Proper medical diagnose and treatment with computer aided system

Tomasz Pedowski[1], Piotr Wąsiewicz[2], Ryszard Maciejewski[3,4], Grzegorz Wallner[1]

[1] 2nd Departament of General Surgery, Medical University of Lublin

[2] Institute of Electronic Systems, Warsaw University of Technology

[3] Departament of Human Anatomy, Medical University of Lublin
University of Information Technology, Rzeszów

[4] Institute of Biomedical Informatics, UITM, Rzeszów

ABSTRACT

Nowadays computers successfully analyze medical data giving results used for futher treatment. Every year we develop new technology which gives us better and more precise diagnose. We chose esophageal manometry (EFT) which has been considered as a "gold standard" test for the evaluation of esophageal motility. EFT allows physicians to get informations about esophageal peristalsis, amplitude and duration of the esophageal contraction and liquid/viscous bolus transit time from mouth through stomach. We examined 80 patients during 2008 year. Everybody got EFT, endoscopy and X-Ray examination. It was important to ask about symptoms which we correlate and connect with data from EFT. We tried to find a good algorithm for this job in order to do a simple and helpful tool for physician to make right diagnose. Connection between data and symptoms seems to be right and clear, but finding a good algorithm for given data is the main problem.

Keywords: bioimpedance technique, esophageal manometry, pH-impedance, esophageal reflux disease, decision tree, support vector machines

1. INTRODUCTION

Esophagus is not only simple tube that transports food from mouth to stomach. It is a straight muscular tube (Fig.1) that is guarded at its two ends by an upper and lower esophageal sphincter[1]. Effective peristalsis is a major determinant of esophageal clearance function. Neuromuscular control mechanisms require fine coordination of the muscles to bring normal functioning of the two sphincters and esophageal peristalsis. Dysfunction may cause of dysphagia, chest pain, vomiting, heartburn.

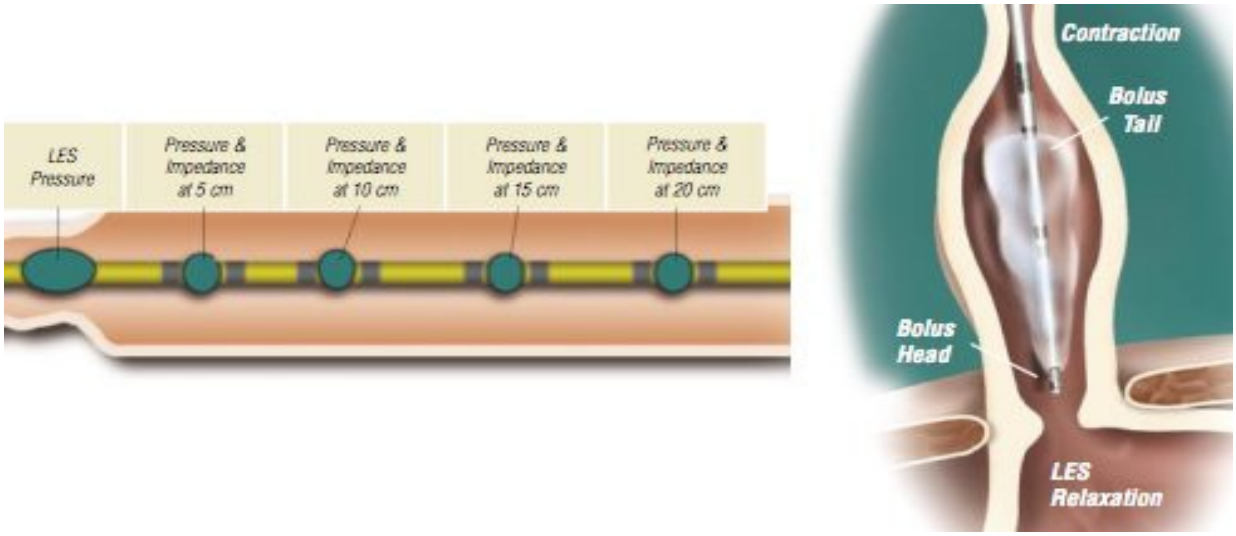

Fig. 1 Manometry probe (pressure channels and localizations)

Esophageal manometry with impedance (EFT)[6,7] brings us a "gold standard" for motility testing[2,3]. Standard manometry was performed after overnight fast and all known medications which interfere with gastrointestinal secretory or motor function where discontinued for 10 days.

During the examinations EFT catheter was inserted transnasally into the esophagus to a depth of 60 cm(Fig.2). Intragastric position of the catheter is verified by the rise in pressure during deep inspiration. After finding LES (lower esophageal sphincter) - placed in high pressure zone, the catheter was taped to the nose in order to prevent displacement during the study. For the evaluation of the esophageal peristalsis, bolus transport and LES pressure measurement 10 liquid and 10 viscous swallows were given in 20-30s intervals. After that the probe was extubate and the examination finished.

Impedance testing depends upon measurement of changes in resistance (in Ohms) to alternating electrical current when a bolus passes by a pair of metallic rings mounted on a catheter (Fig.1). Impedance is inversely related to the conductivity of the medium surrounding the two electrodes. Liquid containing boluses such as saline with an increased number of ions have a higher conductivity and saliva or air has low conductivity (Fig.3). Thus, by using esophageal impedance monitoring the movements of liquids and gas in the esophagus can be detected. After examination we studied measurements using BioView Sandhill program (Fig. 4).

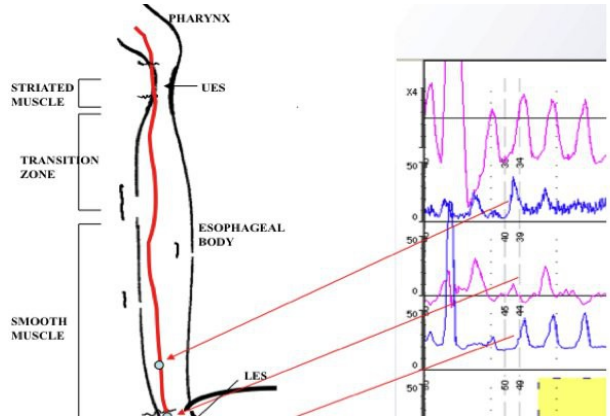

Fig. 2 Pressure readings

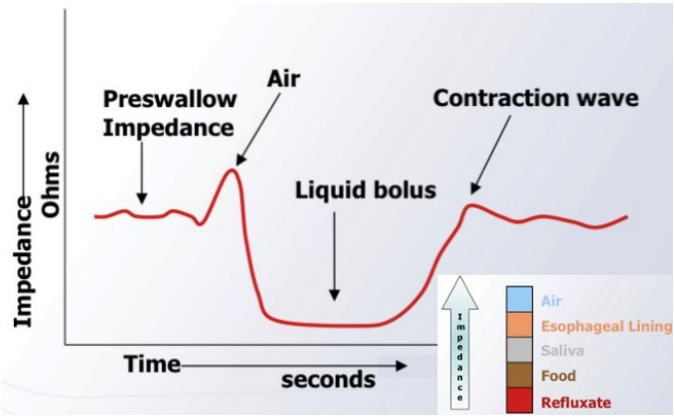

Fig. 3 Bolus transit – impedance

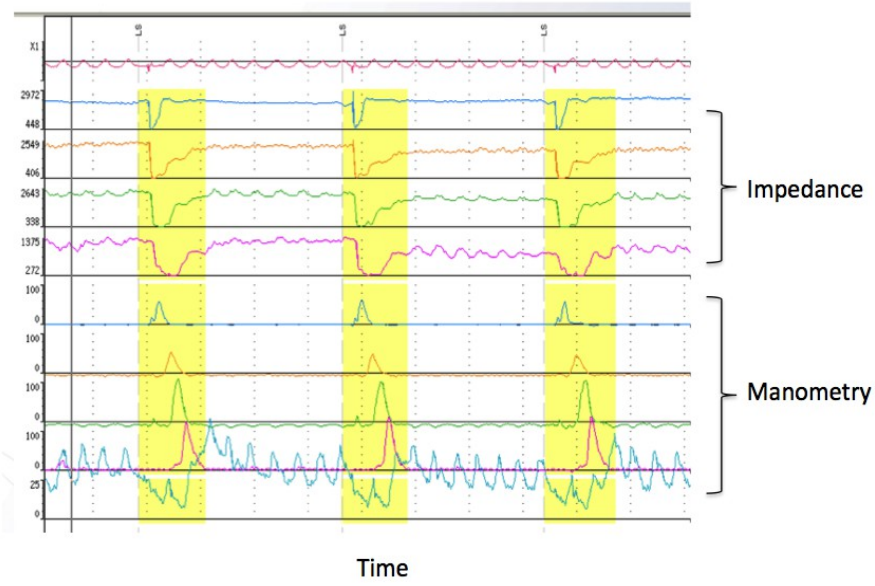

Fig.4 BioView analyze – impedance and manometry

Measurements that we analyze were upper GI endoscopy and X-Ray. We were trying to find esophageal hiatal hernia, chalasia (lower LES pressure) and reflux.

2. MEDICAL MEASUREMENTS

LES pressure	10 - 45 mm Hg
LES lenght	≥ 3.0 cm (> 1.5 cm intra-abdominal)
LES relaxation	≤ 12 sec
Motility - contraction	1-6 sec contraction
Motility - velocity	< 8 cm/sec velocity
Motility - effective	Liquid swallows ≥ 80%, TBTT < 12 sec
	Viscous swallows ≥ 70%, TBTT < 13 sec

Table 1. Normal value for Lower Esophageal Sphincter and esophageal motility

Examinations gave us several parameters that we analyzed (Table 1.). First of all was LES pressure, length and relaxation time that determine how strong barrier between esophagus and stomach is. Its count in mm Hg and normal value is 10 to 45 mm Hg and ≥ 3 cm (>1.5 cm intra-abdominal). LES relaxation could takes no longer than 12 sec. Second important informations were motility parameters like: duration of contraction (1-6 sec), velocity (< 8cm/sec) and effective swallows that gave us % of complete liquid and viscous swallows.
It was mportant to ask for symptoms (careful interview), which were most often the following: chest pain, heartburn, chronic cough, pain in the upper abdomen, throat pain. After doing a good interview we can diagnose such diseases like: achalasia, ineffectual lower esophageal sphincter or esophageal hiatal hernia.

3. DATA RETRIEVAL METHODOLOGY

Decision tree is a graphic construct showing available choices at each decision node of managing a clinical problem along with probabilities (if known) of possible outcomes for patient's freedom from disability, life expectancy, and mortality.
Learning classifiers[8] were divided into unsupervised, which needed sets labeled by physicians to obtain knowledge about patients disease and into supervised classifiers, which under some conditions are able to make classification only with a help of data (from measurements) and distance between exanimated patients - points in the multivariable space (PCA).
Support vector machines (SVMs) are a set of related supervised learning methods used for classification and regression.

4. DATA RETRIEVAL RESULTS

During measurements we examine one group of patients: treated after complete examinations (EFT, X-Ray and endoscopy).
Our data variables were the following: totales - Total LES Length (standard > 3cm), intrables - Intra-abdominal LES Length (standard >1.5cm), LESP9 – LES pressure in channel 9 (standard 10-45mmHg), LESP10 - LES pressure in channel 10 (standard 10-45mmHg), LESP - pressure LES (norma 10-45mmHg), CBTLS - Complete Bolus Transit LS (> 80%), TBTLS - Total Bolus Transit Time LS (<12sec), respres - Residual Pressure LES (norma = lub < 8.0mmHg), velocity - Velocity (norma <8cm/sec), percontr - Peristaltic contractions, retcontr - Retrograde contractions, CBTVS - Complete Bolus Transit VS (>70%), TBTVS - Total Bolus Transit Time VS.

We converted to zscore and discretized data to three levels and obtained groups with lower, about mean, higher LES pressure, LES profile, intra-abdominal LES part and other ones. Z-score, so called standard score is equal to raw score minus mean of this raw score population and this result divided by its standard deviation. It is often used in statistics. All data except age were converted to zscore separately for women and men and for age five intervals (from infinity to mean plus standard deviation, from mean plus standard deviation to mean and so on up to minus infinity). Based on expressed as zscore, discretized or raw data we analyze common symptoms.
First we reduced a number of variables to the ones usually used by medical physicians in order to make similar diagnosis, but in computer. This set contains: totales, intrables, LESP,CBTLS, respres, CBTVS. The trees created from converted to zscore and discretized data are depicted in Fig. 5 and 6 on the left and they classify two typical symptoms: chalasia and upper abdominal pain. The trees on the right side are generated from raw data only with two variables: totales and LESP and they also label these symptoms presence but only depending on les length and les pressure. They are simple and easy to understand and in differential diagnosis are already known in everyday practice, but the trees on

the left have more variables put in node tests, and it is quite interesting, that in first steps other variables than totales or lesp were chosen.
Second we tried to generate trees for detecting five diseases: achalasia, hiatal hernia, reflux, chalasia, inflammation which are seen in Fig. 7, where circles represents patients with achalasia, squares – with hiatal hernia, rhombs – with reflux, triangles – with chalasia, black small circle – with inflammation and X - without any symptoms. We chose the minimal set of variables, which worked with based on PCA procedure of reducing dimensions (where each variable is one dimension) to two "artificial" dimensions in order to display patients as points where distance lengths between them are inversely proportional to their similarities. The minimal set variables are the following: totales, intrables, LESP09, LESP10, LESP, CBTLS, TBTLS, velocity, CBTVS. The diagnostic trees based on this set are depicted in Fig.8 (on the left discretized data, on the right also converted to zscore). The effects were not even adequate. Only two diseases were recognized: hatal hiernia and chalasia. On the same variable set we run support vector machine procedure with linear kernel and results were the same, but their succes ratio was greater.
After this failure we used all possible variables in the second set denoted max: totales, intrables, LESP09, LESP10, LESP, CBTLS, TBTLS, respres, velocity, percontr, retcontr, CBTVS, TBTVS. Trees were placed in Fig. 9 (on the left discretized data, on the right also converted to zscore). The based on converted to zscore data tree detected 4 diseases and no symptoms and made a small improvement. However, svms detected all diseases and procedures operating on discretized zscore were more accurate. The number of support vectors was always about 80.

Min set data discretized tree	42 correctly verified patient diseases
Min set data discretized svm	58 correctly verified patient diseases
Min set data zscore discretized tree	43 correctly verified patient diseases
Min set data zscore discretized svm	54 correctly verified patient diseases
Max set data discretized tree	43 correctly verified patient diseases
Max set data discretized svm	66 correctly verified patient diseases
Max data zscore discretized tree	45 correctly verified patient diseases
Max set data zscore discretized svm	68 correctly verified patient diseases

Table 1. The successfully recognized patient diseases by trees or svms on discretized data or discretized zscore.

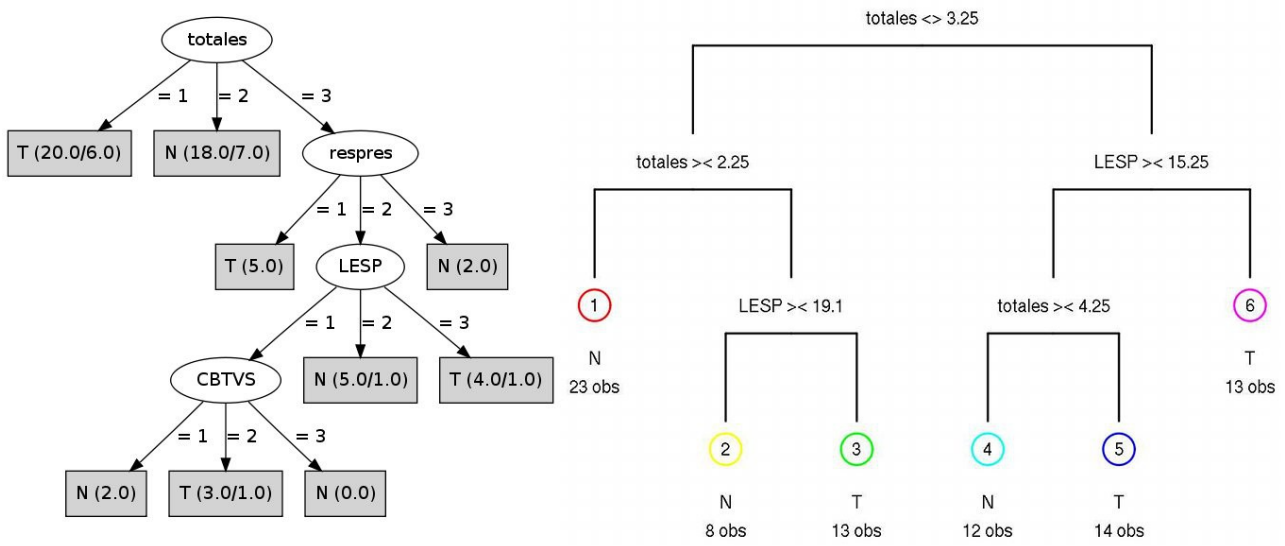

Fig. 5 The decision trees classifying upper abdominal pain (T - yes, N - no)

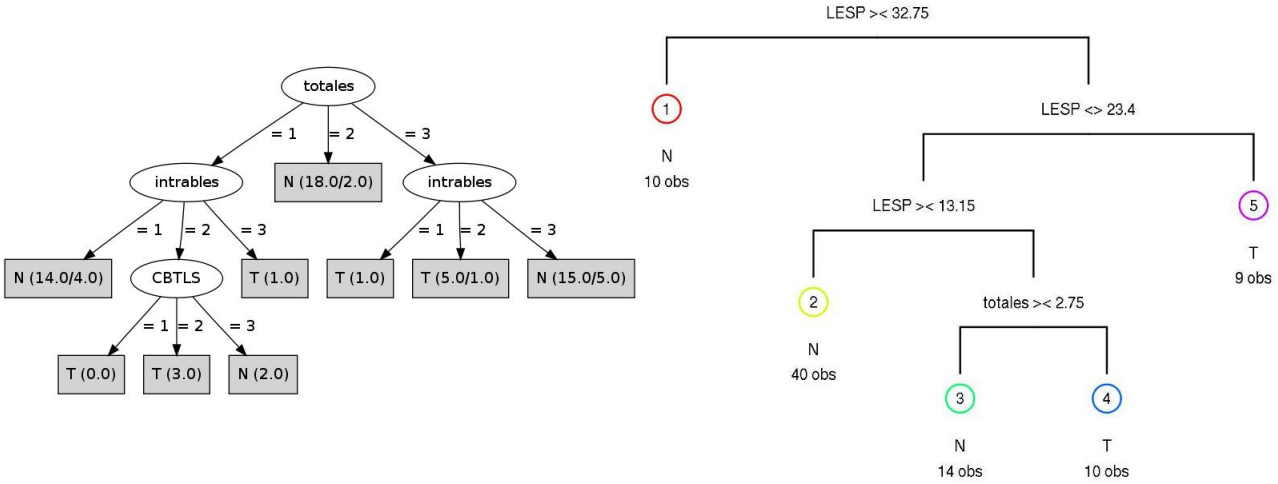

Fig. 6 The decision trees classifying chalasia (T - yes, N - no)

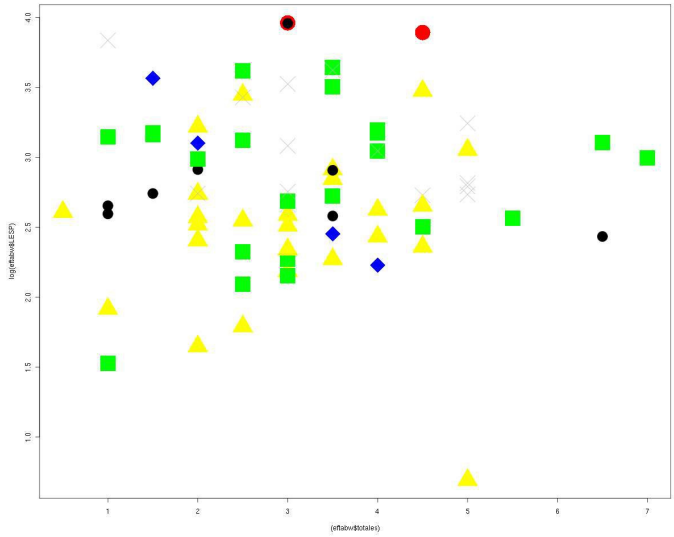

Fig. 7 Plot of patients (points) with diseases, where x=les and y=log(lesp)

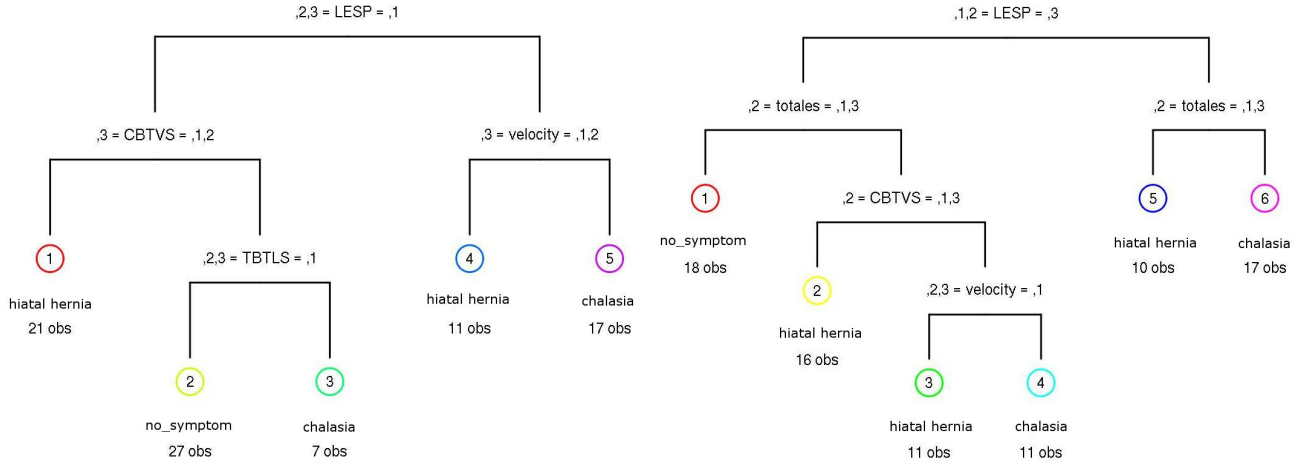

Fig. 8 Decision trees made of the first minimal set of variables.

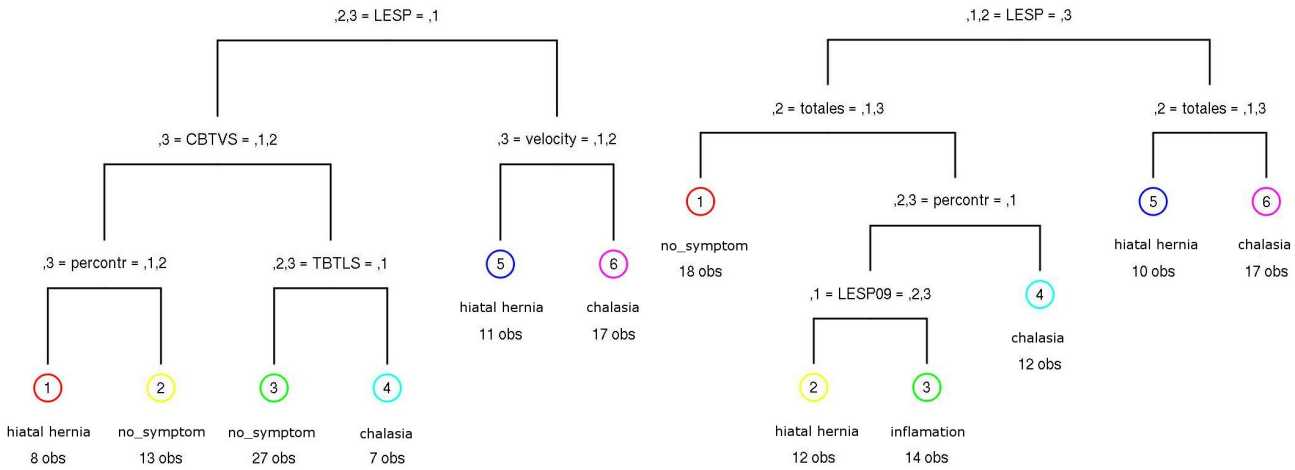

Fig. 9 Decision trees made of the second set of variables.

5. SUMMARY

This experiment shows possibilities of creating good classifiers for detecting patients diseases with a help of data from medical diagnostic equipment. When in differential diagnosis medical physicians use often only two variables: les length and pressure, it is important to get much more data variables, especially for support vector machines, which even with linear kernel works perfectly. For larger variable sets, better tuning of algorithm parameters it will be possible to construct computer aided diagnosis machines.

6. REFERENCES

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