BIG DATA SIGNIFICANCE IN REMOTE MEDICAL DIAGNOSTICS BASED ON DEEP LEARNING TECHNIQUES

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(received: 17 August 2017; revised: 18 September 2017;
accepted: 25 September 2017; published online: 10 October 2017)

Abstract: In this paper we discuss the evaluation of neural networks in accordance with medical image classification and analysis. We also summarize the existing databases with images which could be used for training deep models that can be later utilized in remote home-based health care systems. In particular, we propose methods for remote video-based estimation of patient vital signs and other health-related parameters. Additionally, potential challenges of using, storing and transferring sensitive patient data are discussed.

Keywords: telemedicine, deep learning, multimedia databases, big data

DOI: https://doi.org/10.17466/tq2017/21.4/s

1. Introduction

In recent years, we have observed a trend of global aging and significant changes in demographic structures among societies all over the world. According to the report presented by Moody's Investors Service [1], it is assumed that the number of super-aged countries (nations where more than 20% of the population is over 65) will increase from 3 to 34 by 2030. By reason of the world population aging process, there is a need to find tools and solutions for remote patient monitoring that would allow lowering the number of in-person visits in clinics, hospitals and health care facilities. Telemedicine solutions allow elderly people to remain independent, as the diagnosis can be provided at a distance. In addition, it is possible to detect and respond to potential dangerous situations, as information on the patient's physical activity and health is regularly collected and analyzed. As reported by the latest research, remote medical diagnostic is possible in visible light (*e.g.* heart rate detection [2], diagnosis of glaucoma based on retinal fundus images [3]), as well as in thermography (respiration rate evaluation [4], assessment of facial paralysis using temperature distribution patterns [5]). All of these solutions make use of image processing techniques to evaluate various health conditions or changes of vital signs. As a result, patients' comfort, security and life quality can be improved in a non-invasive and contactless way of supporting them during daily activities, *e.g.* book reading or family video conference.

Due to the increased need for delivering advanced remote diagnostic solutions, more and more studies are focused on methods that allow automatic solving of tasks that previously only people were capable of doing, *e.g.* speech understanding, object recognition or image context understanding. One of these techniques is deep learning. This rapidly evolving field of machine learning, based on deep (with many hidden layers) neural networks, has become an essential tool for computers to solve the world perception problems. Deep learning is an approach that was discovered a long time ago. First deep models consisting of multiple nonlinear operators date back to the early '60s of the 20^{th} century. In 1965 Ivakhnenko and Lapa [6] proposed the first working learning algorithm for a supervised deep feedforward multilayer perceptron based on polynomial activation functions. Unfortunately, at this point of time, deep networks were not effective. The issue was probably simply that these algorithms were too expensive computationally to run experiments on the hardware available at that time. Deep learning has only recently become a key approach used in various applications, *e.g.* in computer vision. One of the reasons is the possibility to run much larger models due to the availability of faster CPUs and GPUs. Moreover, we much better know the regularization techniques nowadays that allow us to train larger networks which achieve a higher accuracy on complex tasks than shallow models. Another important aspect is that today we can provide deep models with the resources they need to be successfully trained. The Big Data trend has made machine learning much easier, because the key burden of statistical estimation (generalizing well to new data after observing only a small dataset) has been reduced [7].

The goal of our research is to present the evaluation of neural networks in accordance with image classification and analysis. We also summarize the existing databases with images which could be used for training deep models that can be later utilized in remote home-based health care systems. Moreover, potential challenges of using, storing and transferring sensitive patient data will be also discussed.

2. Re-invention of Deep Learning

According to Gartner's definition [8] Big Data can be characterized as high-volume, high-velocity and/or high-variety information assets that demand innovative forms of information processing methods to enable decision making, process optimization and inference. Due to the high volume and a lack of structure, Big Data analysis with the means of the techniques used in relational databases is not possible. Medical imaging can be treated as Big Data sets because along with the technology advancements, there is a growing demand for solutions that allow effective medical analysis in order to make proper diagnoses, support clinicians in the decision making process or evaluate the progress of different diseases. Proper inference from the existing databases with huge amounts of data can significantly increase the quality of provided medical services (providing services to patients, selection of appropriate treatment paths, improvement of healthcare systems or support of clinical improvement [9]). However, manual anomaly detection is repeatedly a very difficult task and many human interpretations may be affected by subjectivism, the possibility of making an error and the lack of consistency and repeatability of criteria that allow objective assessment of a given case. In addition, manual processing of large data volumes and proper interpretation of this data is unreal because of the effort and time needed to perform the analysis. Taking it into account, effective data analysis solutions that allow automatic processing of huge amounts of information and support specialists in diagnostic processes are an active research topic. One of the solutions is machine learning that makes computers capable of acquiring their own knowledge by extracting patterns from raw data, and based on this, solve problems that people understand intuitively, but are hard to describe formally. Many machine learning systems have sought to hard code the knowledge and use a strictly defined set of features to make decisions using logical inference rules that correlate each feature with the outcome. For example, logistic regression is not able to examine a patient directly by processing scans acquired with the Magnetic Resonance Imaging technique. Instead, the specialist defines the right set of information that is visible in the image and that could be extracted for this specific task. Each piece of information present in the representation of the image is a feature that in a certain way can be correlated with the outcome. Logistic regression can learn how to make proper predictions using these correlations [7]. Although many artificial intelligence problems can be solved by using a specific set of features, for some tasks this approach is not effective. Frequently, knowing the right collection of features that describe the object is not straightforward. Suppose that we want to implement a face detector. Different facial fragments (nose, eyes, mouth) are characteristic features of the face, so we may use the presence of them for the face detection. Unfortunately, it is difficult to describe exactly what they look like in terms of pixel values, because their shape, size or color may depend on various personal factors, *e.g.* age, gender, race or environment conditions.

In case of tasks for which designing the right set of features is problematic, the approach known as representation learning becomes really helpful. Besides mapping from the representation to a specific output, it also allows computers to learn the representation itself. As a result, adapting models to novel tasks is possible without human interference. In recent years, deep learning has become a widely-used technique in representation learning, as it allows reducing potential factors of data variation, *e.g.* different lighting conditions or poses. Deep learning solves this problem by breaking complex direct mappings from input to output into a series of smaller nested mappings, each described by a different layer of a model. Deep neural networks can naturally model a hierarchical nature of many real-world problems by representing them as a nested hierarchy of concepts, with each concept described by a different network layer. Deep learning appears to be a completely new approach to machine learning, because it has only recently become popular. In fact, this idea was developed and improved many years before [6].

The key concepts among the significant achievements in a neural network that have shaped the current approach to deep networks and remain central in today's machine learning are undoubtedly back-propagation [10] and distributed representation [11]. The distributed learning idea is that each input to a model should contain multiple features and each feature should be shared across many possible inputs. A standard approach for classifying the gender and age defined with 4 classes (child, youth, adult, elder) would be to have 8 neurons, each activated by one of the possible combination (woman-child, man-elder, *etc.*).

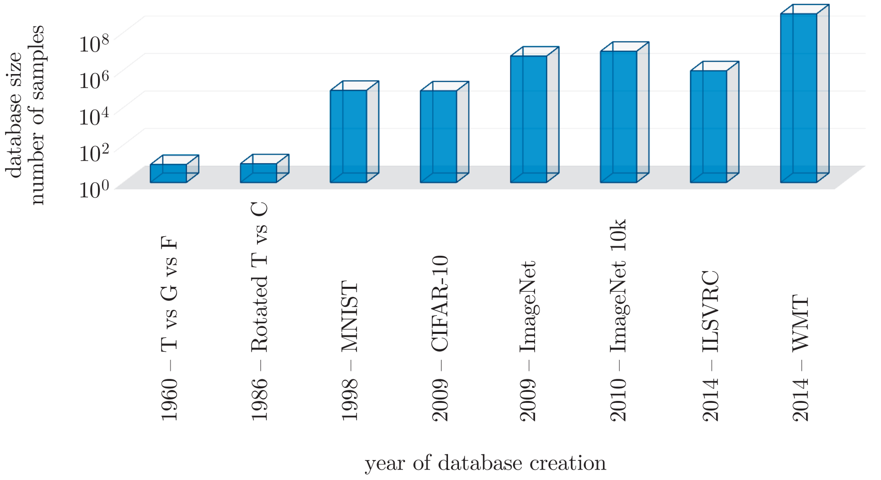

Figure 1. Significant increase in database size over time, based on [7]

While using a distributed representation, only 6 neurons are required to solve this problem: 2 neurons describing the gender and 4 describing the age range. Neurons responsible for the gender description are able to learn about the gender from images of all age categories. In spite of many important advances in neural networks over the years, deep models were not very popular and effective, until recently. The breakthrough began in 2006 with the introduction of the deep belief network [12] and other models [13], which showed that deep learning algorithms could significantly outperform competing machine learning systems in terms of both the achieved accuracy and the data processing time. There are many aspects that have led to the success of deep neural networks observed over the past few years. First of all, due to the development of the Big Data trend and increased availability of different databases, we can provide deep neural networks with the resources they need to make proper predictions. In has turned out that supervised deep learning algorithms achieve the higher accuracy the more training data we use (at least 500 labeled examples in each category to achieve acceptable performance [7]). With the huge amount of training data available nowadays machine learning has become much easier because the main burden of statistical estimation (generalizing well to new data after observing only a small dataset) was reduced [7]. As can be seen in Fig. 1 the size of the available databases has increased remarkably over the years. Another reason for the popularity of deep models nowadays is the possibility to run computations on much larger models. Networks consisting of small collections of neurons are not able to model complex problems. With the increased number of neurons, the network can represent more complicated features, so the system becomes more intelligent. The use of larger models is currently possible because of the availability of faster CPUs and GPUs and also better regularization techniques that prevent from overfitting to the training set, *e.g.* early termination (stopping training as soon as the error on the validation set is higher or does not change), L2 regularization (adding an additional factor that penalizes high-value weights) or dropout (setting weights of randomly chosen neurons to 0).

The increased availability of training datasets and much better hardware resources has resulted in deep learning models being competitive to the previously winning machine learning algorithms in international ImageNet Large-Scale Visual Recognition Competition. In 2012, Convolutional Neural Networks outperformed other solutions and won this challenge for the first time, reducing the top-5 error (the rate at which the model does not produce a correct prediction within the first 5 outputs) from 26.1% to 15.3% [14]. Since then, deep neural networks win this competition every year, continuously reducing the top-5 error. As of this writing, the error rate is currently equal to 3.6%. Due to the fast development of the deep learning technique, there are some models available online that were trained on a huge amount of data what led to the high accuracy achieved by them (Inception model [15] trained on the ImageNet database [16] that contains images divided into 1000 categories achieves the top-5 error of 5.6%). With the transfer learning technique, it is possible to repurpose the existing, already trained, accurate models to novel tasks by randomly initializing weights of a final layer and training them again on a new dataset, while remaining the weights of all previous layers untouched. The transfer learning approach creates a wide range of possible deep learning applications for domains in which the training set is too small to learn a full deep representation or in case of the limited training time. Lately, some research for applying transfer learning to remote medical diagnostic solutions has been conducted. It was shown that retrained deep learning models work surprisingly well in these applications and can enhance the quality of provided services (automated diagnosis of the celiac disease and detection of anomalies from endoscopic images of duodenum [17], face and nostril area tracking for respiration rate evaluation [18]). In both studies, a neural network trained on an ImageNet database was re-trained on a smaller set of images. By making use of the transfer learning approach, the training time was significantly reduced, while preserving the high classification accuracy. Moreover, it was shown that the same model could be easily and quickly adapted to two completely different tasks producing good results in both cases. Taking it into account, it can be assumed that the existing highly efficient networks can be applied to almost any object classification task, as long as we provide models with the right set of input data. Therefore, it has become crucial to create open-access databases of medical images that can be used for transferring networks to novel tasks and making use of these models in home-based diagnostic and patient monitoring systems.

3. Images of people and their features – available datasets

As previously mentioned, in order to make use of deep learning in its full extent and achieve high inference accuracy, models have to be provided with a proper amount of data. In this chapter, we present examples of available image datasets that can be used for training deep convolutional neural networks. This research is limited to databases that include pictures of individuals and their characteristic features obtained using RGB or thermal cameras. Models trained on such data might be used as a base of a remote patient monitoring solution, *e.g.* person tracking and analysis of main vital signs, because it is not difficult to acquire these images in home conditions. Without a doubt, there are also many sets of specialized medical imaging data (GLIMPS Glucose Imaging in Parkinsonian Syndromes [19], DRYAD [20] MRI scans of a brain) that deep models could utilize to gain new knowledge and then be used as a part of clinical decision support systems. Nonetheless, in our study we focused on simpler solutions that can be applied to the home environment at a relatively low cost of implementation. Due to the tremendous breakthrough in health informatics that has taken place in recent years as a result of universal access to the Internet, many medical databases have been digitalized. As a result, there are a lot of image datasets available online that vary in domain, image format and access policies. Figure 2 presents examples of datasets that can be fed to deep networks and used for potential remote medical diagnostic solutions. The first example of such collections are eye image databases. We can distinguish images acquired in visible light (UBIRIS [21] – 1877 samples) and in near infrared (Warsaw BioBase Disease Iris [22] – 603 samples, ND Cosmetic Contact Lenses 2013 [23] – 4200 samples).

The number of images in each set is too small to learn a full deep learning representation from scratch. Nevertheless, by making use of the existing models, *e.g.* Inception, and adapting them to new tasks with the transfer learning technique, it is possible to develop a network that could support diagnosis of eye diseases. A possible application where deep learning could be applied is the analysis of the tear film temperature distribution in a dry eye condition diagnosis [24] from thermal images acquired with a small camera module. Nowadays, it is possible to embed thermal cameras into home-based systems or remote monitoring devices because the availability of small and relatively low cost thermal modules has significantly increased due to technological developments. Another essential example are databases of face images (CAS-PEAL [25] – 99 594 samples, Color Feret [26] – 2413 samples, USTC-NVIE [27] – 100 subjects, the number of samples is not provided). Databases of face images can be used to train models that will be capable of tracking the face. Face detection plays a crucial role in many telemedicine solutions because it allows analyzing changes that may appear within specific regions of the face and detect various signals sent by the human body (*e.g.* heart rate estimation based on forehead pixel color changes [28], respiratory rate evaluation using the changes of temperature distribution in the nostril area [4]). There are also other diseases and medical conditions that could be potentially predicted by means of deep learning algorithms integrated into telemedicine systems. For instance, a neural network trained on foot images can segment the image into proper regions and then analyze changes in specific areas that are correlated with diabetic foot infections ([29]). A similar approach of detecting and tracking different body parts can be also applied as a solution to other problems, *e.g.* preliminary analysis of malignant lesions visible in thermal images of breasts [30]). ADE20K is a database that could be used to implement a system for detecting specific body parts and characteristic features. This dataset contains 20 000 images that are fully annotated with objects and corresponding segmentations [31]. The first segmentation allows extracting objects (*e.g.* human). The second segmentation corresponds to object parts (*e.g.* hand, leg, head) as presented in Fig. 2f, while the third segmentation shows more detailed parts of the object (*e.g.* eyes, mouth, nose).

The presented databases are only some examples among many other available collections, but they ideally show the importance of providing open-access to the resources that can be utilized by deep models to improve the accuracy of medical systems. Medical imaging is a relatively young but very rapidly developing field of study. Solutions based on image processing techniques allow contactless and non-invasive monitoring of patients at home. The process of enabling these applications is very important in the context of the global problem of aging societies. However, a rapid change from the total lack of medical imaging data to the excess of information is the reason why making a proper diagnosis is a difficult task. Therefore, it is very important to further develop and improve image analysis algorithms, including deep neural networks.

4. Medical data security in remote diagnostic systems

Measurement of basic vital signs based on a sequence of images opens many possibilities of remote medical diagnostics, but at the same time it entails considerable responsibility. The privacy and security of medical data is a key requirement and should be taken into consideration during creating remote monitoring systems. Universal Internet access allows communication between the patient and the physician in remote medical diagnosis systems. According to a recent Cisco

(a)

(b)

(c)

(d)

(e)

(f)

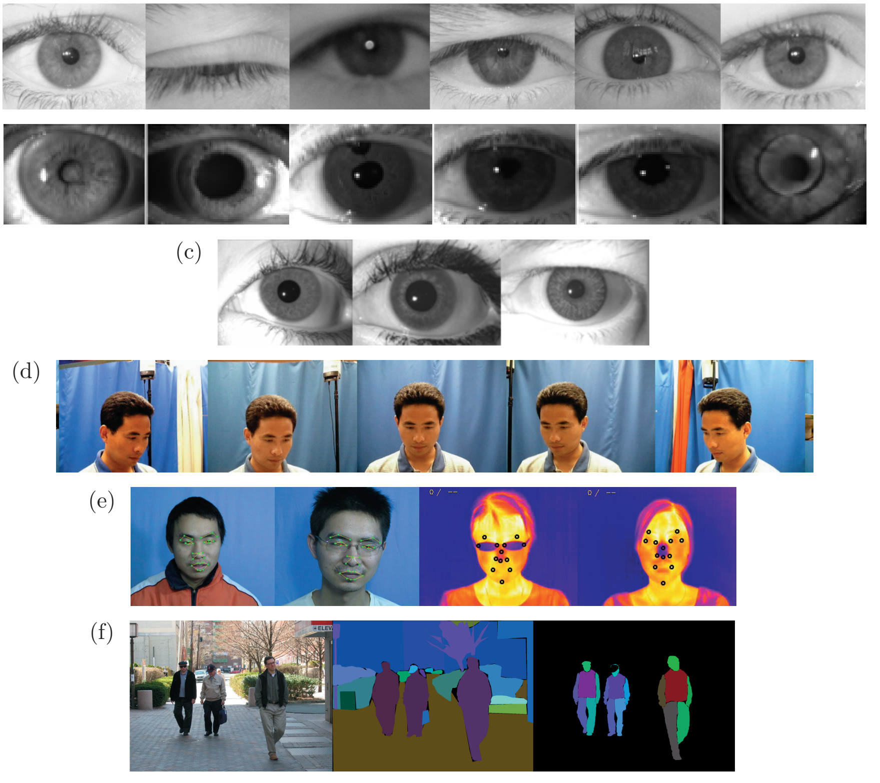

Figure 2. Examples of image databases that can be used for the needs of remote medical diagnostic: (a) UBIRIS [21], (b) Warsaw BioBase Disease Iris [22], (c) ND Cosmetic Contact Lenses 2013 [23], (d) CAS-PEAL [25], (e) USTC-NVIE [27], (f) ADE20K; first and second segmentation – body parts detection

report [32], in 2020 more than 52% of the world's population will become Internet users. This is an increase in the number of users by about 30% compared to 2015. Although the Internet is a key factor in the functioning of telemedicine, it is also the largest source of potential threats. Protection of the privacy and security of sensitive medical data is a key requirement for medical systems [33, 34]. Recommendations for ensuring the safety of patient data are determined by the government in relevant laws, such as the Health Insurance Portability and Accountability Act (HIPAA [35]).They oblige healthcare institutions to make patient information available to designated individuals only. Healthcare organizations also publish various guidelines on medical data security, such as the DICOM standard, which defines ways of communicating and exchanging images in medicine. Medical data should be protected at the collection, transmission as well as storage stage. Data should only be accessed by authorized persons and information should not be destroyed accidentally or without authorization.

We can distinguish the following four subcategories of data protection for the problem of creating and operating medical systems: physical security, technical security, personal and organizational security [36]. Physical security is intended to protect rooms with computers or servers from theft or unauthorized access. It is also a good practice to store large amounts of data off-premises in a private, encrypted cloud. This allows minimization of the necessity to create multiple physical security. Remote access and simultaneous viewing of digital images is possible with Picture Archiving and Communication Systems (PACS). Communication between the Radiological Information System (RIS) and the Hospital Information Systems (HIS) enables an efficient information flow. Medical data is also protected by the use of the https protocol, which provides encrypted communication between the client and the server. The next category is technical security, which includes: backups, anti-virus programs, firewalls, virtual private network (VPN), and software and hardware user authentication systems [34]. For remote VPN access, two-step authentication (username and password, and second identification, such as a verification code sent to a mobile phone) can provide an additional layer of security. A standard procedure for preventing data loss from a medical system are backups. Another security feature is the so-called firewall, which secures the internal computer network of the medical system so that it receives only harmless and tested elements from the outside world. An important element of safety in medical systems is also the identification of users. The wide variety of access rights to medical data is the reason why the identification process must be faultless. Many different authentication methods are available today. These include: access codes, biometric methods, Radio Frequency Identification (RFID) [37], keys, or magnetic cards. Another type of protection is personal security, which is understood as providing appropriate training to staff, physicians and patients. The main purpose of such training is to implement the users in the process of using the offered capabilities of the system. In addition, in case of unwanted situations, such as malicious software attack, appropriate organizational procedures must be provided. It is worthwhile to anticipate all possible scenarios of dangers earlier and insure users for solutions during stressful situations in order to reduce the extent of possible damage. Properly securing a remote medical diagnostics system is a very complex process that has to take into account many factors and only a balanced integration of all four of the above-mentioned protections may be the basis for a well-functioning and secure telemedicine system.

5. Summary and conclusions

Remote medical diagnostics enables patients to have more access to medical services and allows increased health promotion. It also opens up prospects for various preventive actions. Solutions based on the detection of changes in vital parameters by the use of imaging techniques allow non-invasive and non-contact patient monitoring during their daily activities (respiratory rate measurement based on sequence analysis of nostril images [4]. Thanks to the development of deep learning algorithms, image analysis can be performed in real time and on widely available computers with a high accuracy of results (face detection in thermography 42.05 ± 0.21 ms, accuracy 89.2% [18]). Nevertheless, it is important to remember that deep learning models become effective only when we can provide the appropriate amount of data required to make proper observations. The development of Big Data allows us to have much more information which helps us create universal deep neural networks and adapt them to our needs using the transfer learning technology. To be able to use them also in medical and remote medical diagnostics, it is very important to create more databases of people's photographs and medical images that will serve as a training set for neural networks. Models trained on huge amounts of data will allow making appropriate and accurate predictions when analyzing new images.

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