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APPLICATION OF NEURAL NETS FOR THE IDENTIFICATION OF OTORHINOLARYNGOLOGICAL DISEASES

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ABSTRACT

Research devoted to the discovery and identification of diseases in an automated way occur more frequently today. For such, the use of artificial intelligence is conditioned to the learning of the machine, allowing the computer to identify characteristics and learn from new cases, generating new models and identifying in a precise way what it was trained to do. The use of artificial intelligence is not a recent theme but, given the accessibility made available by some platforms that get around the complexity of the algorithm, the theme gained momentum and made possible the use of this technology. This research made use of this technology applied to the identification of three diseases in the field of otolaryngology. The objective was training the computer with the symptoms of these diseases and, then, processing the realization of tests, informing symptoms to the computer and obtaining the answer of the disease it interpreted. After his technique has been applied and some symptoms has been run by it, the computer got the disease right in 90,72% of cases. We intend to expand this research to create models that contemplate more diseases and also make available the interface that shows to the doctor which is the possible disease for that patient.

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INTRODUCTION

Even though modern clinical essays routinely use computer systems for storing and analyzing data, the collection of research data still is, more often than not, a manual task (Shortliffe and Cimino, 2013). The acquisition and implementation of information technology have big implications in operations of health organizations, owing to the fast growth of medical assistance costs, concerns around patient safety issues and medical errors, an improvement in services of evidence-based information and an increase in regulatory requisites (Doebbeling, 2006). Biomedical signals have been widely utilized in the clinical scene for diagnosing, therapeutic orientation, patient monitoring, disease prevention and risk assessment. With the latest developments of health devices, many personal biochemical data are also easily accessible to consumers and virtually all aspects of life are registered (Baumert, 2016). The interest of data use in health assessment research has increased with the growing availability of big data bases and computer programs that make possible its integrated use (Coeli, 2011) Technology and the use of computational resources broadens the horizons of research inside clinical activity (De Oliveira, 2009). Cognitive computation solutions such as IBM Watson make possible the analysis of a great volume of data. This solution can improve fields such as the Sciences of Life, which desperately need innovation. Pilots start to offer information on whether Watson has the potential to improve the precision and speed of detection and codification of adverse events, considering medicine and clinical diagnoses (Chen, 2016). This IBM technology is made up of customized and optimized AI algorithms, for specific cases or consumption in on-demand services. Machine learning techniques is one of the most promising and fastest-growing fields in computing research in health applied to artificial intelligence (Wang, 2019). AI is not a recent theme. Works around this subject started around World War II, most notoriously at the Turing test of 1950. Planned and implemented by Alan Turing, the test consists in knowing whether the computer can pass the test of a human interrogator, after proposing some written questions, not being able to discover whether the written questions come from a person or a computer (Russell, 2012). This theme has nevertheless gained more attention and dissemination in the last years. This was thanks to the accessibility that some platforms offer to final users and technology professionals, with resources that most of the times make use of mathematical calculations and complex techniques. Machine learning techniques were developed to make computers learn concepts and relationships through data analysis. In medicine, such techniques could find useful patterns from the analysis of clinical data, enabling better diagnosis and improving the patient's care (Savage, 2012). Research devoted to the application of artificial intelligence in the otolaryngological clinic has been underway for some years, such as the research realized in 2012 in the Department of Otolaryngology of the Jagiellonian University Medical College in Krakow. In this research, we will present the characteristics of the use of neural nets applied to otolaryngology (Szaleniec, 2012). Artificial intelligence research with image use also has applicability, such as the case of the development of big learning framework for the diagnosis of chronicle otitis media, based in computer tomographies of temporal bones (Wang, 2019). Artificial intelligence is at the forefront of academic research and popular culture. In the last years, it has been complimented for its potential to revolutionize health care services. Up to this moment, nevertheless, it has made few contributions to the actual medical practice or patient service. The future adoption of artificial intelligence technologies can be jeopardized by wrong concepts about the nature of artificial intelligence and the fear that machine errors in otolaryngological intelligence technologies errors might jeopardize the patient service. Nevertheless, with potential clinical and economic benefits, it is crucial that otolaryngological understand the principles and scope of artificial intelligence (Bur, 2019). The neural nets are composed of knots or units, connected by directed links. A link between units can be used to propagate the activation. Each link has a numeric weight which determines the power and the signal of the connection. Just as in models of linear regression, each unit has a fictitious entry with an associated weight (Camastra, 2007). The objective of this research is to train the computer through artificial intelligence so that the machine will be able to identify the possible disease of a certain patient based on his/her symptoms.

METHODS AND PROCEDURES

This research was divided into four steps. The first consists in obtaining the sample, the second defining the technologies that were used, the third preparing the data and, the last, programing the neural net and the test of registrations. The sample was obtained from the Hospital Paranaense de Otorrinolaringologia, IPO. It's a medical center of otorhinolaryngology, located in the South of Brazil. The project was approved by the Human Beings Research Ethics Committee of the IPO Hospital, under the number 79919417.4.0000.5529/2017. The 3.000 clinical registrations of patients obtained via their medical records, were proportionally divided in the following diseases: unspecified allergic rhinitis (ICD-0 J0.4); Acute pharyngitis owing to other mic. Specified (ICD-10 J02); Impacted cerumen (ICD-10 H61.2). These clinical registrations concern the period between January 1st, 2016 and December 31, 2016. The period was chosen by convenience and these are the diseases that predominate in the hospital.

The following technological resources were adopted for the research. We opted for Keras version 2.2.2., which is an API of high-level neural nets, written in Python version 2.7.15 and is capable of executing on TensorFlow version 1.11.0. The computational device adopted operates with Windows 10, with an Intel Core i7-7500U, 16GB of RAM, GPU Nvidia GeForce 940MX 4GB. All of the network processing was realized through the GPU. The data were exported for a CSV archive of the database of the hospital system, the patient's names being hidden. Such archive contained the fields, registration number, patient symptoms and medical diagnosis already classified by the International Classification of Diseases (ICD). As the neural net API realizes the process through a numeric dictionary, a dictionary containing 480 words was created, each numbered from one to 480, corresponding to a symptom. A new CSV file was then created for processing. In this file, the symptoms were separated by commas and corresponded to the dictionary created. In the end of the file, the classification where 0,01 is Impacted Cerumen (ICD-10 H61.2), 01.0 is acute pharyngitis owing to other mics. Specified (CID-10 J02) and 1,0,0 is unspecified allergic rhinitis (ICD-10 J30.4). The columns that did not have a corresponding number of symptoms were marked with a zero. The network training had 2.400 registers. Considering the 480 entry data, and 3 disease classifications, the net was divided into 4 layers, the first with 482 entries, 150 for the second, 90 for the third and 30 for the fourth. After 10 training interactions, the success rate of the neural net remained the same. 600 registers were utilized for testing, taking from the archive the three last columns regarding the diagnosis of Rhinitis, Pharyngitis or Cerumen, as presented in Pic. 1.

```
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
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Picture 1. File Utilized to test the neural net

By doing this, one had the result of the 600 registers being adequately classified for the three diseases registered in this research.

RESULTS

The processing of the training archive took 6,23 seconds, and such processing was realized by the GPU's video card. After the realization of 10 pieces of training, the net obtained a 98,08% precision for the training registrations. After the end of the training, the processing of the test archive was realized, obtaining a 90,72% assertive, as presented in picture 2.

```
acc: 98.08%
Saved model to disk
Loaded model from disk
acc: 90.72%
```

Picture 2. Post-processing result of the train and test files

With this, the implemented neural net got right 90,72% of the 600 test registrations processed, automatically identifying the disease, taking into account what was learned from the 2.400 train registrations. We can thus affirm that the model that was implemented can identify, based on the patient's symptoms, whether he/she has Rhinitis, Pharyngitis or Cerumen.

DISCUSSION

The use of artificial intelligence was intensified in health care research. Practices of image analysis for lab exams and electronic medical records are important in the application of this technology. Deep-learning based models have shown significant results and are known as state-of-the-art methods for many tasks of medical image analysis and biological data analysis (Min, 2016 and Golgooni, 2019). In short, the process is learning rules from data. So, machine learning algorithms behave as a kind of expert system that, when seeking to learn relationships between datasets, leads to conclusions from the application of what has already been learned when exposed to new data, thus being able to inform decisions (Obermeyer, 2016). The way in which the neurons of a neural net are structured is intimately connected to the learning algorithm used to train the net. We can, therefore, talk about learning algorithms (rules) utilized in the project of neural nets as being structured (Haykin, 2018). One fundamental difference between human and machine learning is that humans can learn from relatively small amounts of data by making complex associations and obtaining general rules. Machines, in general, require large amounts of data to reach a reasonable, applicable conclusion. Initially, machine learning tasks are accomplished by relating inputs and outputs from a process called training. For training, the connection between inputs and outputs is accomplished by an algorithm or a set of them, a network, that looks for patterns among the data, such as those that happen most often together. The machine can learn that when the temperature is higher than 37ºC, the diagnosis is fever. A rule is thus created: if temp> 37, it's fever. It's important to notice that in this example, a large amount of data isn't necessary to produce the rule because that rule is very simple. But to relate fever with other symptoms and suggest a treatment may be very hard (Rajkomar, 2019). It's important to know there is a classification, and learning may be: rote learning - learning may be programmed or modified by an external entity (as in the case of computer programming) or may be realized by memorization (databases); learning from instruction - that occurs when instructions are acquired and integrated with prior knowledge; learning by analogy - for example when a computer program is used to a similar but not for the original task for which was developed, using new parameters; or, learning from examples - given a set of examples an induction of a general concept is made. In this last case, the learning tasks can be accomplished in a supervised (the data is a sample of input-output patterns) or unsupervised way (given a training sample and extracting some structure from them), or for reinforcement of previous learning (with a 'reward' to newly obtained knowledge). Finally, some studies that may occur with learning machines may be task-oriented, cognitive simulation or theoretical analysis (Camastra, 2007). Diagnosing a peritonsillar abscess is hard to do, clinically. Besides, otolaryngologists have little sensitivity and training to perform the clinical examination. A machine learning classifier was developed to foresee the diagnosis of this disease based on the patient's symptoms. It obtained 72.3% of the accuracy of the neural net for 916 patients (Wilson, 2019).

Conclusion

The use of artificial intelligence has become more popular due to its applicability and to the possibilities created by it for solving problems and the automation of activities up to now only performed by humans. Artificial intelligence platforms make things less complicated and allow for the dissemination of the use of such technology. The use of such technology is extremely relevant in health care areas, making machine learning possible through text registers, images ad even voice. Realizing the clinical diagnosis based on the symptoms is the main goal of this research. For this, we had samples of three otolaryngological diseases that were implemented through the model of the neural net and made possible, in an assertive way, the identification of the disease of a certain patient based on his/her symptoms. We intend, in the future, to create new models that will include more diseases. We also aime to integrate this technology into the hospital system, making available to the doctor a mechanism which will help with difficult problems.

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