International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:12, No:3, 2018

Long Short-Term Memory Based Model for Modeling Nicotine Consumption Using an Electronic Cigarette and Internet of Things Devices

Hamdi Amroun, Yacine Benziani, Mehdi Ammi

Abstract**—**In this paper, we want to determine whether the accurate prediction of nicotine concentration can be obtained by using a network of smart objects and an e-cigarette. The approach consists of, first, the recognition of factors influencing smoking cessation such as physical activity recognition and participant's behaviors (using both smartphone and smartwatch), then the prediction of the configuration of the e-cigarette (in terms of nicotine concentration, power, and resistance of e-cigarette). The study uses a network of commonly connected objects; a smartwatch, a smartphone, and an e-cigarette transported by the participants during an uncontrolled experiment. The data obtained from sensors carried in the three devices were trained by a Long short-term memory algorithm (LSTM). Results show that our LSTM-based model allows predicting the configuration of the e-cigarette in terms of nicotine concentration, power, and resistance with a root mean square error percentage of 12.9%, 9.15%, and 11.84%, respectively. This study can help to better control consumption of nicotine and offer an intelligent configuration of the e-cigarette to users.

Keywords**—**Iot, activity recognition, automatic classification, unconstrained environment, deep neural networks.

I. Introduction

According to the World Health Organization's report (W.H.O), the number of smokers reached about 1.1 billion people in the world (more than 1/7 of the world's population) in 2014, and this number is expected to double or even triple in the next 30 years. Therefore, it is necessary to encourage smokers to quit smoking and help those who decided to quit smoking [1].

Several devices and medical treatments were already developed and used to help smokers quit smoking, such as nicotine patches, treatments with nicotine replacement therapy [1]-[3], psychic treatments, intensive medical follow up that combines pharmaceutical treatments and psychological treatment sessions [2]. However, most of these techniques have proven their limit in terms of complexity and follow-up.

With the arrival of IOT and smart objects to the market, for instance the e-cigarette, users are able to take control (able to control their consumption) over their consumption of nicotine by setting precise doses with precise concentrations.

Several studies have proved the effectiveness of electronic cigarettes as a smoking cessation solution in [3]-[6]. The heights established a study on the usefulness of the e-cigarette for smoking cessation, with 216 participants for six months [7]. The disadvantage of this kind of study is that it is realized in controlled environments and they did not consider other factors that influence nicotine use such as physical activity [4]-[9].

In order to help smokers to quit smoking, their nicotine intake must be modeled by taking into account the various parameters that can influence their consumption: physical activity and behavior, nicotine concentration, strength and power the e-cigarette as well as the profile of smokers (gender, age, nicotine addiction, etc.) [10]-[19], [20]. We propose in this paper to model the consumption of nicotine taking into account the different factors that can influence it by using not only a smartphone but also a smartwatch. Indeed, the smartwatch is carried permanently by users unlike the smartphone that can be abundant.

II. Contributions

This paper proposes to go beyond current processing methodologies in order to provide a better modelization of consumption of nicotine with usual IoT devices. Based on sensors embedded in an iPhone, Apple watch and e-cigarette, we will address a series of issues to design an efficient processing pipe modeling the consumption of nicotine using machine-learning algorithm [21], [22].

First, the experiment was conducted in an uncontrolled environment where 33 participants were invited to use freely the eGo e-cigarette by wearing an Apple Watch and an iPhone during three months. Indeed, considering only a smartphone to collect data turns out to be insufficient because participants do not keep the phone always close to them [21], [22]. For this reason, we have added a smart Watch that can be worn continually and add more precision to the results.

Second, a data collection platform was developed to extract data from all sensors of the three devices: Apple Watch, Apple iPhone and e-cigarette.

Finally, a new methodology was proposed to predict the nicotine concentration needed by the participants based on the prediction of the e-cigarette configuration (the power, the resistance and nicotine concentration) as well as the recognition of the physical activities and behaviors of participants by using the iPhone and Apple watch devices (see Fig. 1).

Finally, we proposed an architecture-model for predicting the concentration of nicotine, the resistance and the power of the e-cigarette (see Fig. 3).

Hamdi Amroun is with the University of Paris-Sud, France (e-mail: hamdi.amroun@limsi.fr).

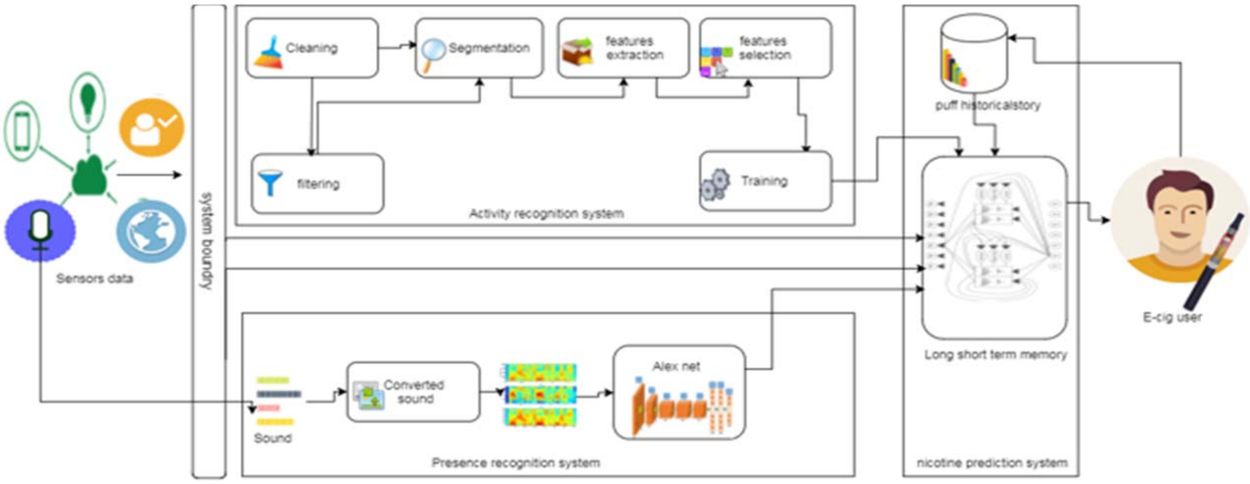

Fig. 1 Prediction system of the configuration of the e-cigarette composed of the part "activity recognition", "presence recognition system" and the system of detection of the configuration of the e-cigarette. The step of recognizing physical activity was made using the smartphone and the smart watch [21], [22]

Fig. 2 Data collection system. The system contains an Exract Load Tranform (ETL) that loads the data and integrates it into a data warehouse for later retrieval. The data warehouse contains several datamarts: a datamart for each sensor data

Fig. 1 shows the different components of the prediction system of the e-cigarette configuration. The system consists of several parts: a part of data collection of the devices (iPhone, Apple watch and the e-cigarette), recognition of activities and behaviors, presence recognition system to recognize whether the smoker is alone or in a group, that is developed according to our previous papers [21], [22] and finally the part that interests us here: the prediction of the configuration of the e-cigarette, which concerns the concentration of nicotine, resistance and power of the e-cigarette. The rest of this paper is structured as follows:

A description of the experiment has been given in Section III.

In Section IV, we will present in detail the process of detection of e-cigarette configuration. Section V presents the results obtained. Section VI summarizes the contributions of the paper. We end with the conclusion and some references.

III. Experimental Setup

The experiment consists in giving an eGo e-cigarette to 33 smokers for use for three months. We also used an iPhone and a smart watch to retrieve the consumption data of the e-cigarette and thus be able to exploit to the maximum the data of the movements of the hands and to compensate the problem of loss of the Smartphone [21], [22].

For data collection, we developed a platform which allows to collect the data of the various sensors "accelerometer, gyroscope, compass", GPS data (latitude and longitude), audio, and save the data of the profile of the user. A data warehouse was created to collect, retrieve, and save data automatically in datamarts (see Fig. 2)

Participants perform their daily activities and used freely the e-cigarette. The platform retrieves the data from the various sensors of the iPhone and the smartwatch as well as the configuration of the e-cigarette (nicotine concentration, resistance and power of the e-cigarette). In the next section, we develop the predictive model of the nicotine configuration (see Fig. 3).

IV. Prediction of E-Cigarette Configuration

Many problems require making predictions based on previous observations that consider the temporal dimension; time series. Neural networks and the usual prediction techniques do not allow this kind of forecast. For this purpose, several other prediction methods are often used to analyze time series such as autoregressive processes and recurrent neural networks [10]-[15].

In our study, the objective consists of predicting the configuration of the most suitable e-cigarette for the smoker based on the following observations: "history of the vapes", details about the context (geolocation, presence of other people, physical activity) as well as the temporal component (time, duration). For this purpose, we chose to use a LSTM (long short term memory) model. LSTM are networks with loops allowing the use of previous data in the prediction of future data. They were designed to solve long-term dependency problems due to their ability to memorize data for long periods.

To obtain the right representative architecture of the predictive model of the configuration of the e-cigarette, we have varied various parameters of the recurrent network and have calculated the mean square error. We have kept the architecture with the smallest mean square error.

We used a LSTM [23]-[28] with six recurring layers. The first layer is the input layer, it contains 26 neurons, and the following three layers are the recurring layers where each layer contains 250 neurons, the 6th layer with three neurons where each neuron corresponds to a parameter (nicotine concentration, resistance and power of the e-cigarette). (See Fig. 3).

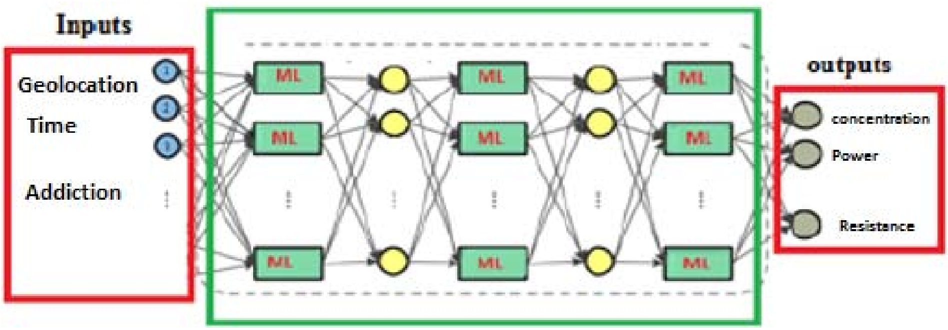

Fig. 3 Architecture of the proposed model (prediction of the configuration of the e-cigarette in terms of nicotine concentration, power and resistance of the e-cigarette)

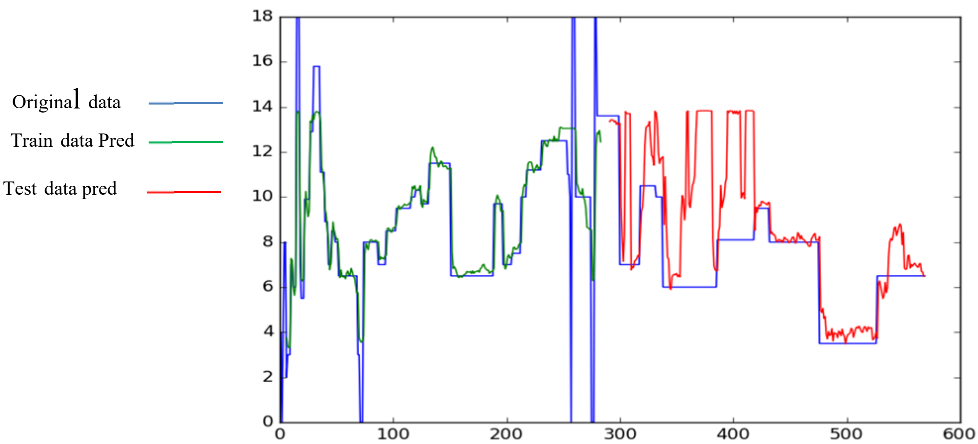

Fig. 4 Prediction of the concentration of nicotine

V. Results

The prediction of the configuration of the e-cigarette was obtained by training our LSTM model shown in Fig. 3. The prediction results are presented in Figs. 4-6.

We can see from Fig. 4 that the model was well trained. After this training phase, the test part shows that there is indeed a correspondence between the predicted data and the actual data. Although there are concentration values that the model does not predict well, it remains consistent. Whenever the model predicts an increase, the participant increases the concentration of nicotine.

Fig. 5 shows the graphic representation of the prediction of the resistance of the e-cigarette and Fig. 6 shows the prediction of e-cigarette's power values.

For the resistance and power of the e-cigarette, it should also be noted that the model learns well during the learning phase and is able to predict well the values of power and resistance of the e-cigarette.

From Figs. 4-6, we note that the model adapts to the needs of the user. Indeed, even if the model predicts a value that does not correspond to the actual need, it adjusts this value in the next inhalation.

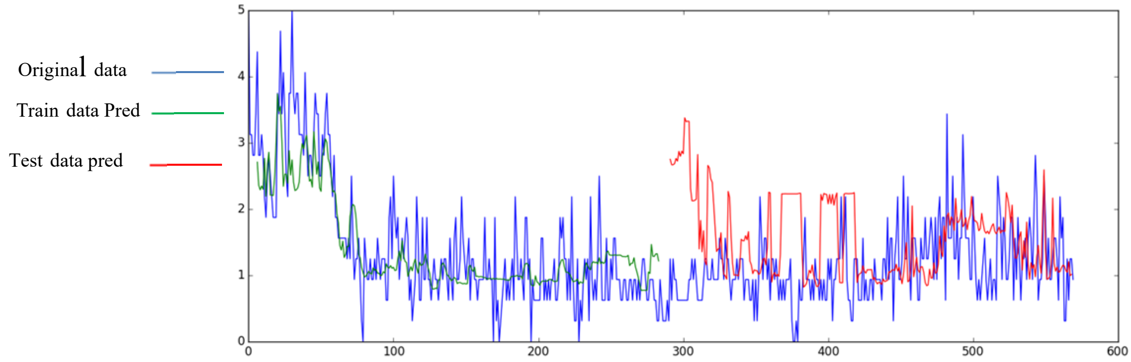

Fig. 5 Prediction of resistance values

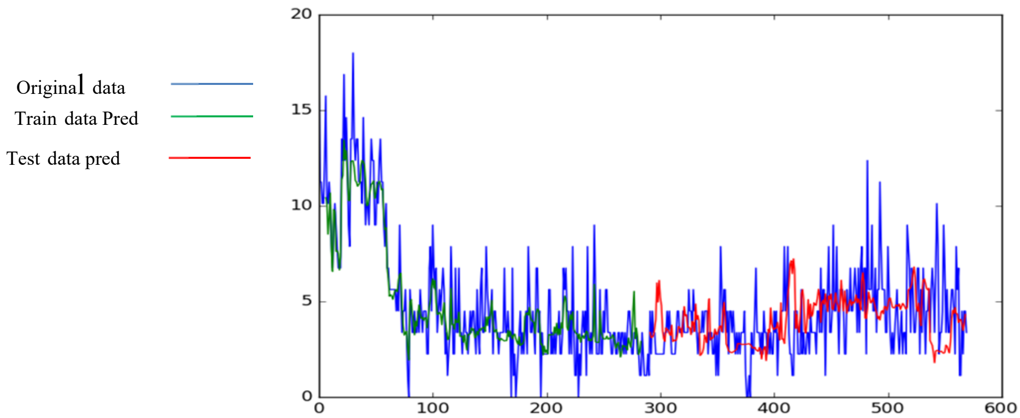

Fig. 6 Prediction of power values

VI. SUMMARIZING

In a very simple way, this paper fulfilled three main objectives

1- Developed a data collection platform for an iPhone, Apple watch and an e-cigarette.
2- Propose a system for predicting the configuration of an e-cigarette for modeling the consumption of nicotine in terms of nicotine concentration, power and resistance of the e-cigarette. This system is based on the use of an iPhone, apple watch and an e-cigarette.
3- We proposed a model of nicotine prediction, power and resistance of the e-cigarette.

VII. CONCLUSION

In this paper, we proposed a new approach to model the consumption of nicotine in order to satisfy the smoker need for nicotine to help him/her to achieve smoking cessation.

The system we have proposed takes into account the different major factors that influence the consumption of nicotine.

The subsequent design of the different parts of our system began with the recognition of physical activities, the recognition of behaviors and presence that were dealt with before, and then the system of predicting the configuration of the e-cigarette. This last part has been deepened by training a LSTM on the data coming from the first two parts of the system. Finally, we presented the system that allows predicting the configuration of the e-cigarette to satisfy the smoker's need for nicotine. The prediction of the configuration of the e-cigarette (nicotine concentration, resistance value, power value of the e-cigarette) was very satisfactory given the amount of data we could collect and the constraints of experience (uncontrolled environment, presence of noise in signals).

ACKNOWLEDGMENT

Above all, we would like to thank the Open Health Institute for funding the project and our trips to conduct experiments and collaborate with other research institutions. We also thank Healthcare Clinic of Vancouver for providing us with participants and providing scientific support. We also thank all the medical staff and tobacco specialists who helped us. Without forgetting to thank the reviewers for this paper

REFERENCES

[1] VIA. Bayat, M. Pomplun, and D. A. Tran, "A study on human activity recognition using accelerometer data from smartphones," Procedia Computer Science, vol. 34, pp. 450-457, 2014.
[2] R. Bittoun and others, "A combination nicotine replacement therapy (NRT) algorithm for hard-to-treat smokers," Journal of Smoking Cessation, vol. 1, p. 3, 2006 2006.
[3] J. Brown, E. Beard, D. Kotz, S. Michie, and R. West, "Real-world effectiveness of e-cigarettes when used to aid smoking cessation: a

cross-sectional population study," Addiction, vol. 109, pp. 1531–1540, 2014 2014.
[4] B. B. Hoeppner, S. S. Hoeppner, L. Seaboyer, M. R. Schick, G. W. Wu, B. G. Bergman, and J. F. Kelly, "How smart are smartphone apps for smoking cessation," A content analysis Nicotine Tob Res, 2015 2015.
[5] M. Mironidou-Tzouveleki, E. Tzitzi, and P. Tzitzis, "Electronic Cigarette (E-Cig) as a Way of Smoking Cessation: Benefits and Potential Harms," Journal of Drug Addiction, Education, and Eradication, vol. 11, p. 235, 2015 2015.
[6] B. Dautzenberg and D. Bricard, "Real-time characterization of e-cigarettes use: the 1 million puffs study," J Addict Res Ther, vol. 6, 2015.
[7] M. SEIGEL and others, "Electronic Cigarettes as a smoking Cessation Tool," American Journal of Preventive Medicine, vol. 40, 2011 2011.
[8] P. E. Grebenstein, D. Burroughs, S. A. Roiko, P. R. Pentel, and M. G. LeSage, "Predictors of the nicotine reinforcement threshold, compensation, and elasticity of demand in a rodent model of nicotine reduction policy," Drug and alcohol dependence, vol. 151, pp. 181–193, 2015 2015.
[9] P. Batel, F. Pessione, C. Maitre, and B. Rueff, "Relationship between alcohol and tobacco dependencies among alcoholics who smoke," Addiction, vol. 90, pp. 977-980, 1995.
[10] R. Bryson, P. M. Biner, E. McNair, M. Bergondy, and O. R. Abrams, "Effects of nicotine on two types of motor activity in rats," Psychopharmacology, vol. 73, pp. 168-170, 1981.
[11] P. C. Hatchell and A. C. Collins, "The influence of genotype and sex on behavioral sensitivity to nicotine in mice," Psychopharmacology, vol. 71, pp. 45-49, 1980.
[12] A. H. Taylor, M. H. Ussher, and G. Faulkner, "The acute effects of exercise on cigarette cravings, withdrawal symptoms, affect and smoking behaviour: a systematic review," Addiction, vol. 102, pp. 534-543, 2007.
[13] M. Todd, "Daily processes in stress and smoking: effects of negative events, nicotine dependence, and gender," Psychology of Addictive Behaviors, vol. 18, p. 31, 2004.
[14] D. Momperousse, C. Delnevo, and M. Lewis, "Exploring the seasonality of cigarette-smoking behaviour," Tobacco control, vol. 16, pp. 69-70, 2007.
[15] H. Wang and D.-Y. Yeung, "Towards Bayesian Deep Learning: A Survey," arXiv preprint arXiv:1604.01662, 2016.
[16] Y. Gal, "ModernDeepLearningthroughBayesianEyes."
[17] J. D. McCaffrey. (2015). Particle Swarm Optimization using Python. Available: https://jamesmccaffrey.wordpress.com/2015/06/09/particle-swarm-optimization-using-python/.
[18] "Bayesian networks: Inference and learning," ed, 2011.
[19] K. Patel, J. Vala, and J. Pandya, "Comparison of various classification algorithms on iris datasets using WEKA," Int. J. Adv. Eng. Res. Dev.(IJAERD), vol. 1, 2014.
[20] J. R. Kwapisz, G. M. Weiss, and S. A. Moore, "Activity recognition using cell phone accelerometers," ACM SigKDD Explorations Newsletter, vol. 12, pp. 74-82, 2011.
[21] T. Saponas, J. Lester, J. Froehlich, J. Fogarty, and J. Landay, "ilearn on the iphone: Real-time human activity classification on commodity mobile phones," University of Washington CSE Tech Report UW-CSE-08-04-02, vol. 2008, 2008.
[22] A. M. Khan, Y.-K. Lee, S. Lee, and T.-S. Kim, "Human activity recognition via an accelerometer-enabled-smartphone using kernel discriminant analysis," in Future Information Technology (FutureTech), 2010 5th International Conference on, 2010, pp. 1-6.
[23] T. M. T. Do and D. Gatica-Perez, "Groupus: Smartphone proximity data and human interaction type mining," in Wearable Computers (ISWC), 2011 15th Annual International Symposium on, 2011, pp. 21-28.
[24] H. Amroun, N. Ouarti, and M. A. M'Hamed Hamy Temkit, "Les transitions de positions du smartphone, quelles conséquences sur la reconnaissance de l'activité humaine?," 2017.
[25] J. Salamon and J. P. Bello, "Unsupervised feature learning for urban sound classification," in Acoustics, Speech and Signal Processing (ICASSP), 2015 IEEE International Conference on, 2015, pp. 171-175.
[26] P. Hough, "'Make Goals Not War': The Contribution of International Football to World Peace," The International journal of the History of Sport, vol. 25, pp. 1287-1305, 2008.
[27] G. Montavon, "Deep learning for spoken language identification," in NIPS Workshop on deep learning for speech recognition and related applications, 2009, pp. 1-4.
[28] N. A. Boukary, "A comparison of time series forecasting learning algorithms on the task of predicting event timing," Ph. D. dissertation, Royal Military College of Canada, 2016.