Systematic Review of Data Mining Applications in Patient-Centered Mobile-Based Information Systems

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Objectives: Smartphones represent a promising technology for patient-centered healthcare. It is claimed that data mining techniques have improved mobile apps to address patients’ needs at subgroup and individual levels. This study reviewed the current literature regarding data mining applications in patient-centered mobile-based information systems. Methods: We systematically searched PubMed, Scopus, and Web of Science for original studies reported from 2014 to 2016. After screening 226 records at the title/abstract level, the full texts of 92 relevant papers were retrieved and checked against inclusion criteria. Finally, 30 papers were included in this study and reviewed. Results: Data mining techniques have been reported in development of mobile health apps for three main purposes: data analysis for follow-up and monitoring, early diagnosis and detection for screening purpose, classification/prediction of outcomes, and risk calculation (n = 27); data collection (n = 3); and provision of recommendations (n = 2). The most accurate and frequently applied data mining method was support vector machine; however, decision tree has shown superior performance to enhance mobile apps applied for patients’ self-management. Conclusions: Embedded data-mining-based feature in mobile apps, such as case detection, prediction/classification, risk estimation, or collection of patient data, particularly during self-management, would save, apply, and analyze patient data during and after care. More intelligent methods, such as artificial neural networks, fuzzy logic, and genetic algorithms, and even the hybrid methods may result in more patients-centered recommendations, providing education, guidance, alerts, and awareness of personalized output.

Keywords: Data Mining, Patient Care, Mobile Health, Information System, Artificial Intelligence

I. Introduction

Patients with chronic illness are constantly faced with decisions that affect their health, and the result of each decision may influence their condition. Tools to support decision-making are often based on facts and skills. There are many resources obtainable to assist patients with self-management. Training patients to recognize, evaluate, and use these resources is a part of self-management care. Skills are worthless if patients cannot move towards health improvement on a continuous basis. Taking action involves readiness to change, adequate information, goal setting, and continuing support for modification [1]. These tasks are attainable
through mobile health applications. Actually, with the rapid expansion of mobile phone technology, there have been rapid advances in the development of mobile-health applications (apps). Studies have shown that users are eager to apply mobile technology for health management [1]. Mobile applications are thus considered very useful for supporting patient-centered care by facilitating various types of patient and physician interaction, and for providing greater access to information. Significantly, the mobility of these interventions is the key to permit patients to participate in their own care and to communicate with healthcare providers outside formal consultations [2]. Even using mobile apps can help patients’ self-manage their conditions by delivering personalized training and treatment plans and by providing support to patients to allow them to monitor their own clinical data [3]. This has been achieved through applying data mining methods in the architecture of mobile apps equipped with special features, such as tracking crucial related values, prediction, estimation, detection, and so forth, which support patients’ self-management [4-7]. Some of these app features are enhanced using data mining methods which are aimed toward personalized care of patients.

Data mining can be defined as the combination of machine learning algorithms, statistical analysis, artificial intelligence, and database management systems to extract hidden, previously unknown, humanly comprehensible, and potentially useful patterns, from large databases [7]. Personalized applications are defined as systems that facilitate a partnership among practitioners, patients, and their families to guarantee that procedures respect patients’ requirements and preferences [8]. Data mining algorithms may be applied as the fundamental step in the overall process of patient-oriented and personalized care. It includes intelligent methods to generate data patterns, which are presented in the features of the mobile apps and improve their function. In this step, to prevent over fitting, data are divided into two sets, namely, training and testing sets. The training set is used as the guide to generate an adequate prediction model and patterns. The test set is used to validate the developed model during the last phase, which is often called evaluation [9].

Although there have been several review articles about m-health apps or the application of self-management methods and evaluation in healthcare [10], this study investigated how m-health applications can benefit from the use of data mining techniques in self-management and patient-centric care. Furthermore, there has been limited research related to big data application in the area of patient-centric care; studies have been mainly related to services rather than self-management or have focused on big data rather than data mining [11]. The objective of this study, thus, was to investigate the application of data mining techniques to improve the self-management features of mobile apps as well as their accuracy and reliability for that specific purpose. To fulfill this aim, we collected information such as application category, disease or condition type, operating system platform, and data mining techniques.

II. Methods

A review of data mining technique usage for patient-centered application was conducted following the preferred approach to reporting items for systematic review and meta-

Figure 1. Process of PRISMA for data collection and analysis.
analysis proposed by Moher et al. [12]. Figure 1 shows the process of PRISMA for data collection and analysis. Different phases of systematic review are displayed in PRISMA flow diagram. Figure 1 shows the course of information collection and analysis.

Table 1. List of studied papers and their specific characteristics, including author/year, task and applied data mining techniques

| Study                        | Year | Accuracy (%) | Task            | Data mining technique                                           |
|------------------------------|------|--------------|-----------------|---------------------------------------------------------------|
| Gatuh and Jiang [14]         | 2016 | 96.4         | Predicting      | Naive Bayes                                                   |
| Tai and Lin [15]             | 2015 | Not mentioned| Predicting      | Data mining techniques                                        |
| Salama and Shawish [17]      | 2014 | Not mentioned| Follow-up       | Data mining techniques                                        |
| Graca et al. [18]            | 2014 | 87.5 ± 23.05 | Gathering data  | Data mining techniques                                        |
| Shahin et al. [9]            | 2014 | 99.9         | Estimation      | DRSAR with multi classifier random forest                     |
| Tragopoulou et al. [19]      | 2014 | 92.81        | Collecting and estimation | Movement classification algorithms and trajectory pattern analysis technique |
| Su et al. [20]               | 2014 | Not mentioned| Predicting      | Recognition algorithms                                        |
| Rani et al. [21]             | 2012 | Not mentioned| Monitoring      | Genetic algorithm and the clustering                         |
| Andrade et al. [22]          | 2012 | Not mentioned| Monitoring      | Data mining and machine learning techniques                  |
| Tartarisco et al. [23]       | 2012 | 90.5         | Monitoring      | Autoregressive model, artificial neural networks and fuzzy    |
| Sufi and Khalil [24]         | 2011 | 97           | Classification  | Expectation maximization-based clustering                     |
| Zhang et al. [25]            | 2014 | 0.84 ± 0.0242| Predicting      | k-Nearest neighbor algorithm                                  |
| Wu et al. [26]               | 2014 | 88.0         | Detecting       | Decision tree algorithms                                      |
| Kailas et al. [27]           | 2012 | Not mentioned| Monitoring      | Probabilistic and non-probabilistic                          |
| Sefen et al. [29]            | 2016 | 87 ± 2.4     | Recognizing     | Naive Bayes                                                   |
| Pham [30]                    | 2016 | 91           | Monitoring      | Gaussian mixture model and universal background model         |
| Jung and Chung [31]          | 2016 | Not mentioned| Recognizing     | Knowledge-based context-aware modeling, Deep learning algorithm |
| Zhou et al. [32]             | 2015 | Not mentioned| Monitoring      | Deep learning algorithm                                      |
| Zhang et al. [33]            | 2015 | 85           | Recognizing     | Hierarchical segmentation                                    |
| Wan Ahmad et al. [34]        | 2015 | >0.90        | Classification  | Gaussian derivatives filter with seven orientations, combined with FCM clustering |
| Sowjanya et al. [16]         | 2015 | 99.99        | Predicting      | DT classifier                                                 |
| Pouladzadeh et al. [35]      | 2015 | 99.79        | Detecting       | Cloud-based SVM                                               |
| Nikolaiev and Timoshenko [36]| 2015 | 89           | Monitoring      | New intelligent sensors and machine learning methods           |
| McGlothlin et al. [37]       | 2015 | 95           | Detecting       | Data mining techniques                                        |
| Lopez-Guede et al. [38]      | 2015 | 81.80        | Detecting       | Data mining techniques                                        |
| Menshawy et al. [39]         | 2015 | Not mentioned| Detecting       | Selection algorithms in terms of redundant features, execution time and classification |
| Behar et al. [40]            | 2015 | 92.2         | Sleep disorder  | SVM classifier                                                |
| Sterling et al. [41]         | 2014 | Not mentioned| Monitoring      | Hidden Markov model                                           |
| Pouladzadeh et al. [42]      | 2014 | 90           | Monitoring      | SVM                                                           |
| Sun et al. [43]              | 2011 | 97.7         | Detecting       | Data mining techniques                                        |

Values are presented as mean ± standard deviation.

DRSAR: dynamic rough sets attribute reduction, FCM: fuzzy C-means, DT: decision tree, SVM: support vector machine.
1. Research Question
The aim of this work was to find out how data mining techniques can be employed to improve patient-centered mobile apps.

2. Inclusion Criteria
Papers included in this study were original papers on the use of smartphone apps for patient-centered healthcare. Non-English papers were excluded as well as those for which the full-text was not available, or those that were any type of publication other than original papers (conference abstracts, review papers, letters, etc.).

3. Search Strategy
PubMed, Scopus, and ScienceDirect were the databases searched in this work. The review was performed from April 20 to June 15, 2017. The PICO criteria were used to define the search string: population [13], intervention [13], comparison (C) and outcome (O) [13]. The population was self-management application, the intervention was patient-centered application; the comparison was excluded; and outcomes were all papers that used data mining techniques for patient-centered applications. We reviewed articles published from 2010 to 2016.

4. Selection Process
Relevant papers were selected by title and abstract and were thoroughly screened by three experts. The experts extracted paper information in seven categories, including author, year, task, accuracy, and data mining techniques. Table 1 shows relevant papers and their characteristics based on study-specific aims [9,14-43].

III. Results
Based on the study search terms, 30 articles were reviewed in detail. Table 1 displays the breakdown of article categories. The features obtained from the studied apps enhanced by data mining methods were categorized as follows: ‘monitoring’ was the most common usages category (25%); ‘predicting’ (21.87%), ‘detecting’ (18.5%), ‘calculating’ (12.5%), ‘classification’ (9.37), ‘data-gathering’ (6.25%), and recommendation and follow-up (3.12%). The apps are described by features connected to the platform and patient condition/disease in Table 1. All of the reviewed articles dealt with apps that operate in 1 of 5 platforms.

As shown in Table 1, in 20 of the 30 reviewed papers, the accuracy of an applied data mining method for the purpose of patient self-management was mentioned. Thirteen of those 20 papers [4] reported accuracy of 90% or more, while 7 of those 20 (35%) reported more than 95% accuracy regarding data mining algorithms performance in the given features embedded in the mobile apps. These successful methods were mainly cloud-based support vector machine (SVM, n = 1; 99% accuracy), decision tree (n = 4; 95% accuracy), and naïve Bayesian (n = 1; 92% accuracy) with highest levels of accuracy. Overall, 16 data mining methods have been reported to be applied in mobile app design, varying from only the application of a ‘genetic algorithm’ for ‘monitoring’ to the application of multiple methods for the enhancement of one or more features. For instance, to improve ‘detection’, ‘monitoring’, and ‘prediction’ as features of self-management apps, the application of 7, 6, and 3 differ-
Table 2. Table of mobile application category, corresponding diseases/conditions and applied development platform

| Application category | Disease/condition                                      | Platform |
|----------------------|--------------------------------------------------------|----------|
|                      |                                                        | Mobile   | Cloud computing | Gadget | Sensor |
| Monitoring           | Cardiac abnormalities                                  | √        |                 | √      |        |
|                      | Stress                                                 |          |                 |        |        |
|                      | Self-wellness                                          |          |                 |        |        |
|                      | Health and security                                    |          |                 |        |        |
|                      | Physical activity                                      |          |                 |        |        |
|                      | Colorectal cancer                                      |          |                 |        |        |
|                      | Sleep disorder                                         |          |                 |        |        |
|                      | Asthma                                                 |          |                 |        |        |
| Predicting           | Malignancy                                             | √        | √                | √      |        |
|                      | BMI                                                    |          |                 |        |        |
|                      | Diabetes levels                                        |          |                 |        |        |
|                      | Motion activity                                        |          |                 |        |        |
|                      | Dementia                                               |          |                 |        |        |
|                      | Cardiovascular                                        |          |                 |        |        |
|                      | Elderly behavior prediction                            |          |                 |        |        |
| Detecting            | Colorectal cancer                                      | √        | √                | √      | √      |
|                      | Estimate the calorific and nutrition content of foods   |          |                 |        |        |
|                      | Potential CRC patients early                           |          |                 |        |        |
|                      | Human activities                                       |          |                 |        |        |
|                      | Epileptic seizures                                     |          |                 |        |        |
| Calculating          | Risk level for each medical case Lebanese healthcare domain | √        | √                |        |        |
|                      | (acute appendicitis, premature birth, osteoporosis, and coronary heart disease) |          |                 |        |        |
|                      | Whole-body vibration exposures                         |          |                 |        |        |
|                      | Food calorie and nutrition                             |          |                 |        |        |
| Classification       | Cardiovascular abnormalities                           | √        |                  |        |        |
|                      | Unsupervised lung                                      |          |                 |        |        |
| Data-gathering       | Early symptoms of Parkinson’s                         | √        |                  |        |        |
|                      | Activity information                                   |          |                 |        |        |
| Recommendation       | Obese management                                       | √        |                  |        |        |
|                      | Elderly behavior                                       |          |                 |        |        |
| Follow-up            | Diabetes                                               | √        |                  |        |        |
|                      | Cardiac abnormalities                                  |          |                 |        |        |
ent data mining methods was reported. The most frequently applied data mining method with the highest level of performance was SVM for the enhancement of 4 features, namely, ‘monitoring’, ‘detection’, ‘calculation’, and ‘data gathering’ with more than 99% accuracy.

As shown in Figure 2, 6.66% of the included studies reported on cardiovascular abnormalities, food calories, and nutrition management. While 13.33% of the studies focused on apps developed for physical activity and colorectal cancer purposes, sleep disorder, elderly behavior, diabetes, and stress were the focus of only 6.66%. Only 3.33% of the studies provided information on unsupervised lung disease, asthma, Parkinson disease, and seizure disorders. Figure 2 presents the percentages of studies focusing on each illness for which mobile apps are used to support patients’ self-management.

A range of data mining techniques were used in the studied apps. Figure 3 shows the frequency with which specific data mining methods appeared in the literature. Support vector machine was the most frequently used method for self-management apps. Table 2 shows the application category of the reviewed apps based on disease/condition and platform. Table 3 shows mobile apps features and their application categories based on data mining methods used.

IV. Discussion

Self-management care is defined as the systematic provision of training and supportive treatment by healthcare expert to improve patients’ abilities and confidence in handling their own health problems, including regular progress, goal setting, and solutions [44]. Self-management involves more active participation in keeping with the realities of chronic disease, whereby responsibility for routine disease management shifts from healthcare professionals to the individual patient [45]. The most common way to provide evidence-based care through designed programs has emerged during the last decade [46]. Technology supports healthcare by offering innovative options for self-management education. Mobile phones are indispensable in people’s lives and can work as a platform for diverse self-management tools [4]. Users desire a mobile platform for information and applications in addition to basic phone capability, email, and access to the internet. Many consumer health informatics tools have been developed over the last decade. As of June 2013, there were 43,689 health apps available from the Apple iTunes store alone [47].

To empower these apps through a wider range of features
and capabilities, several data mining methods have been applied; they address many capabilities, such as prediction, estimation, detection, and so forth, for each patient individually while collecting his or her data. The results of this review suggest that decision trees and rule classifiers have an analogous operating procedure; conversely, decision trees and naive Bayesian generally have dissimilar operational profiles [48]. Furthermore, support vector machine [35] has been used more than other techniques with better accuracy. This might be due to this method's ability to classify cases accurately. Negotiations different aspect of each algorithm are beyond the scope of article. Also, each algorithm has shown great performance in one task. It is generally agreed that SVM achieves better result when handling large amounts of data, but not big data, and continuous features. SVM algorithms achieves great results in terms of accuracy in general, speed of classification, and tolerance to redundant attributes [48]. It is a reliable classification approach that groups patients based on their data for self-management purpose. This predictive modeling method produces the most appropriate evidence-based decisions for patients [49]. As a classifying supervised-learning technique, SVM is based on the concept of a 'margin' placed on either side of a hyperplane separating two data classes. The SVM method works well even when the number of features is large with respect to the number of training instances. However, the SVM method is binary, and in the case of a multi-class problem, it must be reduced to a set of multiple binary classification problems. Besides, SVM is limitation in working with discrete data [48]; therefore, the output of the mobile apps may be restricted to classifying patients into two groups, for example, risky and non-risky. However, in personalized medicine the detection of risky cases requires every single case to be labeled rather than a group of people. Thus, we need not only to support mobile apps by big data analysis; in addition a stronger data analysis technique is needed to focus on the detection, prediction, or estimation of every single risky case.

With the pervasiveness of mobile apps use and the emergence of cloud computing technology, mobile cloud computing tools have been introduced. The integration of cloud computing into the mobile environment might be a solution to overcome obstacles related to the use of data mining methods in mobile apps performance, environment, and security [50]. Patient centered care, which has become a significant trend in healthcare and technology, has had a positive effect on patient safety, access to demographic and clinical information, and clinical decision support systems. Accessibility of data, regardless of the patient and the clinician location, has become the significant factor in both patient satisfaction and enhanced clinical results. Cloud technologies can considerably facilitate this style of health care provision [51].

Holtz and Lauckner [52] reviewed 21 articles describing studies on cellphone use for diabetes management. To establish new systems, such as smartphone apps, as services to patients, the healthcare provider should be involved. It is vitally important that healthcare sectors open up to the application of such up-to-date methods of communication to realize the self-management potential reported in our studies. Thus, researchers should focus on finding ways to utilize the mobile and patient-operated disease-management apps. The application of data mining methods in the development of mobile apps may lead to new ways of delivering healthcare to people living with chronic conditions. As a result, the role of the patient as a passive recipient of care will positively be changed to an active participant in self-management [52].

One limitation of this study was the small number of articles obtained from three databases. Another limitation is that the indicators that were evaluated and the results may not be generalizable. Future investigation are required to review big data apps, which are applied in the area of personal care rather just patient-centric care.

Conflict of Interest

No potential conflict of interest relevant to this article was reported.

References

1. Torous J, Friedman R. Smartphone use among patients age greater than 60 with mental health conditions and willingness to use smartphone applications to monitor their mental health conditions. Am J Geriatr Psychiatry 2014;22(3):S128-S129.
2. Baysari MT, Westbrook JI. Mobile applications for patient-centered care coordination: a review of human factors methods applied to their design, development, and evaluation. Yearb Med Inform 2015;10(1):47-54.
3. Coulter A, Ellins J. Effectiveness of strategies for informing, educating, and involving patients. BMJ 2007;335(7609):24-7.
4. Chomutare T, Fernandez-Luque L, Arsand E, Hartvigsen G. Features of mobile diabetes applications: review of the literature and analysis of current applications compared against evidence-based guidelines. J Med Inform
ternet Res 2011;13(3):e65.
5. El-Gayar O, Timsina P, Nawar N. A mHealth architecture for diabetes self-management system. Madison (SD): Dakota State University; 2013.
6. El-Gayar O, Timsina P, Nawar N, Eid W. Mobile applications for diabetes self-management: status and potential. J Diabetes Sci Technol 2013;7(1):247-62.
7. Mannila H. Methods and problems in data mining. Proceedings of the 6th International Conference on Database Theory (ICDT); 1997 Jan 8-10; Delphi, Greece. p. 41-55.
8. Institute of Medicine. Envisioning the national health care quality report. Washington (DC): National Academies Press; 2001.
9. Shahin A, Moudani W, Chakik F, Khalil M. Data mining in healthcare information systems: case studies in Northern Lebanon. Proceedings of 2014 3rd International Conference on e-Technologies and Networks for Development (IceND); 2014 Apr 29-May 1; Beirut, Lebanon. p. 151-5.
10. Boudreaux ED, Waring ME, Hayes RB, Sadasivam RS, Mullen S, Pagoto S. Evaluating and selecting mobile health apps: strategies for healthcare providers and healthcare organizations. Transl Behav Med 2014;4(4):363-71.
11. Chawla NV, Davis DA. Bringing big data to personalized healthcare: a patient-centered framework. J Gen Intern Med 2013;28 Suppl 3:S660-5.
12. Moher D, Liberati A, Tetzlaff J, Altman DG; PRISMA Group. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. Ann Intern Med 2009;151(4):264-9, W64.
13. Stone PW. Popping the (PICO) question in research and evidence-based practice. Appl Nurs Res 2002;15(3):197-8.
14. Gatuha G, Jiang T. Android based naive Bayes probabilistic detection model for breast cancer and mobile cloud computing: design and implementation. Int J Eng Res Africa 2016;21:197-208.
15. Tai CH, Lin DT. A framework for healthcare everywhere: BMI prediction using kinect and data mining techniques on mobiles. Proceedings of 2015 16th IEEE International Conference on Mobile Data Management (MDM); 2015 Jun 15-18; Pittsburgh, PA. p. 126-9.
16. Sowjanya K, Singhal A, Choudhary C. MobDBTest: a machine learning based system for predicting diabetes risk using mobile devices. Proceedings of 2015 IEEE International Advance Computing Conference (IACC); 2015 Jun 12-13; Bangalore, India. p. 397-402.
17. Salama M, Shawish A. A novel mobile-cloud based healthcare framework for diabetes. Proceedings of the International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC); 2014 Mar 3-6; Angers, France. p. 262-9.
18. Graca R, e Castro RS, Cevada Jo. ParkDetect: early diagnosing Parkinson’s disease. Proceedings of 2014 IEEE International Symposium on Medical Measurements and Applications (MeMeA); 2014 Jun 11-12; Lisbon, Portugal. p. 1-6.
19. Tragopoulou S, Varlamis I, Eirinaki M. Classification of movement data concerning user’s activity recognition via mobile phones. Proceedings of the 4th International Conference on Web Intelligence, Mining and Semantics (WIMS14); 2014 Jun 2-4; Thessaloniki, Greece.
20. Su X, Tong H, Ji P. Activity recognition with smartphone sensors. Tsinghua Sci Technol 2014;19(3):235-49.
21. Rani NS, Vimala K, Kalaivani V. A remote healthcare monitoring system for faster identification of cardiac abnormalities from compressed ECG using advanced data mining approach. Proceedings of the 4th International Conference on Signal and Image Processing 2012 (ICSPIP); 2012 Dec 13-15; Chennai, India. p. 227-36.
22. Andrade J, Duarte A, Arsenio A. Social web for large-scale biosensors. Int J Web Portals 2012;4(3):1-19.
23. Tartarisco G, Baldus G, Corda D, Raso R, Arnau A, Ferrero M, et al. Personal health system architecture for stress monitoring and support to clinical decisions. Compn Commun 2012;35(11):1296-305.
24. Sufi F, Khalil I. Diagnosis of cardiovascular abnormalities from compressed ECG: a data mining-based approach. IEEE Trans Inf Technol Biomed 2011;15(1):33-9.
25. Zhang S, McClean SI, Nugent CD, Donnelly MP, Galway L, Scoyne BW, et al. A predictive model for assistive technology adoption for people with dementia. IEEE J Biomed Health Inform 2014;18(1):375-83.
26. Wu HC, Chang CJ, Lin CC, Tsai MC, Chang CC, Tseng MH. Developing screening services for colorectal cancer on Android smartphones. Telemed J E Health 2014; 20(8):687-95.
27. Kailas A, Chong CC, Watanabe F. Simple statistical inference algorithms for task-dependent wellness assessment. Comput Biol Med 2012;42(7):725-34.
28. Krishnan NC, Colbry D, Juillard C, Panchanathan S. Real time human activity recognition using tri-axial accelerometers. Proceedings of Sensors, Signals and Infor-
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information Processing Workshop (SenSIP); 2008 May 11-14; Sedona, AZ. p. 3337-40.

29. Seifen B, Baumbach S, Dengel A, Abdennadher S. Human activity recognition: using sensor data of smartphones and smartwatches. Proceedings of the 8th International Conference on Agents and Artificial Intelligence (ICAART); 2016 Feb 24-26; Rome, Italy. p. 488-93.

30. Pham C. MobiCough: real-time cough detection and monitoring using low-cost mobile devices. Proceedings of Asian Conference on Intelligent Information and Database Systems (ACIIDS); 2016 Mar 14-16; Da Nang, Vietnam. p. 300-9.

31. Jung H, Chung K. Knowledge-based dietary nutrition recommendation for obese management. Inf Technol Manag 2016;17(1):29-42.

32. Zhou X, Guo J, Wang S. Motion recognition by using a stacked autoencoder-based deep learning algorithm with smart phones. Proceedings of the International Conference on Wireless Algorithms, Systems, and Applications (WASA); 2015 Aug 10-12; Qufu, China. p. 778-87.

33. Zhang W, Yu Q, Siddiquie B, Divakaran A, Sawhney H. "Snap-n-Eat": food recognition and nutrition estimation on a smartphone. J Diabetes Sci Technol 2015;9(3):525-33.

34. Wan Ahmad WS, Zaki WM, Ahmad Fauzi MF. Lung segmentation on standard and mobile chest radiographs using oriented Gaussian derivatives filter. Biomed Eng Online 2015;14:20.

35. Pouladzadeh P, Shirmohammadi S, Bakirov A, Bulut A, Yassine A. Cloud-based SVM for food categorization. Multimedia Tools and Appl 2015;74(14):5243-60.

36. Nikolaiev S, Timoshenko Y. Reinvention of the cardiovascular diseases prevention and prediction due to ubiquitous convergence of mobile apps and machine learning. Proceedings of Information Technologies in Innovation Business Conference (ITIB); 2015 Oct 7-9; Kharkiv, Ukraine. p. 23-26.

37. Mclothlin J, Burgess-Limerick R, Lynas D. An iOS application for evaluating whole-body vibration within a workplace risk management process. J Occup Environ Hyg 2015;12(7):D137-142.

38. Lopez-Guede JM, Moreno-Fernandez-de-Leceta A, Martinez-Garcia A, Grana M. Lynx: automatic elderly behavior prediction in home telecare. Biomed Res Int 2015;2015:201939.

39. Menshawy ME, Benharref A, Serhani M. An automatic mobile-health based approach for EEG epileptic seizures detection. Expert Syst Appl 2015;42(20):7157-74.

40. Behar J, Roebuck A, Shahid M, Daly J, Hallack A, Palms N, et al. SleepAp: an automated obstructive sleep apnoea screening application for smartphones. IEEE J Biomed Health Inform 2015;19(1):325-31.

41. Sterling M, Rhees H, Bocko M. Automated cough assessment on a mobile platform. J Med Eng 2014;2014:951621.

42. Pouladzadeh P, Kuhad P, Peddi SV, Yassine A, Shirmohammadi S. Mobile cloud based food calorie measurement. Proceedings of 2014 IEEE International Conference on Multimedia and Expo Workshops (ICMEW); 2014 Jul 14-18; Chengdu, China. p. 1-6.

43. Sun L, Zhang D, Li N. Physical activity monitoring with mobile phones. Proceedings of International Conference on Smart Homes and Health Telematics; 2011 Jun 20-22; Montreal, Canada. p. 104-11.

44. Panagioti M, Richardson G, Small N, Murray E, Rogers A, Kennedy A, et al. Self-management support interventions to reduce health care utilisation without compromising outcomes: a systematic review and meta-analysis. BMC Health Serv Res 2014;14:356.

45. Barlow J, Wright C, Sheasby J, Turner A, Hainsworth J. Self-management approaches for people with chronic conditions: a review. Patient Educ Couns 2002;48(2):177-87.

46. Barlow JH, Turner AP, Wright CC. A randomized controlled study of the Arthritis Self-Management Programme in the UK. Health Educ Res 2000;15(6):665-80.

47. Bidmon S, Terlutter R, Röttl J. What explains usage of mobile physician-rating apps? Results from a web-based questionnaire. J Med Internet Res 2014;16(6):e148.

48. Kotsiantis SB, Zaharakis I, Pintelas P. Supervised machine learning: a review of classification techniques. Informatica 2007;31(3):249-68.

49. Son YJ, Kim HG, Kim EH, Choi S, Lee SK. Application of support vector machine for prediction of medication adherence in heart failure patients. Healthc Inform Res 2010;16(4):253-9.

50. Dinh HT, Lee C, Niyato D, Wang P. A survey of mobile cloud computing: architecture, applications, and approaches. Wirel Commun Mob Comput 2013;13(18):1587-611.

51. Nigam VK, Bhatia S. Impact of cloud computing on health care. Int Res J Eng Technol 2016;3(5):2804-10.

52. Holtz B, Lauckner C. Diabetes management via mobile phones: a systematic review. Telemed J E Health 2012;18(3):175-84.