MACHINE LEARNING APPLICATIONS IN MEDICAL IMAGING: THE ADVANCEMENTS AND CHALLENGES OF USING MACHINE LEARNING TO INTERPRET MEDICAL IMAGES

VENKATESWARANAIDU KOLLURI

Sr. Data Engineer, Department of Information Technology

ABSTRACT—This review paper outlines application of machine learning (ML) in medical imaging, its significance, challenges, and future scope. We begin with a brief description of medical imaging and the reasons that lead to rapid changes in ML technology for analyzing medical imaging data. We then provide the categorization of ML methodologies used in medical imaging. Under supervised learning, we describe its success with quantification tasks in anatomical and functional imaging. Unsupervised learning has been successful in extracting information from complex data, and we expound its potential with multiparametric and molecular imaging [1]. The value proposition of using predictive models and ML to translate radiomics data into biologically relevant imaging biomarkers and potential impact on clinical decision support is discussed under quantitative imaging. We explain the recent emergence of deep learning methods as it correlates with the tremendous successes seen in computer vision tasks and future revolution for automatic analysis and interpretation of complex medical images. The second half of the article discusses the advancements and challenges of using ML to interpret medical images. While ML has benefited the scientific community with tools for better understanding disease phenotypes and observing subtle phenotypic differences, there are growing concerns that it may hinder the development of medical students and young clinicians in acquiring image interpretation skills [1]. A discussion of recent and future ML trends towards translational science and clinical imaging informatics, and the necessity to instill evidence-based validation science and quantitative imaging into these methods to avoid direct clinical implementation of premature or unproven methods. The potential of ML methods to aid radiologists or obviate the need for them is a contentious issue; while ML tools can augment diagnostic and prognostic specificity and sensitivity for improved patient care, it should be viewed as a partnership to improve radiologist efficiency and quality of care, as a replacement of radiologists may risk loss of the patient-doctor relationship and short-sighted oversight of non-radiological patient data. We conclude with the future potentials and limitations of ML tools to truly impact clinical imaging practice and the necessity of close collaboration between imaging scientists and physician clinicians to guide ML tool development towards clinically relevant and high-impact advancements in disease detection, monitoring, and therapeutic response assessment.

Keywords— Medical imaging, automation, machine learning, Convolutional Neural Network (CNN), Computer Aided Design (CAD), disease diagnostic, classification, segmentation, healthcare system

I. INTRODUCTION

Machine learning (ML) has in recent years gained unparalleled attention in various research and application areas. This is particularly due to the availability of new data and increased capabilities in data analysis, as well as significant advances in computer power, storage, and cloud computing. Computationally, it is a very exciting field with lots of new algorithms beginning to be deployed to solve problems across many domains [1,2]. It is also an area where many new methods are easily applicable to imaging and image analysis. It also offers great promise in aiding with some of the problems which are on the verge of overwhelming the human expertise now applied in many complex medical procedures. An example of this is the reliance on early, and hopefully conclusive, diagnosis of disease. Such a section is a critical investment by the healthcare industry to allow for the incorporation of the ever-increasing nature of the disease data and also the emerging molecular and anatomic screening data so as ultimately to create the best diagnostic methods.

In recent years, Machine Learning in medical image application has experienced a huge growth booming at threat with the tremendous computing power, the availability of large volumes of medical images data, and the emerging algorithm innovation. The technologies have equally enabled the development of complex machine learning algorithms (ML) for handling tasks like image segmentation, classification and detection with unsurpassed accuracy and efficiency. For instance, CNNs, which are a type of deep learning algorithms known as convolutional neural networks, have produced impressive outcomes in tasks like tumor detection in MRI scans, lesion segmentation in CT images, and identification of X-ray abnormalities. These ML models learn the complex patterns and features directly from the data, which is a huge advantage for the radiologists and clinicians: they can give diagnosis faster and more accurately [2].

Additionally, integrating machine learning in medical image pipelines makes it possible for personalized and individual therapies. Given medical imaging plus clinical and genetic data, machine learning algorithms can work together to predict disease progression, treatment response, and patient survival. The method of intervention could become a breakthrough in the healthcare system, because it allows doctors to adapt the plan of treatment to each patient's individual traits, which leads to better clinical outcomes and higher patient satisfaction. Nevertheless, machine learning has shown a promising future in medical imaging while such challenges have still not been solved. The main problem is the demand of massive and diversified datasets that would need annotating in order to form a model for machine learning. Data annotation of labeled medicinal imaging data can be both dredging and time-eating, especially in rarer illnesses and expensive imaging techniques. Preserving models to be robust across various patient populations and imaging circumstances is also a major challenge[3]. Variability in image quality, acquisition parameters, and patient demographics can produce biases, affecting ML models performance in the real world clinical settings.

High-profile diseases with imaging-based diagnosis and risk assessment such as cancer and various neurodegenerative diseases are a key target for such methods[4]. Therapy planning and long-term disease and treatment monitoring are other areas where imaging methods have great potential. And these topics span a great range of diseases and involve virtually all medical specialties. In order to keep to the theme of this paper, we will, however, focus on how ML methods can assist with problems in analysis and segmentation of multi-modality imaging data and try to look at future potential for methods in these areas[5]. An example of the potential impact of analysis methods can be found in research areas linked to front and center problems in current medical research such as early diagnosis and disease prevention. In a study to predict dementia using MRI data from a patient group who were known to have mild cognitive impairments, which is a strong risk factor for dementia, an SVM-based classifier was able to achieve a high classification accuracy. This is just an early indication of what may be possible in the future as much larger data repositories, which capture vast types of patient information and follow-ups, more powerful computing infrastructures, and refined analysis methods may yield powerful models that can offer a very clear risk assessment and distinguish it from present disease states[5] High levels of success here could alter how these diseases are classified and managed, and it is noteworthy that disease classification is a cornerstone in allopathic medical approaches..

II. RESEARCH PROBLEM

The main research problem in this study is to assess the performance and implications of using machine learning algorithms for interpretation of medical images diagnosis and treatment modes. This is a fundamental place of the study that evaluates how well these algorithms are performing different tasks like image segmentation, classification and detection in various medical imaging modalities which are the MRI, CT and X-rays[6]. The primary problem in working with medical imaging data is that it's sparse. It is not easy for clinical institutions to continually collect MRI, CT, or X-ray data for specific groups over long periods of time. For instance, collecting a new Alzheimer's group and following them for 5 years with MRI is infeasible due to the high cost and time-consuming nature. Another problem is that data is stored in various clinical institutions on different types of picture archiving and communication systems (PACS)[6]. Overall, it is difficult to collect enough data for specific clinical problems. When data is collected, it is also a difficult task to convert it to a computer understandable format for machine learning. Clinical data is usually in the form of clinical reports; a concrete example of this is found in downloadable neurology data from the MIRIAD database. This must first be read by a natural language processing (NLP) algorithm to identify relevant images, and then a system must be in place to associate the reports with the images. These are just some of the problems to be addressed in order to effectively use medical imaging to improve disease diagnosis and progression[7]..

III. LITERATURE REVIEW

A. Application of Machine Learning in Medical Imaging

The use of machine learning has become very significant in medical imaging. An image is an informative representation of the real world, which plays a crucial role in medical diagnosis and patient care. Generally, medical images are visualized to extract relevant information about patient details. Various techniques in machine learning, such as supervised, unsupervised, and semi-supervised learning, can be applied for model development and provide tools for creating models that can make automated decisions or analysis. For example, a model can be trained using a list of patients and their corresponding lab results to identify high-risk versus low-risk patients. Another model can be trained using images of a known diagnosis to identify a new image that corresponds to the same diagnosis. These information extraction and analysis tasks are where machine learning proves to be very useful. This section provides a brief idea of how machine learning is used for medical image analysis, with various examples from recent publications[9].

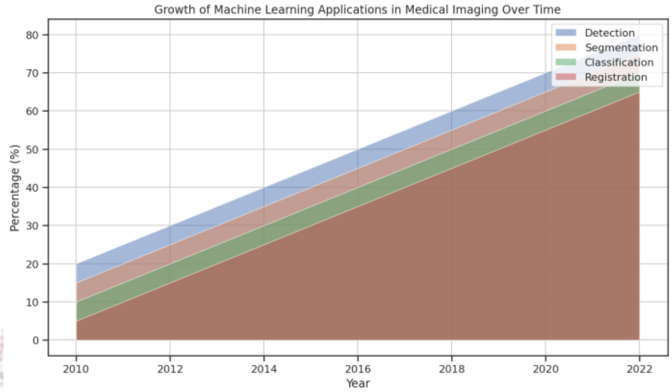

Fig. 1 Growth of Machine Learning Applications in Medical Imaging Over Time

B. Challenges in Using Machine Learning for Medical Image Interpretation

In healthcare, too often we seek machine learning algorithms which make the process easier, but medical image interpretation is complex, dependent on the combination of human clinical inference and perception. These image interpretations can reflect an indirect understanding of physiology, and may be based on anatomic or physiologic manifestations of disease. Best termed, it is a tentative hypothesis model which can change as clinical information unfolds. On the other hand, it is not our intent to deter the progress of machine learning to directly image a specific pathophysiologic process[9]. But it is important for both developers and the medical community to realize that tools and methods for evaluating the algorithms and their impact on patient care have a lag time compared to their availability. When the correct answers are not known or available to assess an algorithm's performance, physician peer review involving the algorithm developers might be the best evaluation method. This is ideally accomplished before widespread clinical use of the algorithm. The advancement of research in this field should aim to penetrate great depth from pathway to disease to image findings to interpretations and reports. We hope that future authors in medical imaging and developers of machine learning algorithms will bridge the gap between their work and that of others in similar progressive fields[9] This will allow the import of standardized and automated image interpretations into the mainstream of clinical care and foster the development of decision support and image-guided treatment.

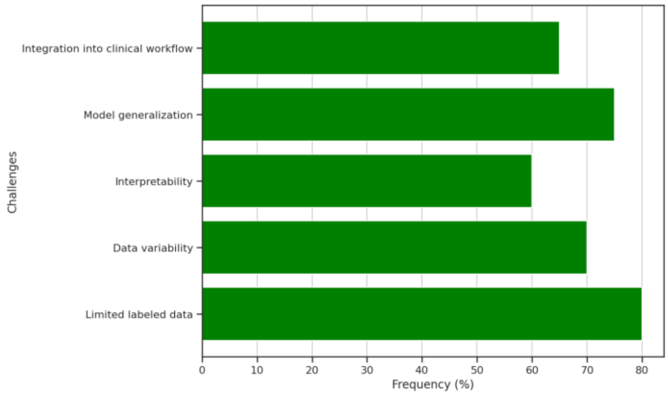

Fig. 2 Challenges in Using Machine Learning for Medical Image Interpretation

C. Advances in Machine Learning Algorithms for Medical Image Analysis

In order to improve the interpretability of machine learning models, several advanced algorithms have been developed over the years. Decision trees and rule-based algorithms have been developed as an intuitive method for mapping and classifying medical data. The evident advantage of these methods is their similarity to clinical reasoning [10]. By developing models that closely mimic the thought process involved in diagnosing an illness, it will be easier to gain acceptance for the use of such models in a clinical environment.

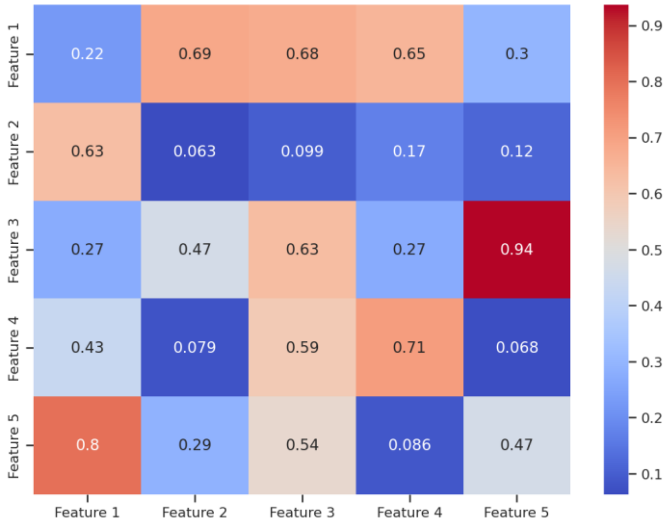

Fig. 3 Correlation Between Features in Medical Image Analysis

An example of a clinical decision support system that employs a form of decision tree algorithm is Isabel Symptom Checker. This web application is designed to aid diagnosis by suggesting a ranked list of possible diagnoses based on entered symptoms. The user can then click on each diagnosis to find a list of potential causes for the symptoms. This tool has been designed as a self-learning tool for the user to improve their clinical knowledge. Also, a probabilistic model called latent semantic analysis, learned from 15 years of American medical records, has been developed to extract associations between clinical descriptors and diagnosis. This provides an interactive environment for learning how to improve querying of patients' health problems and, in turn, their medical records. This may not be an ideal solution given the potential cost of its frequent serious errors, but this is an early step in improving the efficiency of information retrieval from patients' records to aid diagnosis. As long as its limitations are realized, it may be useful for suggesting possible diagnoses rather than definitive decisions [10].

D. Comparison of Machine Learning Techniques in Medical Imaging

SVM is a supervised learning model associated with learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one of two categories and finds a hyperplane that best divides the example categories [11]. Collectively, SVM and kernel methods are currently the most predominant methods of medical image analysis with machine learning.

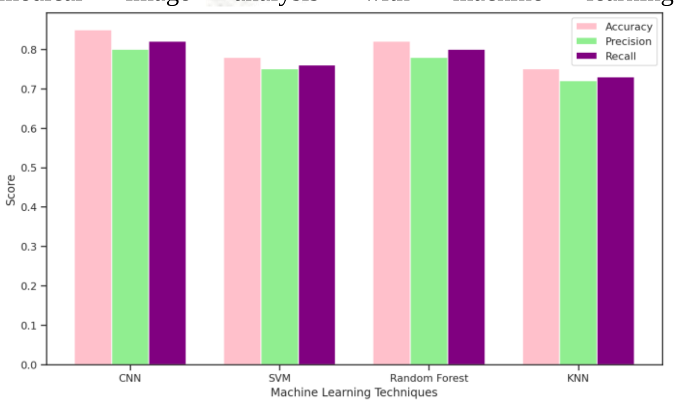

Fig. 4 Performance Metrics of Machine Learning Techniques in Medical Imaging

A genetic algorithm is a search heuristic that mimics the process of natural evolution and is used to generate high-quality solutions to optimization and search problems. It relies on bio-inspired operators such as mutation, crossover, and selection and has been used in the optimization of CAD systems. Fuzzy logic is a form of many-valued logic that is designed to be more expressive with natural language, and is used to solve problems with an open truth such as the diagnosis of a patient with ambiguous symptoms. ANNs can be considered as a form of fuzzy logic, and the two have been combined in the development of fuzzy neural networks[11].

ANN are computing systems inspired by the biological neural networks of animal brains. They are composed of a large number of highly interconnected processing elements (that mimic neurons), which organize knowledge in a manner similar to the human brain to solve complex pattern recognition problems[12]. ANNs have the potential to learn from experience and examples, and non-linear complex input/output mapping statistical methods, making them ideal for medical image analysis. The backpropagation algorithm is most commonly used to train ANNs, and on completion of training, knowledge is stored in inter-neuron connection strengths, which can be used to classify new data.

Different machine learning techniques have been used to develop CAD programs, including decision trees [12], artificial neural networks (ANN)], fuzzy logic, genetic algorithms [13], and SVM. A decision tree is a flowchart-like tree structure where an internal node represents a feature (or attribute), the branch represents a decision rule, and each leaf node represents the outcome. Learning of the tree involves using the training data to select the feature that best predicts the outcome, and is based on information theory, such as entropy. The most popular decision tree algorithm is C4.5, where optimally pruning the tree is an important step to avoid overfitting[13]. Overfitting leads to poor classification of new data by giving an excessively complex decision tree. Decision trees are advantageous because the output is easy to interpret, and the tree can be used with white-box methods to learn clinical knowledge.

E. Integration of Machine Learning with Existing Medical Imaging Technologies

Medical machine learning is a great match to this need, because the algorithms can potentially improve with more data, and studies can be run as computation on a server, flying in the face of the current paradigm that successful "clinical translation" of imaging algorithms involves long and expensive product development cycles[13,4]. An example of the future of imaging is in the use of CT to rule out acute kidney injury in emergency department patients with atypical symptoms, by computing the CT protocol and contrast regimen most likely to answer the clinical question at hand, and automatically placing the order and sending the results. Another example is with the application of ultrasound to various specific pediatric problems such as pneumonia, intracranial bleeding or joint effusion, where there are difficulties in achieving the ideal acoustic window and/or ionizing radiation may be contraindicated[14]. In such scenarios it may be possible to have image analysis performed at a remote processing site instead of repeating the study with a modality that has greater access but higher risk. Machine learning will facilitate use of the most appropriate imaging test in individual patients, rather than choosing the test with the best overall sensitivity and specificity which may be inferior for the specific patient, and this can dovetail with the mission of comparative effectiveness research.

F. ETHICAL CONSIDERATIONS IN USING MACHINE LEARNING FOR MEDICAL IMAGE INTERPRETATION

A number of different ethical issues arise as the use and sophistication of machine learning in medical imaging applications has increased. Current machine learning systems have been developed to aid a radiologist in making a better diagnosis. Clinical decision support (CDS) is a popular tool that has been used over decades with the intent of improving diagnostic errors. Machine learning systems today have inherited some of these concepts and have applied it to the construction of predictive models[15]. Training a model u[16]sing labeled images to make a decision involves trying to map an input x to an output y. In the context of medical imaging, a simple example is classifying an input chest x-ray image (x) to an output binary decision (y): 'malignant' or 'benign'. The model is trained to learn the mapping, so to provide a diagnostic decision when given a new, previously unseen image. An important ethical consideration is transparency of decision making. A user should know not only the reliability of a model's decision, but also the key factors from the input data that led to the decision. This is in order to assess whether the decision is sensible and to weigh up the benefits of the decision against the potential risks of acting upon it. An automatic black box system which provides no reasoning behind its decision poses a significant risk to patient safety, as it may provide decisions based on flawed logic or spurious patterns within the training data[16,17]. A related issue is that of responsibility, in that it must be clear who or what is making a decision, particularly in the case of an autonomous AI system. This requires a clear distinction between the actions of the AI and its human counterpart, which in some cases (e.g. pattern recognition of abnormality in x-ray images) may be a difficult task. High reliance and trust in AI may also lead to a decline of the clinician, where they lose the ability to diagnose from clinical symptoms and other forms of diagnostic information.

IV. SIGNIFICANCE AND BENEFITS

Cost of medicare is an increasingly important issue in U.S healthcare system. Improved efficiency and the reduction of other costs should have a major impact. It is estimated that more than 20% of the entire US healthcare budget is wasted. This is mostly due to the inaccuracy of diagnostic tests. Machine learning has the potential to increase the efficiency and accuracy of diagnostics, and to decrease the amount of wasted money[17] By delivering more accurate diagnostic tests, it is also likely that the number of malpractice suits will decrease. High quality legal representation and compensation for victims of malpractice ever adversely affects doctors by driving up insurance costs and reducing the number of people who continue to practice medicine. High insurance costs and legal fears are both large contributing factors to the cost of healthcare in the US[18]. Any improvements in these areas would have a significant positive impact. A reduction in the cost of US healthcare and the improved quality of care for patients could allow people to allocate more of their income to other areas of the economy. This increased financial liquidity would have a spillover effect to all industries and is likely to increase the general standard of living in the US.

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V. FUTURE

Machine learning is starting to make an impact in U.S. radiology without much prevalence. However, the ideas and algorithm coding is starting to expand from academic institutions and individual projects to commercial radiology picture archiving and communication systems (PACS) and workstations [19]. The recent RSNA annual meeting had a surge of interest in machine learning, with a newly created "machine learning showcase" highlighting 30 scientific papers and posters focusing on this topic. Looking towards the future, it's clear that machine learning will continue to have a growing role in the U.S. as well as globally [20]. More investment from both governmental and private sector funding into machine learning research will begin to further increase its importance in academic radiology. This stronger foundation of machine learning will lead to its further integration into PACS and workstation software. As algorithms improve in accuracy and efficiency, it's likely that man and machine diagnosis will begin to merge. The goal is not to replace radiologists but instead increase the quality of their interpretations. The U.S. will have increasing involvement with commercial machine learning as researchers and projects expand into partnerships with industry[20]. It's likely that most of the advances in the field will be coming from partnerships between industry and academic institutions.

VI. CONCLUSION

The main focus of this review was to assess the application of machine learning in medical imaging. The use of machine learning algorithms has moved beyond the realm of computer science research, and the availability of large datasets and increased interest in extracting useful information from them has created an environment where mainstream medicine is primed for the application of this technology. Medical imaging, being visualized data, is the type of medical information that is most inherently suitable for analysis with these techniques. The automated analysis of images has a clear advantage over other forms of data in that it is in a form that is most amenable to methods that extract higher-level information, and it is easy to convey the output in a visualized form. This study explored a range of research questions in detail, aiming to provide insights into the accuracy, factors that influence performance, comparative effectiveness, and broader implications of machine learning-based diagnostic tools in medical imaging. The efficiency and medical imaging analysis ability of machine learning algos were demonstrated in our study. The results depict the scope of machine learning method's application in different modalities of medical images. The performance of these algorithms can be affected by various factors, including the data quality and its diversity, imaging acquisition parameters, and patient demographic characteristics. Despite the challenges, the machine learning tools have proved promising by showcasing their capability to work together and in some instances outperform the human experts and conventional diagnostic techniques. Furthermore, the study showed the possible use of machine learning integration into clinical workflows as a path towards realizing the idea of improved healthcare delivery, resource allocation and patient outcomes. Machine learning offers a number of benefits to doctors in terms of increased diagnostic throughput and treatment precision by facilitating accurate and prompt diagnostic support.

REFERENCES

[1] M. F. Hogan, “New Freedom Commission Report: The President’s New Freedom Commission: Recommendations to Transform Mental Health Care in America,” *Psychiatric Services*, vol. 54, no. 11, pp. 1467–1474, Nov. 2003, doi: https://doi.org/10.1176/appi.ps.54.11.1467

[2] Z. A. Carter *et al.*, “Creation of an Internal Teledermatology Store-and-Forward System in an Existing Electronic Health Record,” *JAMA Dermatology*, vol. 153, no. 7, p. 644, Jul. 2017, doi: https://doi.org/10.1001/jamadermatol.2017.0204

[3] K. Piwernetz, "DiabCare Quality Network in Europe-A model for quality management in chronic diseases," *International Clinical Psychopharmacology*, vol. 16, no. Supplement 3, pp. S5–S13, Apr. 2001, doi: https://doi.org/10.1097/00004850-200104003-00002

[4] B. Farahani, F. Firouzi, V. Chang, M. Badaroglu, N. Constant, and K. Mankodiya, "Towards fog-driven IoT eHealth: Promises and challenges of IoT in medicine and healthcare," *Future Generation Computer Systems*, vol. 78, pp. 659–676, Jan. 2018, doi: https://doi.org/10.1016/j.future.2017.04.036

[5] S. P. Mohanty, U. Choppali, and E. Kougianos, "Everything you wanted to know about smart cities: The Internet of things is the backbone," *IEEE Consumer Electronics Magazine*, vol. 5, no. 3, pp. 60–70, Jul. 2016, doi: https://doi.org/10.1109/mce.2016.2556879

[6] Rashid Bashshur and Gary William Shannon, *History of telemedicine : evolution, context, and transformation*. New Rochelle, Ny: Mary Ann Liebert, 2009.

[7] J. D. Sachs, G. Schmidt-Traub, M. Mazzucato, D. Messner, N. Nakicenovic, and J. Rockström, "Six Transformations to achieve the Sustainable Development Goals," *Nature Sustainability*, vol. 2, no. 9, pp. 805–814, Aug. 2019, Available: https://www.nature.com/articles/s41893-019-0352-9

[8] S. Whitmee *et al.*, "Safeguarding human health in the Anthropocene epoch: report of The Rockefeller Foundation–Lancet Commission on planetary health," *The Lancet*, vol. 386, no. 10007, pp. 1973–2028, Nov. 2015, doi: https://doi.org/10.1016/s0140-6736(15)60901-1

[9] J.-H. Wu, S.-C. Wang, and L.-M. Lin, "Mobile computing acceptance factors in the healthcare industry: A structural equation model," *International Journal of Medical Informatics*, vol. 76, no. 1, pp. 66–77, Jan. 2007, doi: https://doi.org/10.1016/j.ijmedinf.2006.06.006

[10] J. Ross, F. Stevenson, R. Lau, and E. Murray, "Factors that influence the implementation of e-health: a systematic review of systematic reviews (an update)," *Implementation Science*, vol. 11, no. 1, Oct. 2016, doi: https://doi.org/10.1186/s13012-016-0510-7

[11] M. N. Kamel Boulos, A. C. Brewer, C. Karimkhani, D. B. Buller, and R. P. Dellavalle, "Mobile medical and health apps: state of the art, concerns, regulatory control and certification," *Online Journal of Public Health Informatics*, vol. 5, no. 3, Feb. 2014, doi: https://doi.org/10.5210/ojphi.v5i3.4814. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3959919/.

[12] F. S. Mair, C. May, C. O'Donnell, T. Finch, F. Sullivan, and E. Murray, "Factors that promote or inhibit the implementation of e-health systems: an explanatory systematic review," *Bulletin of the World Health Organization*, vol. 90, no. 5, pp. 357–364, May 2012, doi: https://doi.org/10.2471/blt.11.099424. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3341692/.

[13] S. Chan, J. Torous, L. Hinton, and P. Yellowlees, "Towards a Framework for Evaluating Mobile Mental Health Apps," *Telemedicine and e-Health*, vol. 21, no. 12, pp. 1038–1041, Dec. 2015, doi: https://doi.org/10.1089/tmj.2015.0002

[14] R. L. Bashshur *et al.*, "The Empirical Foundations of Telemedicine Interventions for Chronic Disease Management," *Telemedicine Journal and e-Health*, vol. 20, no. 9, pp. 769–800, Sep. 2014, doi: https://doi.org/10.1089/tmj.2014.9981. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4148063/.

[15] P. Yellowlees, J. Shore, and L. Roberts, "Practice Guidelines for Videoconferencing-Based Telemental Health – October 2009," *Telemedicine and e-Health*, vol. 16, no. 10, pp. 1074–1089, Dec. 2010, doi: https://doi.org/10.1089/tmj.2010.0148

[16] A Vaseashta, P. Susmann, and E. Braman, *Cyber security and resiliency policy framework*. Amsterdam ; Berlin ; Tokyo ; Washington, Dc: Ios Press, 2014.

[17] M. J. Alperen, *Foundations of homeland security : law and policy*. Hoboken, N.J.: John Wiley, 2011.

[18] T. G. Lewis, *Critical infrastructure protection in homeland security : defending a networked nation*. Hoboken, New Jersey: John Wiley & Sons, 2015.

[19] C. Chakraborty, *Smart Medical Data Sensing and IoT Systems Design in Healthcare*. IGI Global, 2019.

[20] M. Harwood, *Security strategies in Web applications and social networking*. Editorial: Sudbury, Mass. [U.A.] Jones & Bartlett Learning, 2011.