Anomaly Detection in Sleep Habits Using Deep Learning

Asma Gasmi, Vincent Augusto, Jenny Faucheu, Claire Morin, Xavier Serpaggi

Anomaly Detection in Sleep Habits using Deep Learning

Asma GASMI[1], Vincent AUGUSTO[1], Jenny FAUCHEU[2]
Claire MORIN[3] and Xavier SERPAGGI[4]

***Abstract*— In the last decade many researchers have shown interest in the sleep analysis field. The reason behind it relies on the fact that it could lead to the early discovery of some health issues, especially for elders. In this article, a new method was presented to detect anomalies in patients' sleep habits. This method is based on creating a new database of 2500 patients divided into 5 different habits. Then we used this data set to test the categorization of the patient by using the mean-shift clustering method. Finally, a presentation of the auto-encoder method to detect the anomalies was made. Using an auto-encoder based on Long Short Term Memory (LSTM) network, we were able to reach satisfying results.**

***Index Terms*— Deep learning, unsupervised learning, sleep analysis, frailty detection, clustering, Anomaly detection.**

I. Introduction

A. Context

Sleep represents almost a third of human life. By analyzing it correctly and efficiently, practitioners can detect, in an early stage, many health problems and cure them or at least stop their evolution. To help doctors in their decision-making, many researchers have been interested in sleep architecture and sleep quality analysis.

Anomaly detection refers to the problem of finding patterns in data that do not conform to expected behavior [22]. Such events deviate significantly from the majority of the data. Anomaly detection and security is a major concern in the Internet of Things domain and in modern society. It is used in a variety of areas such as Smart Cities/Smart Homes, health problem detection, intrusion detection, network security, and financial fraud detection...

B. Related literature

The literature on anomaly detection is rich. [22] propose a formal definition of the problem and a comprehensive review organized upon methods and application areas. In [19], authors have proposed a method that uses an auto-encoder with probabilistic random forest, for detecting credit card frauds. They have used the method explained earlier to detect, based on the customer's habits, they have been able to detect whether a transaction is a fraud or was deliberately carried out by the customer. They claim very good results with 99% accuracy.

Healthcare is also one of the main fields in which anomaly detection is used. Health data can have anomalies due to several reasons such as abnormal patient conditions or instrumentation errors or recording errors [22]. The search for anomalies in health-related behaviors, that could lead to pathologies, seems promising [15]. In [16], authors have used a smart home equipped with sensors in order to detect the anomalies that could occur in the daily routines of an elderly living alone. These anomalies could translate into a drift in the cognitive frailty of this patient. Another study [17] has investigated the correlations between social frailty and physical activity regarding older adults using Machine learning algorithms. By studying this correlation they have ended up detecting that most studied subjects who tend to do less physical activities are likely to end up with a drift in their social frailty.

Sleep anomalies are disorders that badly affect the habits of sleep on a daily or on long-term basis. Any type of sleep issue that could lead to a change in habits, can be considered a sleep anomaly [23]. These changes could be the direct result of many physiological or psychological factors. In this article, we have taken interest in the sleep anomalies that affect cognitive and psychological frailty and could be detected in non-invasive ways, such the Insomnia (a sleep disorder that affects a person's ability to fall asleep or stay asleep), the modification of the architecture of sleep, the sleep disorder due to the of the unbalanced portion of REM, the changes in sleep duration and in sleep agendas, ...

C. Scientific contribution

Anomaly detection is a common problem in the machine learning field. The general structure of most Anomaly Detection Systems is similar. According to [2], anomaly detection is performed in three steps: (i) *Data collection and parametrization*, which consists in collecting data that will be used to train the model; (ii) *Model training*, which consists in modeling the system using machine learning methods; (iii) *Detection stage*, which consists in comparing the system created in the training stage to the specified selected data segment. Threshold criteria will be defined to identify any anomaly within the test data.

Based on this theory, **we propose in this article a new approach to detect anomalies in patients' sleep habits**. The scientific contributions of this paper are threefold:

1) A comprehensive synthetic data set representative of several sleep behaviors that we will use to train our

[1]Mines Saint-Etienne, Univ Clermont Auvergne, CNRS, UMR 6158 LIMOS, Center for Biomedical and Healthcare Engineering, F-42023 Saint-Etienne France name.surname@emse.fr

[2]Mines Saint-Etienne, CNRS, UMR 5307 Laboratoire Georges Friedel, Centre SMS, F-42023 Saint-Etienne France

[4]Mines Saint-Étienne, Institut Henri Fayol, Département ISI, F-42023 Saint-Étienne France

[3]Mines Saint-Etienne, Univ Lyon, Univ Jean Monnet, INSERM, UMR 1059 Sainbiose, Centre CIS, F-42023 Saint-Etienne France

learning model: such data set has been computed based on a sleep sample collected in the literature.
2) A sleep behavior model using an unsupervised clustering method based on the Mean shift algorithm [18].
3) An anomaly detection approach based on the patient's sleep behavior using an auto-encoder method. By studying the previous habits of the patient, we could detect any change in the habits by comparing the reconstructed night with how the night really happened.

Such an approach is useful for residents of long-term care followed by gerontologists. The resulting tool may be used by practitioners in order to detect abnormal sleep patterns due to a change in the medication of the patient for example.

This paper is organized as follows. The sleep profile of patients is formalized in Section II. The sleep behavior model is presented in Section III. The anomaly detection approach is detailed in Section IV. Results are synthesized in Section V. Conclusions and perspectives are given in Section VI.

II. Sleep Profiles definition

A. Motivation

Since data sets that contain more than one or two nights of recording are rare we propose in this paper a method to construct a synthetic data set. This method uses as input a data set containing several nights of one patient. We extract the sleep habits of the patient using Linear regression models and propose a model using the extracted trends from the data set using mathematical equations. Once we have a model, we propose an algorithm to generate habits.

B. Sleep Pattern Definition

Definition 1: Sleep Feature: A sleep feature is a parameter used to characterize one night. All sleep features considered in this chapter are summarized in Table I.

Feat.	Interval def.	Definition
Age	[65,95]	The age of the person.
Sex	[0,1]	The sex of the patient,0 for woman and 1 for man.
Wgh	[55,85]	The weight of the studied patient.
H	[153,187]	The height of the studied patient
SQ	[65,100]	Sleep quality of the patient.In our case,is calculated in [8].
DS	[240,540]	Total duration of sleep
SE	[61,100]	Sleep efficiency [8], calculated by dividing the sleep duration D by the time spent in the bed
St	[22:00,00:38]	Sleep starting time
Wk	[0,240]	Wake duration including the time before falling to sleep.
$WAKEr$	$[0, 1]$	Wake ratio, i.e. percentage of the time that the person is awake while still in bed, or micro wake periods.
$NREMr$	$[0, 1]$	Non-Rapid Eye Movement ratio [5].
$REMr$	$[0, 1]$	Rapid Eye Movement ratio.
$Epworth$	[0,24]	The Epworth scale.
$PSQI$	[0,36]	The PSQI Pittsburgh Sleep Quality Index.
$SEGA$	[0,48]	The Short Emergency Geriatric Assessment grid [3].

TABLE I
Sleep features

Sleep differs from one person to another due to many factors such as age, weight, quality of life, physical state, mental health, cognitive state, and frailty level... Such factors affect one or more sleep features. According to the literature [5], the most important features to consider to evaluate sleep quality are (i) the SEGA grid, (ii) the PSQI, (iii) the Epworth scale, (iv) the sleep efficiency. The rest of the features are equally less important.

Definition 2: Night: A night N is a 15-uple of features that are recorded or calculated during a night of sleep such as
$N = \{age, sexe, Wgh, H, SQ, DS, SE, St, Wk,$
$WAKEr, NREMr, REMr, Epworth, PSQI, SEGA\}$.

Definition 3: Sleep Habit: A sleep habit $H = [N_1, N_2, \ldots, N_n]$ is a sequence of $n \in \mathbb{N}$ nights.

In a sleep habit, the sequence of nights might evolve following different patterns. For a person without any health disorder, the features of each night do not evolve significantly over time. However, with age, one's sleep habits change due to many factors. These changes can affect at least one feature of sleep [9] and are usually permanent, but one can observe sometimes changes that occur for a certain period of time. In this chapter, we consider two types of sleep evolution: (i) sequence of nights without any significant change; (ii) slow evolution of one or more features of sleep. Such sleep evolution is defined as sleep patterns.

Definition 4: Sleep Pattern: A Sleep Pattern PT is a sleep habit having the same variation and the same type of degradation.

Definition 5: Sleep Profile: A sleep profile is a sleep habit having certain characteristics. In this work, we define 5 types of sleep profiles, summarized in Table II.

We propose the following ranking of features from the most important to the least: (i) $SEGA$, (ii) $PSQI$, (iii) $epworth$, (iv) SE. The rest of the features are equally important. Based on practitioners' expertise, we consider that the degradation of features occurs one after another. Such features are selected randomly among the features that are not connected to each other. For example, we have started with the features which are based on the questionnaires.

1) profile 1: sleep profile definition: In order to generate a profile 1 sleep profile (no feature evolution over time),

Sleep profile	Label	Definition
Type I	Constant sleep	The sleep features of each night of the sleep habit do not significantly change over a long period of time.
Type II	Slow degradation of one feature	There is a slow degradation over a long period of time of only one feature.
Type III	Slow degradation of 2 features	In this profile, 2 features are slowly degrading over time. The first feature starts degrading a certain number of nights after the start of the habit, the second feature starts degrading a certain number of nights after the start of the first degradation.
Type IV	Slow degradation of 3 features	Similar to Type III with an additional feature degradation.
Type V	Slow degradation of 4 features	Similar to Type IV with an additional feature degradation.

TABLE II

TYPES OF SLEEP PROFILES

we use an existing data set collected over one-year using actigraphy [4]. In this study, the main objective was to search for predictive algorithms from consecutive wrist actigraphy recordings of a single subject using a MotionWatch8 (CamNtech Ltd) system. The single subject was a 62-year-old male who wore the device for an entire year with no significant change in his sleep features. Let $\mathcal{P}_r$ be this patient.

We have noticed that each feature of the recorded 365 nights in the P_r data, has a small variation to a mean value. This variation of the feature k noted Δ_k, could be represented as the result of subtraction between the real value of the feature k at a j time of the patient i, noted f_{ijk}, and the mean value of this feature $f_{ik_{mean}}$, such as :

$$\Delta_k = f_{ijk} - f_{ik_{mean}} \tag{1}$$

The maximum value of the feature minus the mean value of the feature will give us the maximum value of variation that Δ_k, could reach, noted Δk_{max}, and the minimum value of the feature minus its mean value will give us the minimum value of variation that Δ_k, could reach, noted Δk_{min}. So we could say that the variation $\Delta \in [\Delta k_{min}..\Delta k_{max}]$.

From here came the idea of using the previous relationship to generate all the values of the different features for all the nights.

$$f_{kji} = f_{ki_{mean}} + \Delta \tag{2}$$

2) profile 2-5 : sleep profile definition: Based on previous clinical trials and database obtained from the website "National Sleep Research Resource" [21], we have summarized the variation that occurs in the following table :

For the other patterns, we took each time a feature and we modified the δ interval by increasing it to cover all the possible values for a feature could reach. For each profile,

TABLE III

TABLE SUMMARIZING OF THE NIGHTS OF PATIENTS AFTER THE DEGRADATION OF FEATURES

feature	Sleep quality	Sleep efficiency	Total duration
maximum value	90	90	520
minimum value	70	78	300
feature	Sleep starting time	Wake-up time	The wake ratio
maximum value	01:30	09:00	15
minimum value	23:30	05:00	7
feature	The NREM ratio	The REM ratio	The Epworth scale
maximum value	75	22	14
minimum value	67	14	8
feature	PSQ	The SEGA grid	
maximum value	15	17	
minimum value	7	9	

we have divided the time into the number of patterns equally. Then, we have chosen for each part to change one feature to create one pattern. This time the modified feature is calculated as follows:

$$f_{kji} = f_{kj-1i} + \Delta \forall \Delta \in \left[\Delta_{k_{permin}}..\Delta_{mmax}\right] \tag{3}$$

such that f_{kj-1i} is the value of the degrading feature the previous night, $\Delta_{k_{permin}}$ which is the minimum value of degradation of a feature k and $\Delta_{k_{permax}}$ which is the maximum value of this degradation.
By using the same method of defining the interval bounds described in algorithm 1, we have calculated $\Delta_{k_{min}}$,$\Delta_{k_{max}}$,$\Delta_{k_{permin}}$ and $\Delta_{k_{permax}}$.

III. SLEEP PROFILES CLUSTERING

Knowing the number of patterns in one sleep profile helps better understand which night is "a usual night" compared to the habits and which is not. we consider that the clusters represent the number of patterns. The issue here was that we did not know how many patterns the patient has before analyzing. so we needed a method of clustering that could find on its own the clusters and the number of clusters without human intervention.

The Mean Shift algorithm is the most suitable algorithm for our case. It is an unsupervised clustering technique commonly used in machine learning. Its goal is to find clusters (in our case sleep patterns) within a set of regular-density samples (a region where points are concentrated and where they are separated by areas that are empty. The points that are not part of a cluster are considered as noise). The algorithm approach is focused on center points called centroids [7]. The process begins by applying a sliding window on each data point (each recorded night of the patient).

The centers of the windows are then updated to be the mean of points in a high-density region (a region where there are a lot of points, in our case a region with a high density is a region where there are a lot of nights). Finally, filtration of any near identical centroids is done. Thus, the result is a set

of nonidentical data points. In comparison to the K-means method, the number of clusters in the mean shift is selected automatically, which is useful in our case study since we do not know the number of sleep patterns the person has.

The Mean Shift method steps are as follows: First, a sliding window is created for each point of the data set, i.e. we select a certain number of nights before and after each night of the data set. For all regions, we evaluate the near-region density in order to update centroids to allocate them to higher-density regions. Then, for all overlapping windows considering our new regions, we delete overlapping windows. Finally, we go through all data points (nights) and assign them to the closest sliding windows that become our new clusters.

A. Parameters and evaluation of the clustering approach

The parameters of the mean shift algorithm are summarized in Table IV.

Parameter name	Value	Definition
D	$\sqrt{\sum_{i=0}^{14}(N1_i - N2_i)^2}$	Distance function between two nights $N1$ and $N2$ with i is the feature index.
$minD$	0.000001	The minimal distance between the nights
GDT	0.1	the accepted distance before creating another cluster

TABLE IV

MEAN SHIFT ALGORITHM PARAMETERS

Note that our main objective is not to classify perfectly each night, but rather to know how many sleep patterns a patient has. Thus we consider as the main performance indicator the number of correctly discovered sleep patterns rather than the correct classification of a night in the "right" cluster. The performance of our approach will be evaluated in two steps: (i) Evaluation of the clustering approach for one person; (ii) Evaluation of the clustering of a population of patients, each patient having a different number of sleep patterns.

In the following, we propose a new approach to detect anomalies in a certain sleep pattern.

IV. SLEEP ANOMALY DETECTION

Once we know to which profile a patient belongs, we analyze his sleep habits in order to detect anomalies. The main idea here is to propose to practitioners a tool to analyze the latest recorded nights to predict if a night presents anomalies or not within the studied sleep pattern. To do so we use an auto-encoder with Long Short-Term Memory (LSTM) network layers.

The aim of this part is to detect nights that present anomalies in order to explain the drift in sleep behavior and its effect on cognitive frailty. To do so, we propose a 2-step approach. The first step consists in training the LSTM using a set of nights with the same pattern. As an output, we obtain a meta-vector that models a "standard night" for this pattern, and a reconstruction error which is used to evaluate the encoding quality. The second step consists in applying sleep anomaly detection to a real person. First, the clustering step presented in the previous section is applied to extract a set of nights with the same pattern. Then we apply the LSTM using the meta-vector and the reconstruction error obtained in the first step. We obtain as an output two reconstruction loss curves (training and testing). Anomaly detection is finally performed by comparing the two curves: any point of the test curve higher than the train curves denotes a potentially abnormal night.

A. Definitions

Long Short Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) that guarantees the network to maintain long-range dependencies between data at a given time from multiple previous time steps [**?**]. In this study, the LSTM is used to predict a sequence of nights. At each iteration, the LSTM predicts the next night taking into account information from the previous nights.

The LSTM has the ability to remove or add information to the cell state, regulated by structures called *gates*. Figure 1 summarizes the mechanisms of the LSTM. The cell state contains the information related to the nights (i.e. the memory of the network). In our case, the cell c represents a night of a certain person at time t. In other words, $c(t-1)$ models the short-term memory of the LSTM.

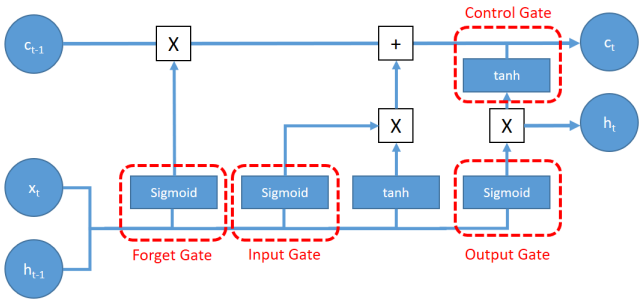

Fig. 1. LSTM architecture

Let x_t be the current input, i.e. the night observed at time t. Let h_{t-1} be the hidden state at $t-1$ and c_{t-1} be the cell state (memory) at time $t-1$.

Gates are used to optionally let information through. They are composed of a sigmoid neural net layer and a point-wise multiplication operation. These gates are the forget gate, the input gate, and the output gate.

The forget gate $fr(t)$ decides which information from the previous cell state should be forgotten. These values are passed into a sigmoid function, which can only output values between 0 and 1. The value 0 means that previous information can be forgotten because there is possibly new, more important information.

The input gate $i(t)$ decides how valuable the current input is to solve the task. For this, the current input is multiplied

by the hidden state h_{t-1} and the weight matrix of the last run. All information that appears important in the input gate is then added to the cell state and forms the new cell state c_t. This new cell state is now the current state of the long-term memory and will be used in the next run. [11].

The output gate $o(t)$ (resp. control gate $cr(t)$) allows the calculation of the new hidden state h_t (resp. of the new cell state c_t).

The functions of the forget, input, and output gates are formally defined as follows [20]:

$$fr(t) = \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \tag{4}$$

$$i(t) = \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \tag{5}$$

$$o(t) = \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \tag{6}$$

$$c(t) = f_t.c_{t-1} + i_t.[\sigma_c(W_c x_t + U_c h_{t-1} + b_c)] \tag{7}$$

such as W_f, W_i, W_o, W_c, U_f, U_i, U_o, U_c are weight matrices and b_f, b_i, b_o, b_c are biases. These parameters are learned during training and can be updated at each iteration in order to improve the prediction.

To summarize, we use an LSTM Autoencoder to capture the temporal dependencies of the data. Its job is to get some input data, pass it through the model, and obtain a reconstruction of the input. The reconstruction should match the input as much as possible. The trick is to use a small number of parameters, so the model learns a compressed representation of the data [6].

B. Methodology

In this study, we propose to use an autoencoder to reconstruct the sleep habits of a person and compare the reconstructed data with the real data to calculate the loss function. Then we define a threshold for each point (i.e. each night) so that we can calculate the loss. The night is considered abnormal if the loss is above the given threshold.

To detect anomalies we use the following method decomposed into 6 steps:

1) Data Prepossessing.
2) Build the LSTM Autoencoder.
3) Train on 80% of the data.
4) Determine the threshold.
5) Anomalies detection

Each step is detailed in the following:

1) Data Pre-prossessing: This first step consists in loading the raw data (i.e. a set of nights with the same pattern) and converting all features into values comprised between 0 and 1. For each feature, we calculate the maximum $f_{k_{max}}$ and the minimum $f_{k_{min}}$. We use the following equation to calculate the standardized values of the feature $f_{ijk_{stand}} \in [0, 1]$:

$$f_{ijk_{stand}} = \frac{f_{ijk} - f_{k_{min}}}{f_{k_{max}} - f_{k_{min}}} \forall i \in P, \forall j \in N, \forall k \in K \tag{8}$$

2) Build the LSTM autoencoder: For each pattern detected by the clustering approach for a patient, we build a model to reconstruct the sleep habits. For this purpose, we train our autoencoder using the parameters listed in Table V.

Name	Value
Number of neurons	Input layer: 32
	First Hidden layer: 16
	Second hidden layer: 8
Learning rate	0.2
Optimizer	MAE
Number of epochs	30
Activation functions	Relu

TABLE V
AUTOENCODER PARAMETERS

Epoch is the number of trials that we are going to run, MAE is Mean Absolute Error, this metric tells us how accurate our predictions are, and Relu is Rectified Linear Activation Function, which is the most common choice of activation function in the world of deep learning. It provides state-of-the-art results and is computationally very efficient at the same time.

The encoder (the first part of the auto-encoder), consists of several layers of recurrent neural networks with short memory, (in our case I chose to have 32 Input layers, 16 First Hidden layers, and 8 Second hidden layers) which takes as input a matrix Me which represents the nights of patients of the same type (in our case the size of Me=500x15x730) after they were standardized and gives us as output a meta matrix which represents the relationships detected between the different nights. This matrix is called a code matrix or latency matrix.

For example, It will take all the nights of all the patients in type I and give us as an output the code matrix that represents the links between the different nights and the detected habits. For the Decoder it was the reverse work of the Encoder. We have considered the same parameters.

3) Training on 80% of the data: The aim of this step is to develop a model that minimizes the training loss by using the mean absolute error. The output of this step is a meta-vector that represents a "standard night" and a reconstruction error (or reconstruction loss). We use 80% of the data for training.

Once the data is reconstructed, we calculate the reconstruction loss by using the (MAE), (which is the error between what we have built with the auto-encoder and the real data) such as:

$$MAE = \sum_{i=1}^{N} |RNi - PNi| \tag{9}$$

with N being the total number of nights, RN_i a night i from the dataset and PN_i is the corresponding reconstructed night. The MAE should be as close as possible to 0. Then we repeat the same method to validate the model with the remaining 20%.

4) Determine the threshold: As we have presented earlier, we calculate a threshold in order to know later on if a night is abnormal regarding the habits or not. The threshold is calculated as follows :

$$Threshold = mean(train_{loss}) + STD(train_{loss}) \quad (10)$$

such as the $train_{loss}$ is the vector that has all the values of the reconstruction loss during the train part.

We have used this formula as a threshold to be sure that the detected anomaly is real and not an error of reconstruction.

5) Anomalies detection: We took a patient with some nights, then we have reconstruct the nights based on two methods; the first is the one learned during the training process and the second one is based on the actual nights in hand. Then we compared the reconstruction losses of both methods, if the error between them exceeds the calculated Threshold then there is an anomaly if not then everything is normal.

V. Numerical results

We have used the presented method to create our data set that contains 5 types of sleep. Each sleep type has 500 patients, and each patient recorded 730 nights.

A. Clustering patients test

We propose in this part a prediction of sleep profile applied to a population of persons: for each person of the population, we predict the type of sleep profile (I-V) the person has.

To do so we generate randomly a cohort of 2.500 persons having a random number of sleep patterns following the profile types I-V. Results are summarized under the shape of a confusion matrix as presented in Table VI. We observe that our classification approach performs better on profile Type I, which contains only one sleep pattern. The accuracy for the classification of Type II-V is lower.

	How the patient were clustered				
	Type I	Type II	Type III	Type IV	Type V
Real Type I	498	2	0	0	0
Real Type II	16	479	5	0	0
Real Type III	32	52	416	0	0
Real Type IV	11	49	68	372	0
Real Type V	9	56	42	81	313

TABLE VI
Confusion Matrix

Table VII summarizes the performance of our approach using the classical indicators Precision, Recall, and F1-score. As mentioned before, we observe that the F1-score decreases when the number of patterns to discover increases to 0.77.

B. Anomalies detection

We conducted a test to validate this model. We took the data set that we have created. For each profile (except profile 5) we have used the whole data set for the training and to test the anomaly detection, 10% of the other profiles

Class	Precision	Recall	F1-score
Type I	0.99	0.88	0.93
Type II	0.96	0.75	0.84
Type III	0.83	0.78	0.81
Type IV	0.74	0.82	0.78
Type V	0.62	0.76	0.77

TABLE VII
Precision, Recall and F1-score metrics for the multi-class classification

are different in a way that the profile must have more pattern than the profile. We have used it for training.

We have chosen to show the results for 30 nights of the same patient. In the presented example we have chosen to test on the patient profile (I) where we have inserted randomly some nights of patients profile (V) to present the anomaly nights.

We have chosen to show the results for 30 nights of the same patient. In the presented example we have chosen to test on the patient profile (I) where we have inserted randomly some nights of patients profile (V) to present the anomaly nights. In figure 2, a presentation of the results obtained from the loss Reconstruction for this profile of patient :

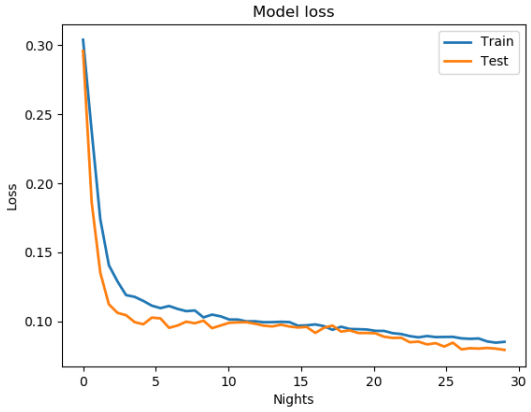

Fig. 2. Reconstruction Loss

Here we introduce our evaluation variables. We used TensorFlow in Python. For the evaluation of our work, we used the SKLearn library which is open-source and efficient in data analysis and mining.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (11)$$

$$Precision = \frac{TP}{TP + FP} \quad (12)$$

$$Recall = \frac{TP}{TP + FN} \quad (13)$$

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} = \frac{2 * TP}{2 * TP + FP + FN} \quad (14)$$

with TP as the true positive, TN as the true negative, FP as the false Positive, and FN as the false negative.

The threshold calculated by using equation (10) is equal to 0.0197 in our case. So we have considered it as 0.02 to simplify the calculations and to be certain that if a reconstruction error exceeds this value it means for sure an anomaly in the habits and not an error in our model.

As explained earlier we have used the 10% of another profile of sleep that contains more patterns. The aim here is to test whether our code will recognize the different nights as abnormal or not.

To measure the performance of our method, we have used the validation variables that we defined earlier. Table 5.20 represents the obtained results.

TABLE VIII
EVALUATION METRICS

	Approximate value
Accuracy	91.20%
Precision	100%
Recall	80.46%
F1-score	89.31%

These results are very satisfying and these results have proven that our method is very accurate. We were able to reach very high scores levels. The minor error that occur was because of the similarities in some nights despite the fact that there is a slight change in the habits.

VI. Conclusions and perspectives

In this article, we have presented a method of modeling the habits of sleep for the elderly. We have created a data set on which we have tested the categorization method. This categorization was very satisfying with an 83,12% precision rate by using the Mean-shift method.

Once we have known to which profile a patient belongs, we applied an LSTM auto-encoder to detect if a night is abnormal or not. We have 91.20% accuracy on our created data set and 93% accuracy on the real data set.

In future work, we plan also to conduct a new clinical trial in order to record four months of sleep features to analyze sleep habits and detect anomalies with a real data set in order to know at which time the habit drift started.

References

[1] Asma Gasmi, Vincent Augusto, Jenny Faucheu, Marine HILAIRE, Claire Morin, Rémi Moulin, Xavier Serpaggi. Frailty Onset Predictions Using Sleep Analysis. 16-18 November 2022, " International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME) ".Maldives.

[2] Waleed Hilal, S. Andrew Gadsden, and John Yawney. 2022. Financial Fraud: A Review of Anomaly Detection Techniques and Recent Advances. Expert Syst. Appl. 193, C (May 2022).

[3] Ellis G, Marshall T, Ritchie C. Comprehensive geriatric assessment in the emergency department. Clin Interv Aging. 2014 Nov 24.

[4] Zhang GQ, Cui L, Mueller R, Tao S, Kim M, Rueschman M, Mariani S, Mobley D, Redline S. The National Sleep Research Resource: towards a sleep data commons. J Am Med Inform Assoc. 2018 Oct 1;25(10):1351-1358. doi: 10.1093/jamia/ocy064. PMID: 29860441; PMCID: PMC6188513.

[5] CRAWFORD ACHOUR, Emilie. Le sommeil physiologique et pathologique du sujet âgé: impact sur la qualité du vieillissement et le vieillissement cognitif. 2013. Thèse de doctorat. Saint-Etienne.

[6] AN, Jinwon et CHO, Sungzoon. Variational autoencoder based anomaly detection using reconstruction probability. Special Lecture on IE, 2015, vol. 2, no 1, p. 1-18.

[7] CARREIRA-PERPINÁN, Miguel A. A review of mean-shift algorithms for clustering. arXiv preprint arXiv:1503.00687, 2015.

[8] Gasmi, Asma , Augusto, Vincent , Baudet, Paul-Antoine , Faucheu, Jenny , Morin, Claire , Serpaggi, Xavier , Vassel, Franck. (2020). Analyse de la qualité du sommeil dans le cadre de la détection de fragilités cognitives au travers d'un lit connecté.

[9] MADRID-VALERO, Juan J., MARTÍNEZ-SELVA, José M., COUTO, Bruno Ribeiro do, et al. Age and gender effects on the prevalence of poor sleep quality in the adult population. Gaceta sanitaria, 2017, vol. 31, p. 18-22.

[10] Staudemeyer, Ralf and Morris, Eric. (2019). Understanding LSTM a tutorial into Long Short-Term Memory Recurrent Neural Networks.

[11] H.D. Nguyen, K.P. Tran, S. Thomassey, M. Hamad, Forecasting and Anomaly Detection approaches using LSTM and LSTM Autoencoder techniques with the applications in supply chain management, International Journal of Information Management, Volume 57, 2021.

[12] M. Zamini and G. Montazer, "Credit Card Fraud Detection using autoencoder based clustering," 2018 9th International Symposium on Telecommunications (IST), 2018, pp. 486-491.

[13] Z. Kazemi and H. Zarrabi, "Using deep networks for fraud detection in the credit card transactions," 2017 IEEE 4th International Conference on Knowledge-Based Engineering and Innovation (KBEI), 2017, pp. 0630-0633.

[14] G. Ketepalli, S. Tata, S. Vaheed and Y. M. Srikanth, "Anomaly Detection in Credit Card Transaction using Deep Learning Techniques," 2022 7th International Conference on Communication and Electronics Systems (ICCES), 2022, pp. 1207-1214.

[15] Darchia N, Oniani N, Sakhelashvili I, et al. Relationship between Sleep Disorders and Health Related Quality of Life-Results from the Georgia SOMNUS Study. Int J Environ Res Public Health. 2018;15(8):1588. Published 2018 Jul 26.

[16] Cyriac. Azefack et al., "An Approach for Behavioral Drift Detection in a Smart Home," 2019 IEEE 15th International Conference on Automation Science and Engineering (CASE), 2019, pp. 727-732.

[17] Chen S et al. (2021) "Correlations of Subjective and Social Well-Being With Sedentary Behavior and Physical Activity in Older Adults—A Population-Based Study." The Journals of Gerontology: Series A.

[18] Carreira-Perpiñán, Miguel. (2015). A review of mean-shift algorithms for clustering.

[19] LIN, Tzu-Hsuan et JIANG, Jehn-Ruey. Credit card fraud detection with autoencoder and probabilistic random forest. Mathematics, 2021, vol. 9, no 21, p. 2683.

[20] Debbagh, Nadir and Baghdadi, Riyadh. (2020). Graduation Thesis - Deep Learning Operators Optimization in Tiramisu (Sparse Neural Networks and Recurrent Neural Networks).

[21] R. Mueller, "Sleep Data - National Sleep Research Resource - NSRR." https://sleepdata.org/

[22] Varun Chandola, Arindam Banerjee, and Vipin Kumar. 2009. Anomaly detection: A survey. ACM Comput. Surv. 41, 3, Article 15 (July 2009), 58 pages. https://doi.org/10.1145/1541880.1541882

[23] Shreshthaa Shukla, and Anjali Sahai. (2022). Sleep Anomalies and Mood Disorders: A Review Study of Adults. International Journal of Indian Psychlogy, 10(1). https://doi.org/10.25215/1001.022