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Research Article

Possibilities of Artificial Intelligence in Predicting Coronary Artery Disease

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Abstract

The purpose of the study is to study the possibility of using neural network analysis to predict the fact and degree of coronary lesion. The task of the study was to compare the accuracy of the trained neural network model on input structured data and ECG records with the conclusion of a cardiologist.

Material and methods: 120 patients who underwent elective or emergency coronary angiography. To predict the damage to the coronary bed, the method of neural network analysis was used. Machine learning was performed with the inclusion of clinical, laboratory, instrumental (ECG-image) signs (23 indicators in total). To solve classification problems, a neural network was used that takes structured data and an image as input and outputs a multifactorial characteristic of the main coronary arteries.

The training/test ratio in the examples was 100/20. The supervised learning method was used on the available data, in which the outcomes were known (coronary angiography data), and the neural network parameters were adjusted so as to minimize the error using the backpropagation method. For this experiment, based on the test sample, 20 tasks were created. An ECG image was attached to each task.

5 cardiologists, daily supervising patients with acute coronary syndrome, separately assessed the pathology of the coronary bed for each main coronary artery and predicted the need for revascularization.

Results: The results of the neural network on a test sample of 20 patients: AUC score - 0.74, accuracy (accuracy) - 80%, precision accuracy (precision) - 63%, recall (recall) - 55%, f1 score (harmonic mean between accuracy and completeness) - 59%. Average response rates of cardiologists: accuracy - 76%, precision - 48%, recall - 55%, AUC score - 0.68, f1 score - 49%. The best values of cardiologists: accuracy - 76%, precision - 48%, recall - 67%, AUC score - 0.72, f1 score - 56%.

Conclusion: Neural network analysis of the prepared clinical, laboratory and instrumental data allows you to adjust the network parameters for subsequent accurate prediction of coronary artery disease. The results obtained in the form of an AUC score allow us to speak about the applicability of the method in the diagnosis of coronary pathology. On the test sample, the neural network works more efficiently than cardiologists on average. Only one in five specialists was able to come close to the accuracy of the trained neural network model.

Keywords: Coronary Arteries; Neural Networks; Artificial Intelligence; Coronary Heart Disease; Deep Learning; ECG; Non-Invasive Predictive AI Coronary Angiography

Abbreviations

AV: Atrioventricular; CABG: Coronary Artery Bypass Grafting; CA: Coronary Angiography; ESC: European Society of Cardiology; AI: Artificial Intelligence; ACS: Acute Coronary Syndrome; ACI: Acute Cerebrovascular Insufficiency; CCS: Chronic Coronary Syndrome; ECG: Electrocardiogram; AUC: Area Under Receiver Operating Characteristic Curve

Introduction

A promising use of AI and machine learning in cardiology is to provide a set of tools to improve the efficiency of a cardiologist. The introduction of polygenome sequencing and streaming of biometric data from mobile devices into clinical practice will soon require cardiologists to interpret and apply information from many disparate areas of biomedicine [1-4].

At the same time, the ever-increasing workload requires physicians and healthcare systems to achieve higher operational efficiency [5]. Patients are also beginning to demand a faster and more personalized approach [6,7]. The amount of data that a specialist has to work with is increasing all the time, their more complex interpretation is required, and an increase in the efficiency of doctors is expected.

Perhaps machine learning will help solve this problem, which will improve every stage of patient care: from research and discovery to diagnosis and choice of therapy. As a result, clinical practice will become more efficient, convenient, personalized. In addition, in the near future, data will not be collected exclusively in medical institutions, but will be accumulated from numerous systems for recording medical parameters (wearable information devices).

With the use of advanced computing hardware such as graphics processing units (GPUs) and tensor processing units (TPUs), as well as an increase in the amount of data available for training, deep learning algorithms are gradually surpassing previous methods and are gaining more and more popularity in research.

In addition to computing power, another important advance that expands the capabilities of machine learning has been the acquisition and storage of data. “Big data” is a term used to describe the ever larger and more complex datasets that form the basis of machine learning models.

Nowadays, there is an increase in the availability and use of large amounts of information. This has become possible with the advent of electronic medical records, implantable electronic devices, and modern wearable monitors, each of which records unprecedented amounts of biological data every second [8].

In order to clarify the possibility of the effectiveness of the use of AI in assessing the pathology of the coronary bed, we conducted this study.

Materials and Methods

The study involved 120 patients who underwent coronary angiography on a planned or emergency basis. Indications for CA were verified according to the recommendations of the European Society of Cardiology (ESC). The study was performed in accordance with Good Clinical Practice and the principles of the Declaration of Helsinki. The following inclusion and exclusion criteria are defined.

Main inclusion criteria

Signing informed consent prior to the study, including for statistical processing of medical history data, age >18 years, indications (scheduled or emergency) for CA, documented ECG recording (speed 25 mm) performed one day and/or less before CA.

Key exclusion criteria

ECG rhythm disturbances in the form of atrial fibrillation, AV nodal or ventricular tachycardia at the time of recording; previously performed stenting and/or bypass coronary arteries; the presence of pronounced interference and artifacts on the recorded ECG, ECG registration for more than 24 hours before CA; any surgical or medical condition that, in the opinion of the researcher, could significantly interfere with the performance of the machine learning algorithm in relation to the accuracy of the results.

The doctor conducting the study analyzed the medical record data (complaints, anamnesis, objective, laboratory and instrumental data) and entered these results into a machine learning database in a binary format.

At the first stage of data collection for each observation, the structured parameters were entered into a tabular form, and images of the ECG record in jpeg format were entered into the database.

Numerous morphometric, objective, laboratory and instrumental data of patients were used to train neural networks. Such data were age, gender, diagnosis of ACS or CCS, pathology of the ST segment on the ECG, the presence or absence of concomitant pathology (diabetes mellitus, hypertension, obesity, anemia, acute cerebrovascular accident, atherosclerosis, arrhythmia , dyslipidemia), aggravated heredity, the presence of bad habits (smoking, alcohol abuse), the presence of stress factors, low physical activity, menopause, increased nutrition.

The above factors were recorded in a structured binary form (0, 1) in a tabular format. ECG registration was carried out using one type of device, the record was transferred to the machine learning operator in electronic form in jpeg format. Thus, a total of 22 parameters (key features) were used to develop a neural network training algorithm.

The neural one was trained on the data obtained from the analysis of coronary angiograms. The presence of atherosclerosis of the coronary artery, stenosis or subocclusion of the trunk of the left coronary artery, occlusion, subocclusion or stenosis of the anterior interventricular artery, occlusion, subocclusion or stenosis of the circumflex artery, occlusion, subocclusion or stenosis of the right coronary artery, performed CABG were taken as target values according to the results of the CA. The values of coronary artery stenosis were entered into the table in digital form as a percentage, then converted into binary form (1 - stenosis >50%), the rest of the indicators were filled in binary form according to the presence or absence of a lesion. The above target values were predicted by a trained machine learning algorithm.

The algorithm needed to solve the problem of classifying coronary lesions, predict the absence or presence of stenoses and their severity. To classify CA lesions according to the “0; 1” system, a neural network was used that takes structured data and an image as input, and a multifactor classification of CA was obtained at the output. The ratio in the training and test examples was 100/20. Forecasting and evaluation of the results were carried out on a test sample.

Patients in the test sample were with an atypical clinical picture and complex CA pathology. This condition was taken specifically to test the operation of the algorithm in real clinical practice.

As software for building the architecture of the neural network, sets of libraries for the Python programming language were used (pandas - for working with tabular data; tensor flow - for designing neural networks and training them). Supervised learning was used on available data, in which the outcomes were known, and the parameters of the neural network were adjusted to minimize the error.

The analysis of structured tabular data of a training sample consisting of 100 patients was carried out.

The mean age of the patients was 64 years, ranging from 31 to 89 years. Distribution by sex - 52 men, 48 women. The median age of men is less than that of women. In 62 out of 100 people, ACS was verified. ST segment elevation was diagnosed in 19 patients with ACS. In 53 patients out of 62 with ACS, typical anginal pains were determined.

The task of the study was to compare the accuracy of the trained neural network model on input structured data and ECG records of cardiologists.

For this experiment, based on the test sample, 20 tasks were created. An ECG image was attached to each task. 5 cardiologists, daily supervising patients with ACS, separately predicted the need for revascularization and assessed the pathology of the coronary bed for each main coronary artery.

The obtained data was loaded into a table. A comparison was made with the correct answers according to invasive CA. The AUC score was taken as the main method for calculating the error.

The input of the neural network simultaneously received ECG images of size (200x200x1) and structured tabular data. At the output, the neural network predicted multilevel values of affected coronary values in a probabilistic form.

Fully connected, convolutional, batch normalizing (batch normalization layer), dropout (exclusion layer) were taken as neural network layers for image processing. For processing structured data, only fully connected layers are taken. Inside the neural network, a concatenate layer was used to generalize the weights of the image and the dataset. After the generalizing layer - 2 fully connected layers. The output layer consists of 13 neurons for predictions for each parameter. Adam was taken as an optimizer (an adaptive learning rate optimization algorithm by calculating an exponential moving average gradient and a quadratic gradient), the loss function is binary cross entropy. Training was performed on 100 epochs (1 epoch - 1 forward pass and 1 reverse pass of all training examples). The batch size (the number of training examples per iteration) is 8, the size of the validation set is 0.1. The selection of parameters and structure of the neural network was carried out empirically. AUC was chosen as the starting metric for assessing the quality of the model.

Results and Discussion

On a test sample of 20 patients, the result of the neural network was: AUC score - 0.74, accuracy (accuracy) - 80%, precision accuracy (precision) - 63%, recall (recall) - 55%, f1 score - 59%.

Average response rates of cardiologists: accuracy - 76%, precision - 48%, recall - 55%, AUC score - 0.68, f1 score - 49%. The best values among cardiologists: AUC score - 0.72, accuracy - 76%, precision - 48%, recall - 67%, f1 score - 56% (Table 1).

	AUC	Accuracy	Preci-sion	Recall	F1 score
Non-invasive predictive AI coronary angiography	74	80	63	55	59
Average answers of specialists	68	76	48	55	49
Best expert answer	72	76	48	67	56

Table 1: Prediction of damage to the main coronary arteries and transient myocardial ischemia.

The study used a relatively small amount of data: 22 signs, ECG images obtained from 120 patients. In this regard, a neural network architecture was built with a small number of parameters.

The result of the multilevel classification of the alleged lesions for each main CA with the chosen neural network architecture showed a good quality of the model (AUC = 0.74). The created model of neural network analysis makes it possible to predict damage to main SCs with a fairly high probability.

Every year, thanks to the work of researchers, a large number of models for assessing cardiovascular risk appear. Most of the models are based on data from randomized clinical trials and registry studies. However, only a small part of the models is used in real clinical practice. Obviously, instead of creating another unviable model, a qualitatively different approach is needed. The study used a relatively small amount of data: 22 signs, ECG images obtained from 130 individuals. In connection with these, a neural network architecture was built with a small number of parameters.

Neural networks see patterns that are not available to humans. The introduction of AI in medical diagnostics has been going on for a long time.

The results obtained allow us to speak about the possible practical application of the neural network analysis method in clinical practice. An important additional advantage of neural network data analysis is the fact that when CCS is curated, cardiologists do not have reliable tools for an undoubted referral to CAG. Under these conditions, AI allows you to correctly interpret the data set and direct the doctor to perform the interventional technology. It is also worth noting that in senile patients without symptoms, with limited ability to perform stress testing in case of CCS, the deep machine learning technique provides an invaluable prospect for the timely referral of the patient to CA.

Conclusion

Neural network analysis of the prepared clinical, laboratory and instrumental data allows you to adjust the network parameters for subsequent prediction of damage to the main CA. The neural network trained by us predicts damage to the main CAs with a sensitivity of 63%, a specificity of 88%, and an AUC of 0.74. The obtained results in the form of an AUC score allow us to speak about the efficiency of the method in diagnosing the pathology of the main CA. On the test sample, the neural network works more efficiently than the average cardiologists, and, most importantly, it allows the doctor to be directed to perform invasive examination methods in cases where there is not enough input data for this decision. Only 1 out of 5 specialists could come close to the accuracy of the trained neural network model.

Conflict of Interest

All authors who have taken part in this study declare that they have nothing to disclose.

Bibliography

1. Kuo FC., *et al*. "The relative utilities of genome-wide, gene panel, and individual gene sequencing in clinical practice". *Blood* 130 (2017): 433-439.

2. Muse ED., *et al*. "Towards a smart medical home". *Lancet* 389 (2017): 358.

3. Steinhubl SR., *et al*. "The emerging field of mobile health". *Science Translational Medicine* 7 (2015): 283rv3.

4. Shameer K., *et al*. "Translational bioinformatics in the era of real-time biomedical, health care and wellness data streams". *Brief Bioinformation* 18 (2017): 105-124.

5. Konstam MA., *et al*. "The academic medical system: reinvention to survive the revolution in health care". *Journal of the American College of Cardiology* 69 (2017): 1305-1312.

6. Steinhubl SR and Topol EJ. "Moving from digitalization to digitization in cardiovascular care: why is it important, and what could it mean for patients and providers?" *Journal of the American College of Cardiology* 66 (2015): 1489-1496.

7. Boeldt DL., *et al*. "How consumers and physicians view new medical technology: comparative survey". *Journal of Medical Internet Research* 17 (2015): e215.

8. Wasserlauf J., *et al*. "Smartwatch performance for the detection and quantification of atrial fibrillation". *Circulation: Arrhythmia and Electrophysiology* 12 (2019): e006834.