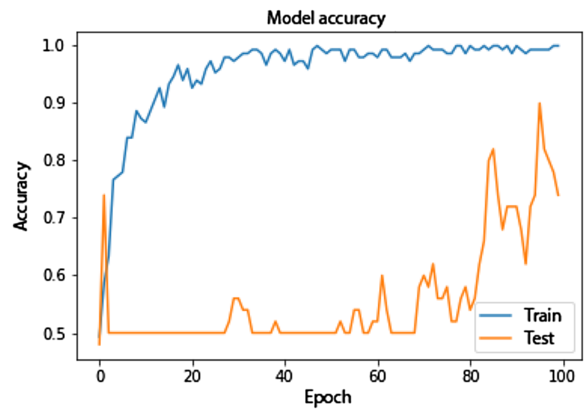

Fig. 10 Accuracy per epoch of the model [27]

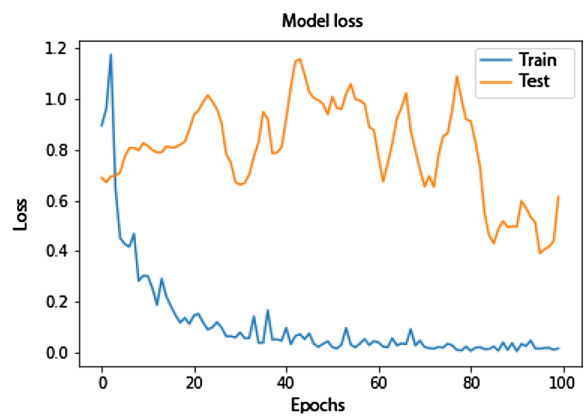

Fig. 11 Learning curve representation of the model [27]

trained for 100 epochs with the train/test dataset. The optimizer algorithm used was the Adaptive Moment Estimation (adam).

The tuning of the model hyperparameters based on the train/test set and evaluating on the same set would leak information of the validation set on the model that may influence the results [8]. Based on that, besides the test set used in training to calculate the model accuracy and loss seen in Figs. 10 and 11, we've generated separately a validation dataset, consisting of 10 h of stress and 10 h of normal movement, an equivalent of 10% the size of the data used for training with the objective to evaluate our model and avoid information leaks.

To measure the accuracy of the models, we utilized the following evaluation metrics: precision, recall and $F1$ score. In Eqs. 1–3, we present each one:

$$\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}} \tag{1}$$

$$\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}} \tag{2}$$

$$F1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}. \tag{3}$$

We could evaluate our final model with the validation dataset and had a precision of 100% followed by a recall of 60% and an $F1$ score of 75%. The hyperparameters were chosen empirically by adjusting based on the two curves.

The trained model was able to identify all the movement patterns presented in Table 3. Figure 12 shows a sample of a random path from the validation dataset that was identified by our model correctly as wandering.

The model obtained a satisfactory result considering the small amount of data. Besides that, the proposed architecture is lightweight and can be embedded into small scale devices. As noted in "Dataset Generation", the generated data are synthetically generated to simulate the real-world scenario. Since the architecture of the neural network is simple and robust, it is expected that it generalizes in the real world in a similar of related work. More specifically, it is expected that the machine learning approach proposed in this work can predict not only patterns as the ones present in the literature [11, 24, 25] but also non-perceived ones. As raised by [23] it is important to perform a personalized user wandering recognition model since those wandering activities might have different characteristics depending on the person and even environmental conditions. Our method paves the way for a reinforcement learning approach that can be used for the network to adapt itself to the specific elderly movement in that house.

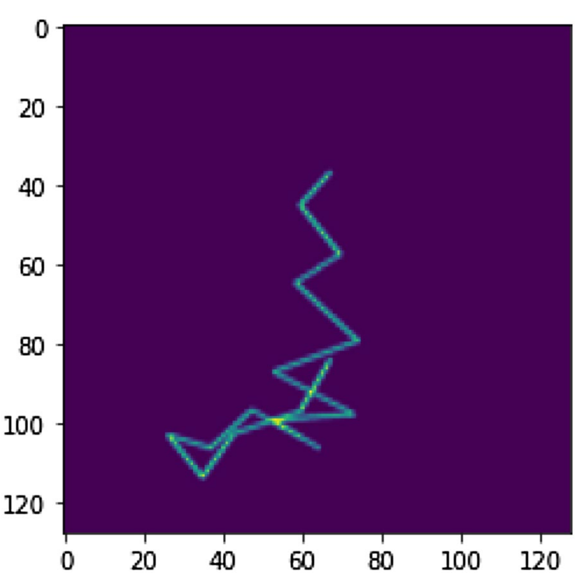

Fig. 12 Sample of a random path generated with wandering movement [27]

Comparison of Intervals of Analysis of the Dataset

To build a graphical path to be analysed, this work stipulated a fixed interval analysis of 1 h to aggregate the points. It was estimated that 1 h would be enough time to obtain a wandering path since the elderly can walk and get still in many places around the house during the interval of analysis. The current interval of 1 h has an average of 16.21 points per path. As this value was derived from the 1-h estimation and the synthetic dataset generation, we propose an experiment to verify the generated dataset and the CNN behaviour with fewer points per path.

We propose to create another dataset based on the first one presented in "Dataset Generation". This new dataset represents paths with a 30-min interval. To achieve this, each 1-h interval in the original dataset was transformed into 30 min by splitting each hour path in half. The algorithm to perform this split followed tree rules. (i) For paths that were composed of an even number of points, the path was simply sliced in half. (iii) In the cases of a path composed of an odd number of points, the path was sliced at the ceiling of half its length. (iii) In the cases for the paths with only one point the entire path was duplicated. Only one point means that the elderly have stood in the same place for the entire hour. More specifically, 1 h with only one point was split into two 30 min slices with one point each. The Table 4 shows the characteristics of each dataset. The total number of points, wandering points and normal points increased in

Table 4 Comparison between the two datasets with different interval of analysis

Dataset name	1 h	30 min
Interval of analysis (min)	60	30
Total points	3242	3249
Wandering points	1786	1786
Normal points	1456	1463
Avg points per path	16.21	8.12
Min points per path	1	1
Max points per path	73	37
Wandering paths	100	200
Normal movement paths	100	200

the 30 min dataset because of the duplication mentioned in rule (iii) above. As expected, the average points number per path was divided by half, and the number of paths doubled in the 30 min dataset.

The CNN presented in “Implementation” was trained with the 30 min dataset. To measure the performance of the model with the data, the following metrics were calculated: precision, recall and F1 score. In comparison with the 1-h interval of analysis, the 30 min dataset had a difference of precision 55.56% lower, a recall of 20% higher and an F1 score of 17,86% lower. With this result, the 30 min dataset did was not sufficient to train the network and obtain satisfactory results. More evidently, with much lower precision than the 1-h dataset.

According to the Table 4, the average points of the 30-min dataset decreased approximately 50%. Thus we speculate that the 30-min dataset does not have enough points for the model to learn. This reduction in points is mapped to shorter paths and with less visual information for the network to learn. Another hypothesis is that the split rules applied may negatively bias the model, justifying the lower evaluation metrics from the 30-min dataset.

Conclusions

In this paper, data preparation and lightweight CNN architecture were proposed to detect the wandering of Alzheimer’s patients using data from non-intrusive sensors. By transforming all the data paths into images, we could use techniques such as data augmentation to expand the simulated dataset and reach better results with a convolutional neural network. Conventional tracking such as wearables and cameras enters into a deep discussion about the privacy of the users. Therefore, one of the challenges of this work was to propose a predictive method that could fit the environment with non-intrusive sensors. Another big challenge was the lack of data to develop the machine learning model, so we have generated using known patterns to simulate the real world. Although the data is synthetic, it is expected that the machine learning architecture also works with real-world data.

For future work, collecting real patients’ data is vital to validate our model in the real world and learn even more wandering patterns. The conversion from the path to images, as done in this work, can be expanded to other disease movement anomalies and also outside the health field. For example, the same method can be used for classifying potential customers of a store based on the movement. This comes with as much needed privacy concern, as the only input our method needs is a path of movement inside an indoor scenario. In the future, this idea can also be applied to identify wandering in an outdoor scenario. The use of reinforcement learning is a future challenge to bring interesting comparative results with this work. Since reinforcement learning tends to choose actions to maximize a reward based on the environmental information [8], these actions could be something to mitigate the patient stress, such as aromatherapy or music. It is also expected to enhance the dataset with data capturing to reach better results with an interval of analysis lower than 1 h. And also to test how the model performs with intervals higher than 1 h. Moreover, to further improve the model in question, as mentioned in [13, 15, 16], performance gains could be obtained utilizing bilateral filtering in the intermediate layers of the convolutional network.

Acknowledgements The authors would like to thank Unilasalle-RJ for encouraging and financially supporting this work.

Funding This work was partially funded by UNILASALLE-RJ.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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