Convolutional Neural Network for Elderly Wandering Prediction in Indoor Scenarios

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Abstract: This work proposes a way to detect wandering activity of Alzheimer's patients from path data collected from non-intrusive indoor sensors around the house. Due to the lack of adequate data, we've manually generated a dataset of 220 paths using our own 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 finding patterns specially on images. The Convolutional Neural Network model was trained with the generated data and achieved an f1 score (relation between precision and recall) of 75%, recall of 60%, and precision of 100% on our 10 sample validation slice.

1 INTRODUCTION

Alzheimer is a type of dementia, characterized as a neurodegenerative disease that affects especially memory and behaviour. Wandering is one of the most common behavioural problems of Alzheimer's patients as seen in (Teri et al., 1988).

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 (Ballard et al., 2009). This task is usually done by family members or contracted professionals. 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 (Radziszewski et al., 2017).

In the current context, the COVID-19 pandemic has increased even more the necessity to monitor Alzheimer patients, because they eventually suffer from anxiety and even increased health risks (Boutoleau-Bretonnière et al., 2020). Which in turn, contributes to the caregiver burden.

Since wandering behaviour is most times coupled with agitation in Alzheimer patients (Ballard et al., 2009), a system that automatically and correctly detects wandering behaviour in a smart-home can take

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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 (O'Neil et al., 2011). Thus, by utilizing a smart-home to perform such tasks, a system can alleviate some of the caregiver burden.

Therefore a prerequisite to such a system is to correctly detect a wandering behaviour. This work proposes a machine learning technique for identifying wandering patterns. The focus of the paper being the detection of wandering in an indoor scenario.

By observing the difficulties faced by caregivers in monitoring Alzheimer patients, the necessity of continuous supervision was noticed and it highlights the importance of this work. By using the Internet Of Things (IoT) (Karimi and Atkinson, 2013), we could obtain the movement data of the elderly in a non-intrusive way, however, due to the massive quantity of data, it's hard to identify wandering patterns.

In Figure 1 we have 6 different patterns of movements between point A and a point B. It was identified that some of these patterns were more present in wandering than normal activity (Martino-Saltzman et al., 1991), (Delaunay and Guérin, 2017). In Figure 1 (a) the first pattern is present in both wandering and non-wandering movements, but mostly in non-wandering movement. So it was not associated as a wandering

activity, differently from the other two patterns of this figure, pacing, and random. Figure 1 (b) 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've reproduced manually the likely wandering patterns represented in Figure 1 to create the anomalous activity data and also normal data mostly composed of direct movements.
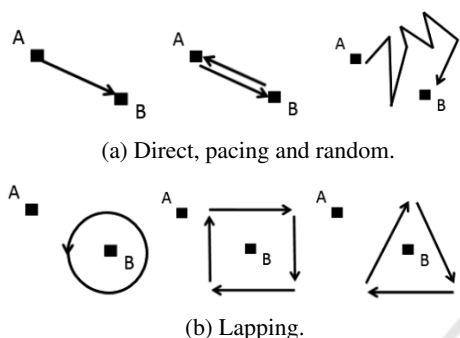

(a) Direct, pacing and random.

(b) Lapping.

Figure 1: Wandering and non-wandering movement patterns (Delaunay and Guérin, 2017).

Thus, in this work is proposed a method that can based on the estimated recent position with IoT and a neural network model for the deep learning approach, infer the patient stress so that we can act in trying to mitigate the negative effects of it. It is hoped that this can be an important tool to help caregivers and relatives of Alzheimer's patients.

Even though this work reaches especially the machine learning part of the project, to understand it is crucial to have an overview of the entire system's architecture. The system's architecture represented in Figure 2 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 system's configuration, REST API (Masse, 2011) is a double way to communicate with other components. With that, the client can request to the API, data from the machine learning engine and NoSQL Database (Han et al., 2011). Temporal data from the database is 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. Treatment of the sensors data, data fusion between sensors, and intermediate system communications are the roles of the controller. The controller treats the data, by analyzing the raw simple sensors activations around the house and, with data aggregation, generates the path of the elderly that will be used to identify anomalies. Raw and treated data are
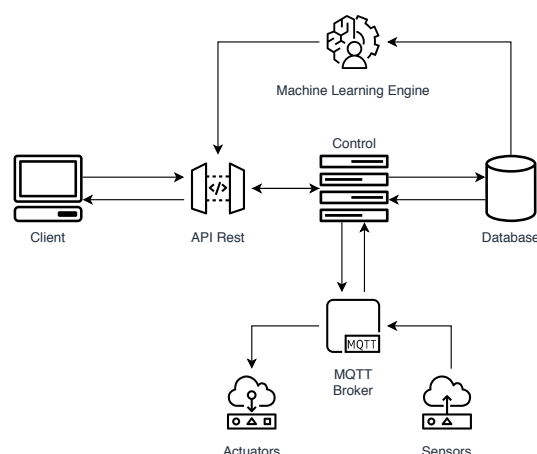

Figure 2: Architecture of the system.

stored in the Database. The data is captured through non-intrusive sensors such as distance, presence, pressure sensors. It is the sensor part of the IoT module, in which direct communication protocol between devices is done with the Message Queuing Telemetry Transport(MQTT) interface (Light, 2017). Also in the IoT module, we have the actuators which are responsible to help to mitigate the elderly stress, being able to produce aromas, and turn on and off the lights. The work shown in this paper is based on this entire architecture. With this, our work presents a method to utilize machine learning to detect wandering using data coming only from non-intrusive sensors.

This work is organized as follows, the related work of IoT monitoring and the use of machine learning will be shown in Section 2. Section 3 overviews the application developed for the data generation and the composition of the data used in our learning structure. Section 4 approaches the data pre-processing and the construction of our neural network model. In Section 5 we discuss the performance of our model and experiments. Finally, in Section 6 we show future applications and conclude our work.

2 RELATED WORK

As stated in (Ordóñez and Roggen, 2016), 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 using machine learning techniques. The use of machine learning was already present in activity tracking, an example is (Akbar et al., 2019) that uses data from wearable sensors such as a wristband for heart rate monitoring and neural networks to learn sleep patterns of the users, in order to turn off the

lights after they fall asleep. And as well in (Oniga and Sütő, 2014), IoT data is used to train an artificial neural network model that, given the information of the arm and body pose of the patient, it could track activities such as the walking movement or even predict if the user was sitting down.

(Khan et al., 2018) surveys and compare the literature about agitation and aggression detection. The tracking modalities presented was by using wearable devices, computer vision and multimodal, it also presents a correlation between agitation and aggression in dementia patients and actigraphy. Relating this overview of papers to our work, we focus on the well-being of the patient by assuming that the ambient only employs sensor-tracking. That the elderly do not need to wear, neither feel the hostility of a camera watching him.

In (Vogado et al., 2020) CNN (Convolutional neural network) is used to help the diagnostic of leukemia, using images of blood smears, complemented with the application of transfer learning and data augmentation techniques, reaching a result of 98.28% of accuracy. Compared to our work, we use CNNs that can detect anomalies in images and also the use of data augmentation to generate more data.

In (Amin et al., 2020a) and (Amin et al., 2020b), machine learning is used to detect brain tumors. (Amin et al., 2020a) uses CNNs and (Amin et al., 2020b) autoencoders to approach the problem. They were trained and evaluated using BRATS challenges databases and had good results in comparison to the literature. In relation to our work, we similarly have an image classification problem. However, in the work of (Amin et al., 2020a), the CNN has 14 layers whereas our networks have only 4 layers.

(Doughty et al., 1998) 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 event activations such as sitting down, moving to the chair, opening and closing drawers, and then calculating a score based on repeated events 5 minutes. 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 data pattern in the movement. With the advantage of adapting to new patterns if needed.

Contrasting to related work, our method focus on predicting wandering using sensing information collected in a non-intrusive way. Similar to (Doughty et al., 1998), but coupled with a machine learning approach which makes possible the detection of known patterns in the literature such as (Martino-Saltzman et al., 1991). Also, being able to detect other patterns

by the data distribution with the machine learning engine and having a lightweight architecture, capable of running on an IoT device.

3 DATASET

Due to the lack of indoor datasets containing normal and anomalous activity, the data generation strategy was adopted similar to the one presented in (Arifoglu and Bouchachia, 2017). 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 a real patient. With this tool, we generated movement patterns of wandering and normal activity.

In order to make easier the work of data generation, we've created a web application, as shown in Figure 3. In the application, we 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 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 activity. Is important to note that although the generated data of the datasets were synthetic and don't 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 (Arifoglu and Bouchachia, 2017) does.

As seen in Figure 3, on the left we have the ground floor plan and on the right the statistics created to help to monitor the data balance, such as the number of hours with wandering and normal activity. 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 was exported in JavaScript Object Notation (JSON) (Severance, 2012) 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' represents it's respective coordinates in the ground floor plan image starting from the upper left. The 'date' attribute, which date and hour the point belongs. Each point has the attribute stress that indicates if the elderly is wandering. Even though each point has the attribute stress,
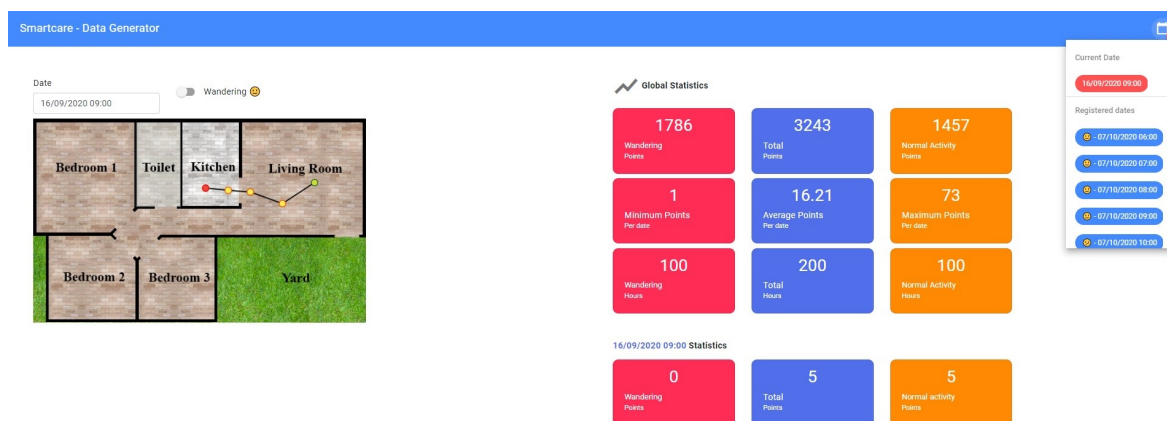
Figure 3: Developed application for data generation. The user interacts with the floor-plant to place movement points, define the hour of the movement and if it was wandering. On the right side of the page shows the statistics created to visualize the generated data. In the upper right a menu that shows all the registered movement dates and hour.

the application considers a time interval to account for a wandering activity. It is not able to have two points in the same time interval with different stress values. In order to know where the movement starts and ends, the points of the same data and interval are inserted in the order as the elderly movement.

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 hours, being 100 hours of normal activity and 100 hours of stress. As seen in table 1, they are sliced into training and test part being respectively 75% and 25%. The validation dataset to be used in the evaluation of our machine learning model is consisted of 20 hours, being 50% anomalous activity and the other 50% normal activity. The composition can be seen in more depth in table 2.

For the purpose of generating consistent anomalous data, patterns present in (Martino-Saltzman et al., 1991), (Delaunay and Guérin, 2017) 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 (Martino-Saltzman et al., 1991). Random patterns are described by (Martino-Saltzman et al., 1991) as roundabout or haphazard travel to many locations within an area without repetition and is mostly composed of direct movements.

Table 1: Distribution of the train/test dataset.

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

Table 2: Distribution of the validation dataset.

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

4 IMPLEMENTATION

Data Processing. With the generated dataset, it's still needed to do some processing in order to use our artificial neural network model (ANN). 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 Figure 4, 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 to the model big images with very small features and it would impair the generalization of the model. To account for the aforementioned problems, the images were rescaled to 128x128 resolution.

Data Augmentation. Even with the generated dataset we do not have much data. In order to prevent overfitting and help the model generalization, we used data augmentation techniques. As seen in Figure 5, each train image generates more training images.
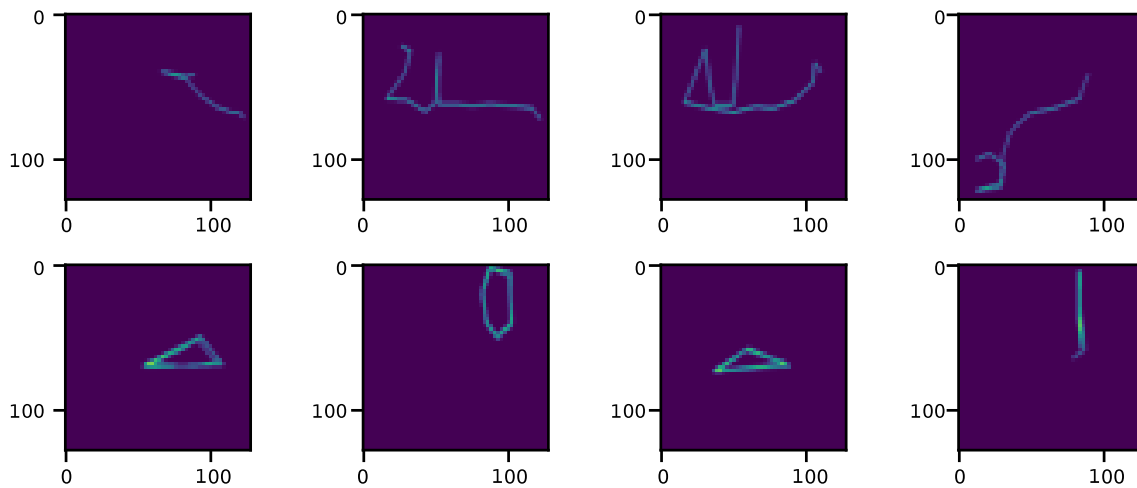
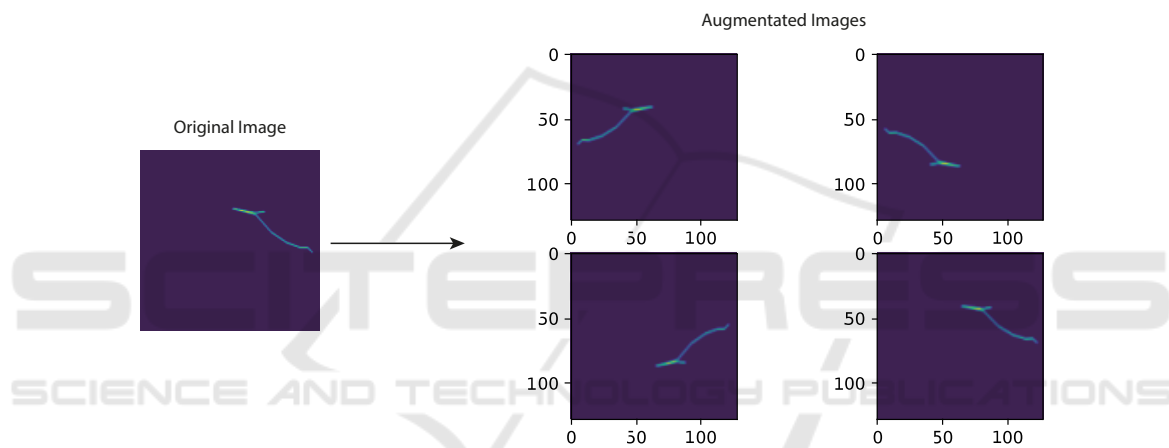Figure 4: Samples of the path data plotted as images after rescaling.

Figure 5: Data augmentation technique applied in movement path.

Differently from (Vogado et al., 2020) 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. By using path images, it was seen that the Convolutional Neural Network (CNN) approach could be an interesting idea. Since it could identify the anomalous movement activities by learning the shapes and pixel distribution of the paths. The CNN architecture is presented in Figure 6. 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 between 0 and 1, which 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) (Srivastava et al., 2014).

For the prediction, it is used the backpropagation algorithm that on 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 the weights of the neurons to reduce errors (Gron, 2017). From the convolutional to the fully connected layers, we opted to use Rectifier activation function (ReLU) in all of them since it reduces the probability of vanishing gradient problem (Talathi and Vartak, 2015). The loss function was binary cross-entropy that is good with binary classification problems.

The architecture was implemented using Keras (Chollet et al., 2018) with TensorFlow (Abadi et al., 2015) as backend. To train the network, we used 150 epochs and trained in mini batches of 64 samples
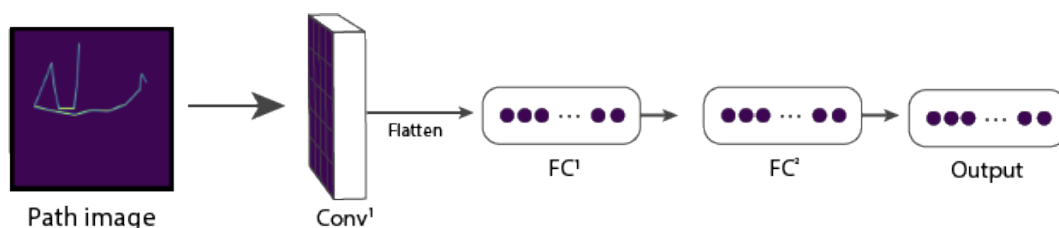
Figure 6: Architecture of our neural network model.

with a learning rate of 0.001. The model and dataset will be available at https://github.com/Unilasalle-SmartCare/smartcare-machinelearning.

5 RESULTS

The accuracy of the model, which represents the model performance on the train/test data, is presented Figure 7. The loss, that is the distance between the true target and the prediction, is presented in Figure 8. The model was 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 (Chollet, 2017). Based on that, besides the test set used in the training to calculate the model accuracy and loss seen in Figures 7 and 8, we've generated separately a validation dataset, consisted of 10 hours of stress and 10 hours of normal activity, 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 accuracy of the models, we utilized the following evaluation metrics: precision, recall and f1 score. In Equations 1,2 and 3 we present each one.

$$Precision = \frac{true\,positives}{true\,positives + false\,positives} \quad (1)$$

$$Recall = \frac{true\,positives}{true\,positives + false\,negatives} \quad (2)$$

$$F1 = 2 \times \frac{precision \times recall}{precision + recall} \quad (3)$$

With the validation dataset, we could evaluate our final model and had a precision of 100% followed by a recall of 60% and the 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 2. Figure 9 shows a sample of random path generated 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. Therefore it is expected that the machine learning approach proposed in this work can predict not only patterns as the ones present in the literature (Martino-Saltzman et al., 1991), (Delaunay and Guérin, 2017), (Lin et al., 2012) but also non-perceived ones. As raised by (Lin et al., 2014) 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.
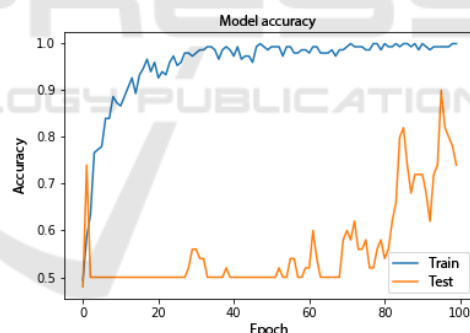

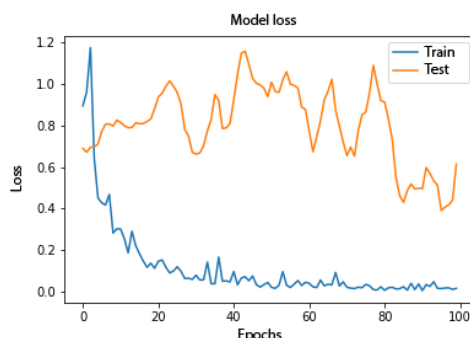Figure 7: Accuracy per epoch of the model.

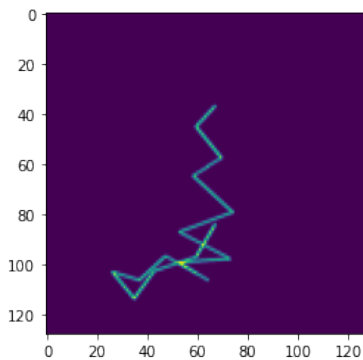Figure 8: Learning curve representation of the model.

Figure 9: Sample of a random path generated with wandering activity.

6 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've generated using known patterns to simulate the real world, although the data being synthetic, it is expected that the machine learning architecture also works with real-world data.

For future work, collecting real patient's data is vital to validate our model in the real world and also 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 from 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 environment information (Chollet, 2017), these actions could be something to mitigate the patient stress such as aromatherapy or music.

REFERENCES

Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., Corrado, G. S., Davis, A., Dean, J., Devin, M., Ghemawat, S., Goodfellow, I., Harp, A., Irving, G., Isard, M., Jia, Y., Jozefowicz, R., Kaiser, L., Kudlur, M., Levenberg, J., Mané, D., Monga, R., Moore, S., Murray, D., Olah, C., Schuster, M., Shlens, J., Steiner, B., Sutskever, I., Talwar, K., Tucker, P., Vanhoucke, V., Vasudevan, V., Viégas, F., Vinyals, O., Warden, P., Wattenberg, M., Wicke, M., Yu, Y., and Zheng, X. (2015). TensorFlow: Large-scale machine learning on heterogeneous systems. Software available from tensorflow.org.

Akbar, M. F., Putrada, A. G., and Abdurohman, M. (2019). Smart light recommending system using artificial neural network algorithm. In *2019 7th International Conference on Information and Communication Technology (ICoICT)*, pages 1–5. IEEE.

Amin, J., Sharif, M., Anjum, M. A., Raza, M., and Bukhari, S. A. C. (2020a). Convolutional neural network with batch normalization for glioma and stroke lesion detection using mri. *Cognitive Systems Research*, 59:304–311.

Amin, J., Sharif, M., Gul, N., Raza, M., Anjum, M. A., Nisar, M. W., and Bukhari, S. A. C. (2020b). Brain tumor detection by using stacked autoencoders in deep learning. *Journal of Medical Systems*, 44(2):32.

Arifoglu, D. and Bouchachia, A. (2017). Activity recognition and abnormal behaviour detection with recurrent neural networks. *Procedia Computer Science*, 110:86–93.

Ballard, C. G., Gauthier, S., Cummings, J. L., Brodaty, H., Grossberg, G. T., Robert, P., and Lyketsos, C. G. (2009). Management of agitation and aggression associated with alzheimer disease. *Nature Reviews Neurology*, 5(5):245.

Boutoleau-Bretonnière, C., Pouclet-Courtemanche, H., Gillet, A., Bernard, A., Deruet, A.-L., Gouraud, I., Lamy, E., Mazoué, A., Rocher, L., Bretonnière, C., et al. (2020). Impact of confinement on the burden of caregivers of patients with the behavioral variant of frontotemporal dementia and alzheimer disease during the covid-19 crisis in france. *Dementia and Geriatric Cognitive Disorders Extra*, 10(3):127–134.

Chollet, F. (2017). *Deep Learning with Python*. Manning Publications Co., USA, 1st edition.

Chollet, F. et al. (2018). Keras: The python deep learning library.

Delaunay, A. and Guérin, J. (2017). Wandering detection within an embedded system for alzheimer suffering patients. In *2017 AAAI Spring Symposium Series*.

Doughty, K., Williams, G., King, P., and Woods, R. (1998). Diana-a telecare system for supporting dementia sufferers in the community. In *Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. Vol. 20 Biomedical Engineering Towards the Year 2000 and Beyond (Cat. No. 98CH36286)*, volume 4, pages 1980–1983. IEEE.

Gron, A. (2017). *Hands-On Machine Learning with Scikit-Learn and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems*. O'Reilly Media, Inc., 1st edition.

Han, J., Haihong, E., Le, G., and Du, J. (2011). Survey on nosql database. In *2011 6th international conference on pervasive computing and applications*, pages 363–366. IEEE.

Karimi, K. and Atkinson, G. (2013). What the internet of things (iot) needs to become a reality. *White Paper, FreeScale and ARM*, pages 1–16.

Khan, S. S., Ye, B., Taati, B., and Mihailidis, A. (2018). Detecting agitation and aggression in people with dementia using sensors—a systematic review. *Alzheimer's & Dementia*, 14(6):824–832.

Light, R. A. (2017). Mosquitto: server and client implementation of the mqtt protocol. *Journal of Open Source Software*, 2(13):265.

Lin, Q., Zhang, D., Chen, L., Ni, H., and Zhou, X. (2014). Managing elders' wandering behavior using sensors-based solutions: a survey. *International Journal of Gerontology*, 8(2):49–55.

Lin, Q., Zhang, D., Huang, X., Ni, H., and Zhou, X. (2012). Detecting wandering behavior based on gps traces for elders with dementia. In *2012 12th International Conference on Control Automation Robotics & Vision (ICARCV)*, pages 672–677. IEEE.

Martino-Saltzman, D., Blasch, B. B., Morris, R. D., and McNeal, L. W. (1991). Travel behavior of nursing home residents perceived as wanderers and nonwanderers. *The Gerontologist*, 31(5):666–672.

Masse, M. (2011). *REST API Design Rulebook: Designing Consistent RESTful Web Service Interfaces*. " O'Reilly Media, Inc.".

O'Neil, M. E., Freeman, M., Christensen, V., Telerant, R., Addleman, A., Kansagara, D., et al. (2011). *A systematic evidence review of non-pharmacological interventions for behavioral symptoms of dementia*. Department of Veterans Affairs Washington, DC.

Oniga, S. and Sütő, J. (2014). Human activity recognition using neural networks. In *Proceedings of the 2014 15th International Carpathian Control Conference (ICCC)*, pages 403–406. IEEE.

Ordóñez, F. J. and Roggen, D. (2016). Deep convolutional and lstm recurrent neural networks for multimodal wearable activity recognition. *Sensors*, 16(1):115.

Radziszewski, R., Ngankam, H. K., Grégoire, V., Lorrain, D., Pigot, H., and Giroux, S. (2017). Designing calm and non-intrusive ambient assisted living system for monitoring nighttime wanderings. *International Journal of Pervasive Computing and Communications*, 13(2):114–129.

Severance, C. (2012). Discovering javascript object notation. *Computer*, 45(4):6–8.

Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., and Salakhutdinov, R. (2014). Dropout: a simple way to prevent neural networks from overfitting. *The journal of machine learning research*, 15(1):1929–1958.

Talathi, S. S. and Vartak, A. (2015). Improving performance of recurrent neural network with relu nonlinearity. *arXiv preprint arXiv:1511.03771*.

Teri, L., Larson, E. B., and Reifler, B. V. (1988). Behavioral disturbance in dementia of the alzheimer's type. *Journal of the American Geriatrics Society*, 36(1):1–6.

Vogado, L. H., Veras, R. M., and Aires, K. R. (2020). " leuknet"-a model of convolutional neural network for the diagnosis of leukemia. In *Anais Estendidos do XXXIII Conference on Graphics, Patterns and Images*, pages 119–125. SBC.