ANN Model to Predict Coronary Heart Disease Based on Risk Factors

H.S. Niranjana Murthy and Dr.M. Meenakshi

Abstract--- *This paper presents a neural network based on Levenberg-Marquardt back-propagation algorithm for prediction of degree of angiographic coronary heart disease. The novelty of this work is training a one hidden layer neural network with Levenberg-Marquardt back-propagation algorithm for multivariate large dataset. An ANN model is developed for prediction of degree of angiographic coronary heart disease, and subsequently, its performance is evaluated using heart disease database obtained from Cleveland Clinic Foundation Database with all attributes are numeric-valued. About 88 cases of different aged angiographic coronary heart disease subjects with 13 attributes have been tested in this model. This study exhibits ANN based prognosis of coronary heart disease and improves the diagnosis accuracy to 95.5 % which is comparably higher with earlier works.*

Keywords--- *Artificial Neural Network (ANN), Back propagation Network, Coronary Heart Disease, Multilayer Perceptron (MLP)*

I. INTRODUCTION

The term Heart disease includes the different diseases that affect the heart. In 2007, heart disease was the main cause of fatalities in the United States, England, Canada and Wales. Heart disease kills one person every 34 seconds in the United States [1]. The annual cost of CHD exceeded to $300 billion in 2010 in United States [2]. Coronary heart disease, Cardiomyopathy and Cardiovascular disease are various forms of heart diseases. Contraction of the coronary artery results in the reduction of blood and oxygen supply to the heart and leads to the Coronary heart disease (CHD). Myocardial infarctions, generally known as a heart attacks and angina pectoris or chest pain are encompassed in the CHD. The principal reason for heart attack is the sudden blockage of a coronary artery, generally due to a blood clot. Chest pains occur when the blood received by the heart muscles is insufficient.

It has been noticed from the estimate of World Health Organization that 12 million deaths occur worldwide, every year due to the coronary heart diseases. The risk factors for coronary heart disease include blood pressure, cigarette smoking, cholesterol (total cholesterol), LDL-C, HDL-C, and diabetes. Also, several other factors such as obesity, left ventricular hypertrophy, family history of premature coronary heart disease and estrogen replacement therapy (ERT) adds to the coronary heart disease risk. Several years of follow-up of the risk factors based on blood pressure, smoking history, and total cholesterol (TC), HDL-C levels, diabetes and left ventricular hypertrophy on the ECG has facilitated the diagnosis of coronary heart disease. The algorithms developed for prognosis of CHD will complement the clinician in diagnosing multivariable CHD risk & reduce his burden.

Artificial Neural network is a prime tool for broad spectrum of classification problems. ANN performs prediction when its output is continuous and it performs classification when the output has distinct values. ANN has obtained its capability in prediction/classification due to its ability in reconfiguring the weights of the neurons. ANN based decision support in medicine plays in important role in improving the reliability of health care of general population. It has the capability to uncover unusual abnormal conditions, since no clinician can have information bank of all the evidences of diseases, even within a specialized domain. Availability of wide range of patient data in electronic form makes easy the ANN model to more accurately detect the variability of physiological parameters during the onset of an arrhythmia, which is the primary thing in automated disease identification. In some cases, ANN model based diagnoses have been proved to be even more accurate than those by clinicians. Hence, there is a significant scope for the research on development of an automated system for diagnosis of CHD.

In the last decade, several studies have applied neural networks in the diagnosis of cardiovascular disease, primarily in the detection and classification at-risk people from their ECG waveforms [3]. In the works of Celler et al. [4], six different disease conditions were classified by an ANN model inputting the statistical parameters derived from pathological ECG waveforms. However, a significant shortcoming in this work was the reduced overall accuracy of 70.9%. Elmer Andreas et al. [5] compared five methods of ANN based urea estimators for hemodialysis treatment adequacy. Costas papaloukas et al. [6], developed an automated technique for the detection of ischemic episodes in long-duration ECG recordings. The automated system performed at a positive predictive accuracy of 89%.

In the study by Peter Gjertsson et al. [7], fully automated methods using ANNs were compared with the clinical interpretation. The neural networks trained with both perfusion and ECG-gated images had a 4-7% higher specificity compared with the corresponding networks using

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perfusion data only, in four of five segments compared at the same level of sensitivity. Ham et al. [8] applied ARTMAP in medicine for classifying cardiac arrhythmias and Modai et al. [9] used ANN model based on Adaptive Resonance theory for treatment selection for schizophrenic and unipolar depressed in –patients.

The comparison was carried out using seven algorithms to train the multi-layered ANN model for prediction of patient's post-operative recovery area [10]. The comparison showed that back propagation is one of the faster and more reliable methods. The study by D.Shanthi et al. [11], an ANN model with back propagation algorithm was used to predict the thrombo-embolic stroke disease. In this case, the ANN model exhibited the overall predictive accuracy of 89%. M.Cengiz Colak et al. [12] compared eight different learning algorithms of ANN model for predicting the CHD. They were able to predict the CHD with an accuracy of 81%.

In the above mentioned works, the considerable limitation is the reduced overall predictive accuracy. Very little effort is directed towards the development of ANN model for predicting CHD using multivariate large dataset. This paper presents the development of an ANN model for prediction of coronary heart disease based on multiple risk factors. The main contribution of this paper is the application of Levenberg-Marquardt back propagation learning algorithm for one hidden layer MLP and validation of ANN model using multivariate (88subjects & 13 attributes of risk factors) dataset in order to meet high percentage of sensitivity, specificity and accuracy. The overview of this paper is as follows. Section II gives a brief description of structure of MLP with Levenberg-Marquardt training algorithm. Section III evaluates the performance of the proposed ANN model in terms of accuracy, sensitivity and specificity. Finally conclusions are drawn in section IV.

II. Neural Network Model

A. Structure of MLP

MLPs are the simplest and most commonly used neural network architecture due to their structural flexibility, good representational capabilities and large number of programmable algorithms. MLPs are feed forward neural networks which can be programmed with various back propagation training algorithms. They are supervised networks so they require a desired response to be trained. They are able to transform input data into a desired response, so they are widely used for pattern classification. It is proved experimentally that with one or two hidden layers, they can map any input to target output. Generally, an MLP consists of three layers: an input layer, an output layer and an intermediate or hidden layer. In this network, every neuron is connected to all neurons of the next layer, in other words, an MLP is a fully connected network. Figure 1 shows the structure of a MLP network.

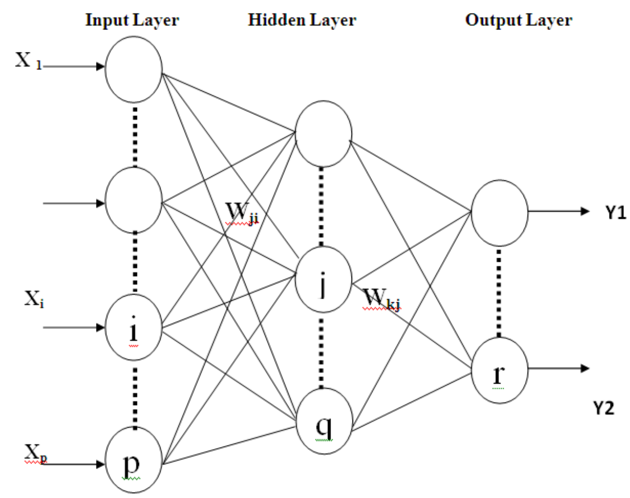

Figure 1: Structure of a MLP Network

A vector of input variables (x_1.....x_p) is presented to the input layer. Before feeding to the input layer, the preprocessing of these variables takes place to normalize these values in the range from -1 to 1. The input layer allocates the values to each of the neurons in the hidden layer along with a bias value of 1.0. Weights are initialized by assigning small random values. After receiving the inputs, the hidden neuron calculates the activation function and sends it to output neurons. The output unit calculates the activation function to form the response of the ANN for the given input pattern. In the regression analysis (target values are continuous), then there is a single neuron in the output layer, and it generates a single y value. For classification problems (target variables are categorical), there are N neurons in the output layer producing N values, one for each of the N classes of the target variable.

B. Levenberg – Marquardt Back Propagation Learning Algorithm

Levenberg-Marquardt (LM) is an advanced non-linear optimization algorithm [13]. It is the fastest algorithm available for multi-layer perceptrons. However, limitations of the LM algorithm are as follows:

- It can only be applied on the ANN model with a single output unit.
- It can only be used with ANN model with less number of neurons (a few hundred weights) because its memory requirements are proportional to the square of the number of weights in the network.
- It is specially designed to work with sum squared error function and it is only appropriate for predictive problems.

The Levenberg–Marquardt algorithm (LMA) provides a numerical solution to the problem of minimizing a function, generally nonlinear, over a space of parameters of the function. Its characteristics fall in between the Gauss-Newton algorithm and Gradient Descent method. Gradient descent method has a shortcoming of reaching local minima of error surface whereas the Gauss-Newton method has fast convergence, but computationally expensive [14].

The primary application of Levenberg – Marquardt algorithm is in the least squares curve fitting problem and is specially designed for minimizing sum of square error function. In a known practical data set of independent and dependent variables, (x_i, y_i), LM algorithm optimize the parameters β of the model curve $f(x, \beta)$ so that the sum of the squares of the deviations S(β) becomes minimal.

$$S(\beta) = \sum_{i=1}^{m} [y_i - f(x_i, \beta)]^2 \quad (1)$$

In each step of weight change, the parameter vector, β, is substituted by a new approximate, β + δ. To determine δ, the functions f (x_i, β +δ) are approximated by their linear equivalent [15].

$$f(x_i, \beta + \delta) \approx f(x_i, \beta) + J_i \delta \quad (2)$$

Where $J_i = \dfrac{\partial f(x_i, \beta)}{\partial \beta}$ is the gradient of f with respect to β.

To obtain the minimum of the sum of squares, S (β), we take the derivative of S w.r.t δ and set the result to zero, which gives:

$$(J^T J + \lambda I)\delta = J^T [y - f(\beta)] \quad (3)$$

$$J = \begin{bmatrix} \dfrac{\partial y_1}{\partial x_1} \cdots & \cdots \dfrac{\partial y_1}{\partial x_n} \\ \vdots & \vdots \\ \dfrac{\partial y_m}{\partial x_1} \cdots & \cdots \dfrac{\partial y_m}{\partial x_n} \end{bmatrix} \quad (4)$$

Where J is the Jacobean matrix, **I** is the identity matrix, $\boldsymbol{\delta}$ is the incremental factor added to the parameter vector **β** and λ is damping factor & adjusted at each iteration.

If the variation of S is fast, a smaller value can be used, bringing the algorithm closer to the Gauss-Newton method. Whereas for slow change of S, λ can be increased, giving a step closer to the gradient descent method [16]. In Levenberg-Marquardt algorithm, the identity matrix (I) is replaced with the diagonal matrix consisting of the diagonal elements of $J^T J$.

With LM technique, components of the gradients can be scaled according to the curvature so that there are larger movements along the directions of small gradients and thus avoids slow convergence in the direction of small gradient.

III. Performance Evaluation using Levenberg Marquardt Algorithm

C. *Patient Data Analysis*

The data for this study have been collected from 88 patients who have symptoms of angiographic coronary heart disease. At first step, the data have been analyzed to clear the missing values, wrong type values & outliers, which are not processable by the ANN [15]. The data was collected from the open source Cleveland Clinic Foundation Data base which is in the instance format. While the databases have 76 raw attributes, only 13 of them are actually used. All attributes are numeric-valued. Table-1 shows the various input parameters for the prediction of angiographic heart disease and % of importance in the performance of the developed ANN model.

Table 1: Input Parameters for Prediction of Angiographic Coronary Heart Disease

Sl. No.	Parameters	Importance, %
1.	Age in years	3.149186
2.	Sex (1 = male; 0 = female)	1.905409
3.	Chest pain types: 1= typical angina 2=atypical angina; 3=Non-angina pain 4=asymptomatic	13.890818
4.	Resting B.P in mm of Hg	2.735086
5.	Serum cholesterol in mg/dl	5.05939
6.	Fasting blood sugar > 120mg/dl 1 = True; 0 = False	5.639362
7.	Resting ECG results 0 = Normal; 1 = T wave inversion/ST elevation; 2 = left ventricular Hypertrophy	8.689595
8.	Maximum heart rate achieved	0.360368
9.	Exercise induced angina 1 = yes; 0 = no	11.127196
10.	ST depression induced by exercise	5.929346
11.	Slope of peak exercise ST segment 1 = up sloping; 2 = flat; 3= down sloping	6.012446
12.	Number of major vessels (0 – 3)	10.400797
13.	3= Normal; 6 = fixed defect; 7 = reversible defect	25.101
14.	diagnosis of heart disease (angiographic disease status) Value 0: < 50% diameter narrowing Value 1: > 50% diameter narrowing	Target Value

D. *Preprocessing of Data*

After data analysis, feature selection methods are used to recognize the datasets that are not useful and do not improve the performance of neural network considerably. In the proposed work, backward stepwise method is used for input feature selection. Through this method, the action of the ANN model is significantly improved by elimination of the unimportant datasets. In this method, the algorithm at every step, detects the input datasets that degrades the working of the ANN model and starts eliminating them from the input data set matrix.

E. *Development of Neural Network Architecture*

The structure of the ANN model used in this study is the multilayered feed forward network architecture with 13 input nodes, 13 hidden nodes and 1 output node. In this ANN model, number of neurons at input are judged by the number of input dataset attributes and the number of hidden neurons are decided by trial & error method to figure out the integer which drastically improve the working of ANN model. This

ANN model does prediction, uses the target values (degree of CHD) which are continuous and hence require 1 neuron at the output. The most widely used neural-network learning method is the BP algorithm [16]. Learning in the ANN model requires adjusting its weights and biases to minimize a cost function. The cost function involves an error term which is a measure of closeness of the ANN models outputs to the target values.

The activation function employed for each node in the ANN model is the binary sigmoidal function which is defined (with $\sigma = 1$) as output = $1/(1 + e^{-x})$, where x is the sum of the weighted inputs to that particular node. This function restricts the output of all nodes in the ANN model to be between 0 and 1. The end point of training of ANN model is determined by the iteration at which the error has stopped decreasing. Figure 2 shows the architecture of the proposed ANN model for the prediction of degree of coronary heart disease. The multivariate input datasets (with 13 attributes) are given to the ANN model, whose output corresponds to the diagnosis of degree of coronary heart disease.

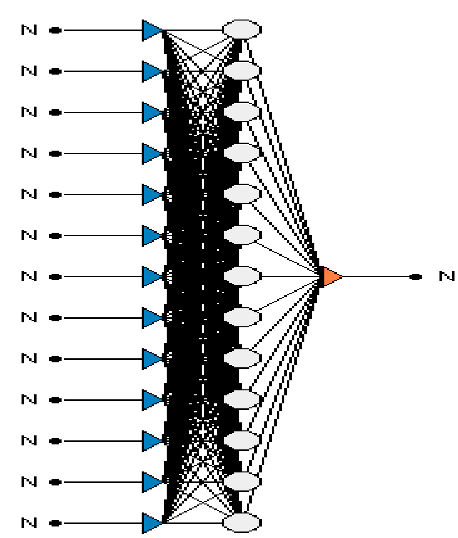

Figure 2: ANN Architecture for Diagnosis of Coronary Heart Disease

F. *Training Process of MLP Networks*

The main function of the training phase of ANN model is to reach to the weight values at which the actual output from the ANN model matches to the target values as closely as possible. The training of the ANN model was carried by using Levenberg-Marquardt Algorithm (LM). The important step in training phase of the MLP network is to decide the number of neurons in the hidden layer. This is because, the MLP network may become incapable to model multivariate data, and the resulting fit will be poor, if an insufficient number of neurons are used in the network. Similarly, if too many neurons are used, network may over fit the data at the cost of training time. It is also observed experimentally that when over fitting occurs, the model fits the training data tremendously well, but its performance reduces to new and unseen data. Validation phase is used to verify this condition.

The MLP neural network model with 13-13-1 architecture is experimentally found to be the best suitable network for the prediction of CHD with the given multivariate data set. The search, at first, was done through heuristic method by changing the number of neurons in the hidden layers from 2 to 30. After the heuristic search, to detect the best network, exhaustive search method is adopted. After comparing the 6 different architectures, the network architecture with 13 input neurons, 13 hidden neurons and 1 output neurons has been chosen to be the best network since it gives the best fitness in terms of weights as well as error function.

The data sets have been analyzed using PC based software package [17]. During analysis, the last column is considered as the target one and the other columns will be considered as input columns. The input patient dataset is partitioned into training set, validation set and test set as shown in Table 2. The various data set errors with respect to training set, validation set and the best network obtained by training through repeated iterations is shown in Table 3. The details of the architecture used are given in Table 4.

Table 2: Data Set Partition

Sl. No.	Data partition Set	Records	Percentage
1.	Training set	60	68 %
2.	Validation Set	14	16 %
3.	Test set	14	16 %
4.	Total Records	88	100 %

Table 3: Comparison of Different Architectures with Network Parameters

Sl. No.	Architecture	No. Of Weights	Fitness	Train Error	Validation Error	Test Error
1.	13-2-1	31	1.65597	0.6484	0.7962	0.6038
2.	13-8-1	121	1.2265	0.9033	0.9233	0.8153
3.	13-13-1 Best network	207	1.8002	0.1817	0.5908	0.4295
4	13-16-1	241	1.5766	0.0631	0.8163	0.6342
5.	13-19-1	286	1.5647	0.5466	0.7953	0.6390
6.	13-21-1	316	1.5270	0.8193	0.9154	0.6548

Table 4: Network Architecture Parameters

Iteration:	47
Training speed, iter/sec:	7.5806
Architecture:	[13-13-1]
Time taken in secs:	31
Training Algorithm:	Levenberg-Marquardt
Error function:	Sum-of-squares
Activation:	Sigmoid
Classification model:	Winner-takes-all
Search method:	Heuristic Search
Fitness Criteria:	Inverse Test error

G. *Performance Evaluation of Proposed ANN Model*

In the training phase of an ANN model, the objective is to adjust weights such that the output of the network is as close to the target as possible for as many of the examples in training set as possible. The validation set is used to choose the best network by changing the number of neurons in the hidden layer and also it detects the instant at which the ANN model working started to decline. The test set is used to test how well the ANN model will work on new and unseen data. The test set is used after the ANN model is trained and validated through data sets. Fig.2 shows the data set errors with respect to training set, validation set and the best network. After training the network with repeated iterations, it reaches the level of best network.

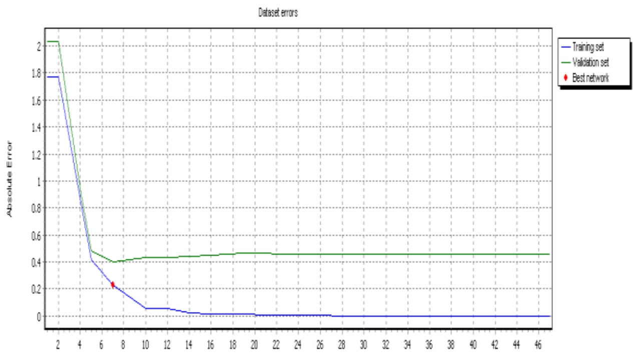

Figure 2: Data Set Errors (Absolute Error vs. Iterations)

From the fig.2, it is inferential that both training set error and validation set error has reached a minimum at very less number of iterations (7th iteration). Figure 3 shows the variation of absolute error for iterations of the best network (Network with architecture [13-13-1]). From the graph it is observed that there is a linear reduction in the absolute error of the network which is an indication of most efficient neural network architecture.

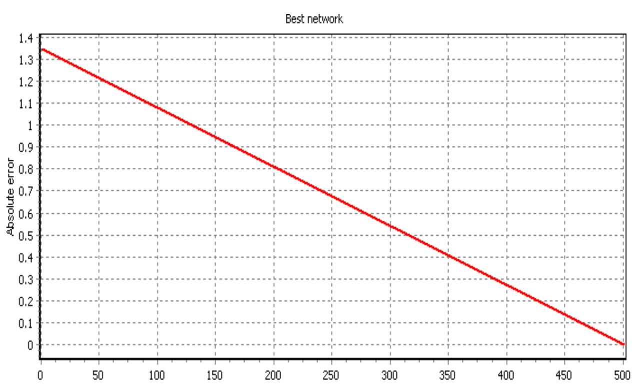

Figure 3: Absolute Error vs. Iterations for Best Network

The performance of the proposed model is evaluated by computing the percentages of Sensitivity (SE), Specificity (SP) and Correct Classification i.e. Accuracy (AC). These validation parameters are defined as:

$$\text{Sensitivity(SE)} = \frac{TP}{TP + FN}\ ; \quad \text{Specificity(SP)} = \frac{TN}{TN + FP}$$

Correct classification, i.e. $\text{Accuracy(AC)} = \dfrac{TP + TN}{TN + FP + TP + FN}$

Where TP (True Positive) is the number of subjects correctly classified as healthy, TN (True Negatives) is the number of subjects correctly classified as abnormal; FN (False Negatives) is the number of subjects misclassified as abnormal when actually normal, and FP (False Positives) is the number of subjects misclassified as normal when actually abnormal [18]. In the classification problems, the purpose of the network is to assign each case to one of the classes.

Table 5: Confusion Matrix for the Proposed Method

	Classified healthy	Classified Unhealthy
Healthy	TP (65samples)	FN (2 samples)
Unhealthy	FP (2 samples)	TN (19 samples)

While assessing the classification ability of the network, most important marker is the classification summary spreadsheet i.e. confusion matrix. Table 5 shows the confusion matrix of the proposed method with the number of sample cases belonging to each element after training, validating and testing. Using the confusion matrix and computing SP, SE and AC using the formula mentioned, the proposed ANN model results in 97 % Sensitivity, 90.5 % Specificity and 95.5 % Accuracy. From the comparison chart shown in Fig. 4, it is observed that the proposed method outperformed with high values of SE, SP & AC in comparison with earlier works.

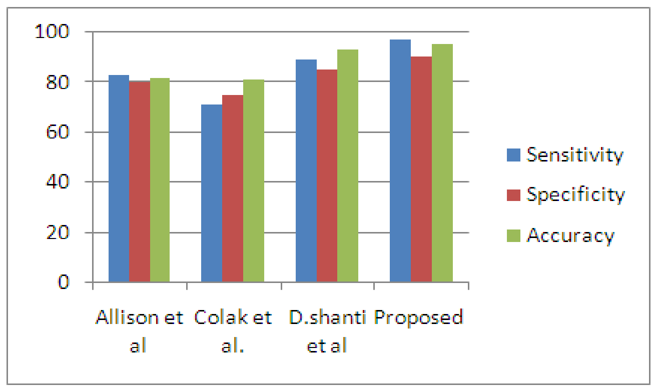

Figure 4: Comparison of SE, SP & AC with other Methods

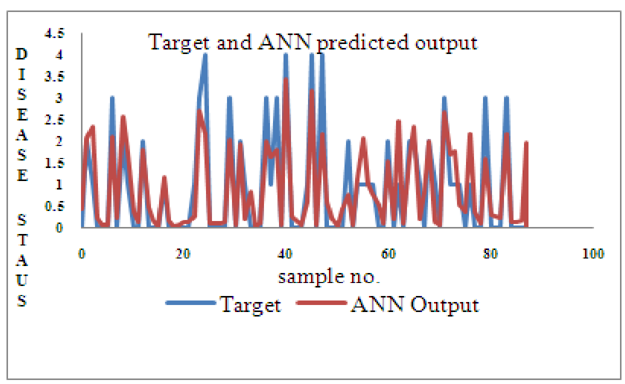

Figure 5: Actual vs. Output Graph for all Input Records

Fig.5 shows Actual vs. Output Graph which displays a line graph of the actual and network output values for records in the x-axis. The record selected in the Actual vs. Output Table is marked on the graph with blue and red points. Horizontal axis displays the row number of the input dataset and vertical axis displays the range of the output values. The proposed ANN model results in correlation co-efficient of R=0.9080 which shows that a good agreement between the predictive model values and the target values.

IV. Conclusion and Future Work

A new approach on design of neural network architecture for prediction of degree of coronary heart disease is developed. The design technique uses one layer of hidden neurons architecture trained with Levenberg-Marquardt back propagation algorithm on multivariate data set. The heuristic search for the efficient network architecture shows that the ANN model with architecture 13-13-1 gives best results. In conclusion, when the ANN was trained, validated and tested after optimizing the input parameters, the overall predictive accuracy obtained was 95.5% with 47 iterations in 31 secs. The results generated by this system have been verified with medical expert's data and are found correct. Thus, the proposed ANN model can be successfully used towards identifying persons at risk for coronary heart disease and it figures out the risks faced by patients in future.

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