A Review of Smart Phone Applications Used for Health Care, Epilepsy and Activity Monitoring Systems

Mohammed Fahmy Abdul Ghafoor Dr. Saad Abdalratha Makki
Mustansiriyah University, College of Education, Computer Science Department

Mohammedfahmy@uomustansiriyah.edu.iq
drsaadamakki@yahoo.com

Abstract

The modern technology has been increasingly found its way to the healthcare applications. One of those widely used technologies is use of the smartphone devises. This kind of technology has involved mainly in almost all life aspects, nonetheless, the medical and health care aspect. One of the health impairments the required a constant monitoring is the epileptic attacks. For these patients who have the neurological disease, it is very dangerous to leave them alone during the epileptic attack due to the fact that it is unknown how long that attack would last. In this review paper we explain the most recent trends in this field. We explain first the activity monitoring systems including the normal and abnormal activities. Later, we explain the most recently published academic works related to the epilepsy detection apps. a design of a suggested epilepsy detection system is also given in this paper . As a result of this review, we discovered that using the machine learning methodologies has been increasingly used in this field. This involves the discrimination of the tasks and classifying them as normal and abnormal activities of epilepsy patients. It is also discovered that using the data mining supervised techniques such as the Support Vector Machines (SVM) and the Convolutional Deep Neural Networks (CNN) has been efficient in order to make this classification.

Keywords: epilepsy, data mining, smartphones, Deep learning,

مراجعة لتطبيقات الهواتف الذكية المستخدمة في أنظمة الرعاية الصحية والصرع ومراقبة النشاط

محمد فهمي عبد الغفور د. سعد عبدالرضا مكي
الجامعة المستنصرية ، كلية التربية ، قسم علوم الحاسبات

الخلاصة

وجدت التكنولوجيا الحديثة طريقها بشكل متزايد إلى تطبيقات الرعاية الصحية. واحدة من تلك التقنيات المستخدمة على نطاق واسع هي استخدام أجهزة الهاتف الذكي. لقد شارك هذا النوع من التكنولوجيا بشكل أساسي في جميع جوانب الحياة تقريبًا ، ومع ذلك ، في الجانب الطبي والرعاية الصحية. أحد الإعاقات الصحية التي تتطلب المراقبة المستمرة هي نوبات الصرع. بالنسبة لهؤلاء المرضى الذين يعانون من مرض عصبي ، من الخطير جدًا تركهم بمفردهم أثناء نوبة الصرع نظرًا لحقيقة أنه من غير المعروف كم من الوقت سيستمر هذا الهجوم. في ورقة المراجعة هذه ، نشرح أحدث الاتجاهات في هذا المجال. نشرح أولاً أنظمة مراقبة النشاط بما في ذلك الأنشطة العادية وغير العادية. في وقت لاحق ، نشرح أحدث الأعمال الأكاديمية المنشورة المتعلقة بتطبيقات اكتشاف الصرع. تم أيضًا تقديم تصميم لنظام اكتشاف الصرع المقترح في هذه الورقة. نتيجة لهذه المراجعة ، اكتشفنا أن استخدام منهجيات التعلم الآلي قد تم

استخدامه بشكل متزايد في هذا المجال. وهذا ينطوي على تمييز المهام وتصنيفها على أنها أنشطة عادية وغير طبيعية لمرضى الصرع. تم اكتشاف أن استخدام التقنيات الخاضعة للإشراف للتنقيب في البيانات مثل آلات المتجهات الداعمة (SVM) والشبكات العصبية العميقة التلافيفية (CNN) كانت فعالة من أجل إجراء هذا التصنيف.

الكلمات المفتاحية : الصرع ، التنقيب عن البيانات ، الهواتف الذكية ، التعلم العميق

1. Introduction

The smart mobile phone technology uses in health care field has increasingly becoming very effective and strong, and by delivering tailor made provision as well as access of facts to sophisticated advices mostly each particularity [1]. This concept has an extremely promising impact on the decision making in complicated events, results of a clear reduction in a size of medical-based flaws due to the more comprehension in the medical personnel that leads to an enhanced and efficient patients' services [2]. Based on estimation, higher than 13,000 mobiles Apps has been used in health sector are available from various application stores [3]. These applications are necessary to train health-care personnel as well as delivering a simple way to many different tasks like reference range, hospital or physician locator, appointments reminders, calorie counters, body mass surfaces, region calculator, etc.. This is providing significant assistance in a daily basis; decisions' pertain for the diagnoses, treatments and in recovery processes [4]. Medical-based Applications, which might be in straightforward manner, be downloaded on any smart mobile, have an increased familiarity among medical personnel and patients [5]. Based on a recently conducted research survey in England, it was estimated that about 84% of medical staff had an opinion that smart phones and associated Medical-based Applications are very helping in their purposes [6]. As a result, one might think that using smart phone Applications would assist every whom had a relation with a medical service such as patients, physicians, doctors, nurses, instructors, etc.. [7]. One of the medical services that might be automated by a smart phone is the diagnosis of the epilepsy seizure using the mobile Apps. Epilepsy is considered chronical neurological-based syndrome known by unprovoked recurrently occurring seizures [8]. For those who have this chronological disorder and living with epilepsy might be exposed to different kinds of challenges. In addition to the seizures effect that has a direct impact on their physical health. Patients might face problems ranging from disruptions of education and work, limitations on normal daily activities.

The main aim of this review paper is to explore the smart mobile applications used for the motion and activity monitoring Systems. Especially those apps used for the detection of the epilepsy attacks. The significance review paper is to highlight the main contributions of the researchers in this area and to detect the areas of this field which were not covered by the other researchers. As a motion and activity detection apps include a wide range of applications contributing to the health care field, a paradigm of epilepsy attack detection is presented in this paper.

2.General App Design and Implementation

Mobile phone applications would remarkably help neurologists in finding the right treatment for those who suffer from epilepsy. Based on what the academic studies published in the International-Journal-of-Epilepsy, it is stated that "Carefully selecting and using epilepsy apps by the healthcare providers, epilepsy sufferers, and their assistants with correct comprehension of their crucial advantages and restrictions, would be resulting in more accurate diagnoses, prognoses, and treatments".

In this paper, we discuss a model for a mobile application that is capable of recording the movement patterns of the patient which must be capable of differentiating between the normal movement of the patient and the one resulted from an epilepsy seizure.

As figure 1 shows that the general app proposed in this paper. Mainly the proposed app is designed as any pattern recognition system that is based on training the model with examples. These examples are represented by the signals generated by an accelerometer sensor. The data collection is the first step represented by collecting the accelerometer sensor data, These obtained data cases are composed from 4-dimensional coordinates [x,y,z,d]. The duration of collecting the samples equals to 5 seconds. The Filtering step in figure 1 is responsible of feature extraction. The trapezoidal integration was used as a feature extractor for each single case as represented in the following mathematical model:

$$J = \int_a^b f(x)dx \qquad (1)$$

$$h = \frac{b-a}{n} \qquad (2)$$

$$J = \int_a^b f(x)dx = h[\frac{1}{2} f(x_0) + f(x_1) + f(x_2) + \cdots \ldots \ldots + f(x_n)] \quad (3)$$

Error bound

$$K = \frac{b-a^3}{12n^2} \qquad (4)$$

$$k = f''(a) \leq E \leq f''(b) \qquad (5)$$

Pattern recognition systems mainly perform two functional phases which are the enrollment and the testing phases. After training the model with the signals generated by the accelerometer a pattern-matcher that compares an input signal to referential pattern utilizing a distances measures), referencing templates memory (where the input patterns is matched), and a classifier (for making the last decision as to which referencing templates is the nearest to the inputting patterns).

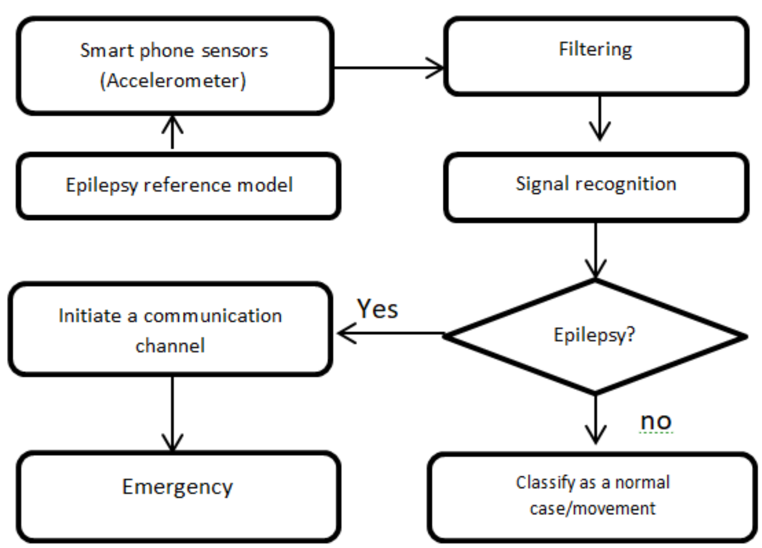

Figure 1. a flowchart of an epilepsy attack diagnosis app

In order to mitigate the severe consequences of the epilepsy, there has been an increasing appreciation in clinical guidelines of the necessity of epilepsy self-managing systems in the improvement of the management of seizures and the reduction of the negative effects of epilepsy on patients. A report made by the Institute of Medicine showed the importance of the expansion and development of epilepsy self-managing programs. Thus, they would be capable of having a better advantage of opportunity given by technologies such as computer systems and smart mobile phones. By using this, it is expected that patients would be capable to be feeling in higher controllability of their case and be enjoying an improved quality of their lives.

3. Background

3.1 Evolution of Smart Phones

In 1992, IBM declared a ground breaking devices called Simon Personal Communicator that made together the different functionalities of a Personal Digital Assistant (PDA) cellular phone. This leaded to the entire new concepts of the smartphone in the cellular phone industries. Simon made a 4.5” by 1.4” mono-chrome LCD touchscreens and invented a stylus and charging base stations. Along with traditional voices communications, the devices were further able to communicate faxes, emails, and web-pages. Simon made a collection to an address book, write in, world clock calendar, and appointment schedulers, and was more flexible to third party usages [9,10,11]. Despite of that fact that there is a huge leap into the markets by IBM, still it was expensive, it costs $899 with service assistance. Being very ahead of its time and with this expensive price tags, Simon didn’t make success for attracting customers. Even though the tech giant sold estimated 50,000 items per 6 months [12], it chose out to make a second generation Simon.

In 1996 Nokia announced clamshell phones, Nokia 9000 Communicators, which started to a full QWERTY keyboards and physical navigational buttons using a mono-chrome LCD screens approximately as large as the devices themselves. It featured Web browsers capability on top of most of the capabilities that IBM of Simon offered. Nonetheless, Ericsson coupled the term Smart-phone for its Ericsson GS-88. The GS-88, also pronounced as Penelope, strikingly resembled the Nokia 9000. Due to its weight and poor battery quality, it was not released to the public. Later, in 2000 Ericsson first used the term Smartphone officially for the Ericsson R-380, which was cheaper, lighter smaller in size and then the Nokia 9000. Ericsson R380 was the first device to use the mobile Symbian operating systems and only second to IBM of Simon to have a touchscreens in phones. R380 was considered as one of the first few smartphone devices used the wireless application protocols (WAPs) for smoother and faster web browser.

In 2002, RIM and Handspring released their first smartphone devices Tre 180 and Blackberry 5810 (5820 in Europe) in the markets, in a respective manner[11,12].

In 2000, both Sharp and Samsung announced camera phones in their respective local market. In South Korea Samsung announced SCHV200 that has a 1.5″ TFT LCD displays and 0.35 megapixel video graphics arrays (VGA) camera that is capable of capturing up to 20 image. In Japan, few months later, Sharp released the JSH04 with 256 color display and an integrated 0.11 megapixel CMOS cameras. Despite the fact that the camera’s resolution of JSH04 was very less than that of the SCHV200, it has a phone integrated cameras in the true senses for the first times and permitted for exchanging of images in a direct manner of it, while the SCHV200 made two separate devices in one enclosure and thus required the transferring the pictures to a computer for sharing. None of the cameras’ phones supported Web browsing and emailing communication until Sanyo launched the first smartphones with integrated cameras in 2002. The Sanyo SCP-5300 came in a clamshell formats and made dual-color display screens, WAP browsers, and an built-in 0.3 megapixel cameras with short range LED light-sensors pro flashes. It also had white balance control and brightness, digital zoom, self-timer, and several filter effects like as black-and-white, sepia, and negative colors. The development of the smart phones is summarized as shown in figure (2).

Figure 2. mobile apps development over years

Currently with a fast development of technology, modern smartphone devices featured a wide range of sensors like high-speed and high resolution CMOS image sensor, GPS, accelerometers, sensors, gyroscope, magnetometers, ambient light sensors, microphones, and fingerprint sensors. Additionally, the data storage and processing capabilities of current smartphone devices has been improved remarkably. Figure (3) shows the integrated sensors that most currently available smartphone devices would have.

Figure 3. Mobile sensor types

3.2 Classification

Data mining methodologies can be classified as supervised or unsupervised methods. In the design of an activity app, the unsupervised scheme is needed as it is responsible of classifying the activity according to previously defined labels of that activity. In supervised learning, the algorithms runs with a collection of samples whose labels are previously determined. Classification of objects is considered a process of the comprehension, recognition, and gathering objects as well as ideas to sub-populations and predefined classes. As was mentioned earlier that the data are collected from the accelerometer sensors. Datasets which were already classified are used in classification for the training purposes. In machine-learning techniques a wide range of algorithms are used for classifying future incoming data into distinct groups. Such algorithms of the classification are utilizing input train data for predicting the possibility that the upcoming data will be falling into the pre-determined groups[13].

4.Related work

In this section we would be focusing on explaining the human activity recognition systems and apps used for the medical services. We also focus on explaining some of the recently proposed epilepsy attacks diagnosis.

4.1 Human Activity Recognition (HAR)

In the last decade, there has been an increasing interest in utilizing smartphone equipped with build-in motions sensors (embedded sensors) like gyroscopes, magnetometers, accelerometers and locations sensors like GPS sensors for real-time surveillance of people gaits and tasks of Daily-Living-Routines (ADL). such sensor devices are measuring the linearity and angularity of the movements of human or moving objects, and the locations of the users, that could be utilized for quantifying and classifying human beings gait happenings and tasks in real-time. Figure (4) shows a general structure of the classification model used for classifying sensor data.

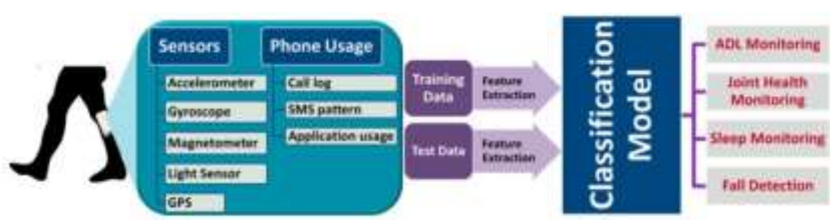

Figure 4 the classification models used for classifying sensor data

At the core of a recognition system and activity detection is the recognition or the classification algorithm. Features extraction/selection of appropriate attributes or signal processing methods are also playing an important role in realizing a computationally reliable and efficient system. Signal processing methods might be including filtering, data windowing, segmentation and or normalization. As a consequence, an acceptable number of key attributes from the temporal, statistical, and spatial and frequency ranges are selected or extracted for feeding into the data mining model such as the classifiers or the clustering systems.

Thus, in [14], the authors explored the power of triaxial accelerometer and gyroscopes integrated in a smartphone in the recognition of physical activities of humans in situations where they are used separately or simultaneously. A new feature selection method is then suggested for selecting a subset of discriminative feature attributes. This technique is based on the construction of an online activity recognition system equipped with better generalization ability. In fact this would contribute to reduce

the smartphone energy consumption. The test results on a bench mark dataset show that combining both accelerometer and gyroscope data is capable of contributing to have a better recognition performance than that of utilizing single data source, and that the proposed feature selection method performed better than three other comparative methods.
In [18], the authors, proposed a powerful human beings tasks identification system that considers the placement, direction, and subject variation according to Coordinates-Transformations and Principal-Component-Analysis (CT PCA) as well as an Online-based Support Vector Machine (OSVM). The suggested CTPCA design was used in order to estimating the impact of orientations variations. The Experimental results showed that the suggested design remarkably enhanced the task identification accuracy and performed better than other tested methods on-leave-one-orientation-out tests that demonstrated the generalizations capability of the suggested scheme on the data from unseen orientations. In fact, the legacy differences of signal properties for various placements and subjects significantly reduced the recognition accuracy. Therefore, the efficient OSVM approach was presented, such that online independent support vector machine (OISVM), which utilized small portions of data from the unseen placements or subjects for updating online the parameters of the SVM. The experimental results demonstrated the effectiveness of this OISVM technique on placement and subject variation. On the other hand, In the paper, proposed in [18], the authors proposed a method that uses a multiclass SVM using integer parameters. This method showed accuracy levels comparable with traditional approaches like as the MC SVM that uses floating point arithmetic. The test results showed that even with reducing of bits equal to 6 for representing the learned MC HF SVM model parameter β it is possible to exchange the MC SVM. This observation brings positive consequences for smartphone devices as it might assist to releasing system resources and lessen the energy required. Not only the SVM was successful in this field the deep learning has also been successful in the human activity using the smartphones such as in [15]. The use of the deep convolutional neural networks (conv-nets) was intended to performing effective, efficient, , and data-adaptive human activity recognition (HAR) using the gyroscope and accelerometer on smartphones. Conv-nets not only exploiting the inherent temporal local dependency of time series 1D signal, and the translation invariance and hierarchical traits of activities, however, it also provides an approach for data-adaptively and automatically extract relevant and robust attributes without the need for advanced pre-processing or time consuming feature hand crafting. In [16] the same concept was used, however, this time the deep convolutional neural networks were used. In [17] a two directional feature for Bi directional Long Short-Term Memory (BLSTM) for incremental learning in human activity recognition was proposed. In order to further enhance the performance, an new ensemble classifier named Multi-column Bi-directional Long Short-Term Memory (MBLSTM) was also used, that was effectively combined different acceleration signals attributes for further improving activity recognition accuracy.

4.2 Epilepsy Attacks Diagnosis

In the area of artificial intelligence, machine learning methodologies, computer science and statistics are used for developing algorithms whose performance improves with exposure to useful data, not only explicit instructions. Along-side with the extensive range of ubiquitous applications used for audio recognition, images classification, and texts translating, machine-learning has been used in a wide spectrum in medical-based purposes in an increasing manner, that includes triage of ophthalmology referral-based on optical coherency tomography data, diagnoses of malignant-melanoma from dermo-scopic and photo-graphics image, and identifying influenza from emergency dept. encounter record, in the entire triple cases exceeding, and matching the performances of clinical experts personnel. Same steps have done for epileptic based seizures, run by continual enhancements of data collection, storage, and processing [21].

Form the survey conducted in this paper, it was discovered that there is no much research effort was made in academia that specialized in studying the epilepsy seizer attacks. Except some papers such as in [22], an automatic-based system for epilepsy-detection has been suggested, which addresses binary detection issues (epileptic case, or non-epileptic case) or (seizure case or non-seizure case), and tertiary detecting problems (ictal case, regular, or inter-ictal). The suggested design has been implemented as a collection of a memory efficient and simple paramedical 1D-deep convolutional neural network (P 1DCNN) model that takes as input the EEG signal, feeds it to various base P-1D-CNN models, and last combines their decision using majority of votes. In order to address the impact of small datasets, couple of data augmentations patterns have been used. The model is simple for training that have few, data and simple to be deployed on chip where memory is. It would help neurologist in diagnosing small epilepsy and would significantly reducing their burden, and maximize their efficiency.

In [23], the authors aimed to handle the epilepsy detection problem with aim to have an increased accuracy, enhance universality and functionality of epilepsy seizure detection. An approach using wavelet transformation based genetic algorithm and non-linear analysis optimized by support vector machine (GA-SVM) was proposed to be dealing with five challenging classification problems. The double density discrete wavelet transform (DDDWT) was used instead of the traditional discrete wavelet transform (DWT). Thus, the ability of decomposing the original EEG into specific sub bands was tested. The fuzzy entropy (FuzzyEn) and Hurst exponent (HE) are extracted as input features and then entered into the two classifiers. The system is clearly shown in figure (5)

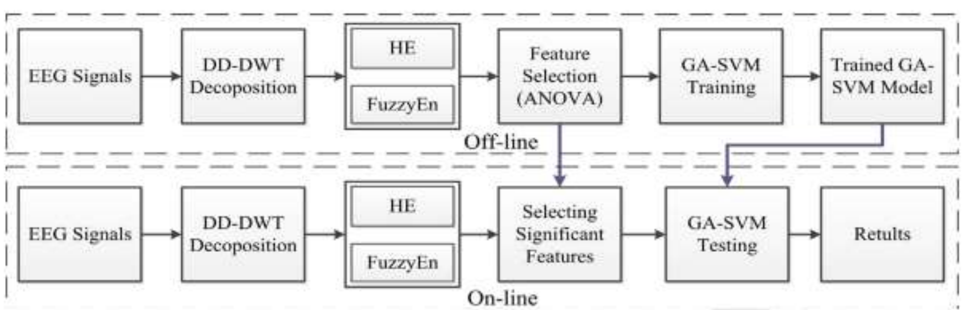

Figure 5. The double density discrete wavelet transform

In [24] the authors presented a new analyses technique to detect epilepsy seizures from EEGs signals utilizing the Improved-Correlation-based-Feature-Selection method (ICFS) with Random-Forest classification method (RF). The analyses incorporated, first using ICFS for the selection of the highly dominant attributes from the time-domain, frequency-domain, and entropy attributes. A collection of Random-Forest (RF) classifier was later learnt on the selected subset of attributes.

In [21] parallel progresses conducted in epilepsy were reviewed in this paper. This review involved focusing on apps in automated seizures detection from, video, electroencephalography EEG, and kinetic data, pre- surgical planning, automated imaging analysis and prediction of medications responses, and prediction of surgical and medical outcome using a broad range of data resources. Machine learning methods in epilepsy were given in this paper. With existence of efficient machine learning methods, increasing computational capabilities and accumulations of large datasets, researchers and clinicians would be increasing the benefit from familiarity with these methods.

5.Conclusion

In this review paper we discussed the trends concerning the fields of the motion and activity patterns detection. First the activity monitoring systems including the normal and abnormal activities are highlighted. Then, the most recent academic studies of the epilepsy detection apps are considered. This review paper also proposed an ideal monitoring system. The outcomes of this review showed that using the machine learning methods has been widely emerged in the medical and health care sector. In terms of the epilepsy detection, the reviewed papers showed that the classification methods played an important role in the discrimination of the tasks and classifying them as normal and abnormal activities of epilepsy patients. It is also discovered that using the data mining supervised techniques such as the Support Vector Machines (SVM) and the Convolutional Deep Neural Networks (CNN) has been efficient in order to make this classification.

References

[1] Boulos MN, Wheeler S, Tavares C, Jones R. How smartphones are changing the face of mobile and participatory healthcare: an overview, with example from eCAALYX. Biomed Eng [Online] 2011;10(1):1.

[2] Prgomet M, Georgiou A, Westbrook J. The impact of mobile handheld technology on hospital physicians' work practices and patient care: a systematic review. J Am Med Inform Assoc 2009;16.6:792—801.

[3] Wu R, Rossos P, Quan S, Reeves S, Lo V, Wong B, et al. An evaluation of the use of smartphones to communicate between clinicians: a mixed-methods study. J Med Internet Res 2011;13(3):e59.

[4] Robinson T, Cronin T, Ibrahim H, Jinks M, Molitor T, Newman J, et al. Smartphone use and acceptability among clinical medical students: a questionnaire-based study. J Med Syst 2013;37(3):1—7.

[5] Kwee CK, Jun KW, Sivasanggari S, Chithralekha V, Lee GY, Chun TN. Medical student's perceptions regarding the impact of mobile medical applications on their clinical practice. JMTM 2014;3(1):46—53.

[6] Wu R, Morra D, Quan S, Lai S, Zanjani S, Abrams H. The use of smartphones for clinical communication in internal medicine wards. J Hosp Med 2010;5(9):553—9.

[7] Low D, Clark N, Soar J, Padkin A, Stoneham A, Perkins GD, et al. A randomized control trial to determine if the use of the iResus© application on a smart phone improves the performance of an advanced life support provider in a simulated medical emergency*. Anaesthesia 2011;66(4):255—62.

[8] Wu RC, Morra D, Quan S, Lai S, Zanjani S, Abrams H, et al. The use of smartphones for clinical communication on internal medicine wards. J Hosp Med 2010;5(9):553—9.

[9] Tweedie S. The World's First Smartphone, Simon, Was Created 15 Years Before the iPhone. Business Insider. [(accessed on 4 January 2019)];2015 Jun 14.

[10] The Evolution of the Mobile Phone, from the Motorola DynaTAC to the Samsung Galaxy S9. The Telegraph. [(accessed on 4 January 2019)];2018 Feb 23

[11] Woyke E. The New Press; New York, NY, USA: 2015. The Smartphone: Anatomy of an Industry.

[12] Sager I. Before IPhone and Android Came Simon, the First Smartphone. Bloomberg.com. [(accessed on 4 January 2019)];2012 Jun 29.

[13] Gola, Jessica, et al. "Advanced microstructure classification by data mining methods." Computational Materials Science 148 (2018): 324-335.

[14] Wang, A.; Chen, G.; Yang, J.; Zhao, S.; Chang, C.-Y. A Comparative Study on Human Activity Recognition

Using Inertial Sensors in a Smartphone. IEEE Sensors J. 2016, 16, 4566–4578. [CrossRef]

[15] Tao, D.;Wen, Y.; Hong, R. Multicolumn Bidirectional Long Short-Term Memory for Mobile Devices-Based Human Activity Recognition. IEEE Internet Things J. 2016, 3, 1124–1134. [CrossRef]

[16] Shoaib, M.; Scholten, H.; Havinga, P. Towards Physical Activity Recognition Using Smartphone Sensors. In Proceedings of the 2013 IEEE 10th International Conference on Ubiquitous Intelligence & Computing and 2013 IEEE 10th International Conference on Autonomic & Trusted Computing (UIC/ATC), Vietri sul Mere, Italy, 18–21 December 2013; pp. 80–87.

[17] Anguita, D.; Ghio, A.; Oneto, L.; Parra, X.; Reyes-Ortiz, J.L. Human Activity Recognition on Smartphones Using a Multiclass Hardware-Friendly Support Vector Machine. Adv. Nonlinear Speech Process. 2012, 7657, 216–223.

[18] Chen, Z.; Jiang, C.; Xie, L. A Novel Ensemble ELM for Human Activity Recognition Using Smartphone Sensors. IEEE Trans. Ind. Informatics 2018, 1. [CrossRef]

[19] Ronao, C.A.; Cho, S.-B. Human activity recognition with smartphone sensors using deep learning neural networks. Expert Syst. Appl. 2016, 59, 235–244. [CrossRef]

[20] Ronao, C.A.; Cho, S.-B. Deep Convolutional Neural Networks for Human Activity Recognition with Smartphone Sensors. Adv. Nonlinear Speech Process. 2015, 9492, 46–53.

[21] Abbasi, B., & Goldenholz, D. M. (2019). Machine learning applications in epilepsy. Epilepsia. doi:10.1111/epi.16333

[22] Ullah, I., Hussain, M., Qazi, E.-H., & Aboalsamh, H. (2018). An automated system for epilepsy detection using EEG brain signals based on deep learning approach. Expert Systems with Applications, 107, 61–71. doi:10.1016/j.eswa.2018.04.021

[23] Li, M., Chen, W., & Zhang, T. (2016). Automatic epilepsy detection using wavelet-based nonlinear analysis and optimized SVM. Biocybernetics and Biomedical Engineering, 36(4), 708–718. doi:10.1016/j.bbe.2016.07.004

[24] Mursalin, Md, et al. "Automated epileptic seizure detection using improved correlation-based feature selection with random forest classifier." Neurocomputing 241 (2017): 204-214.