Assessment of the applicability of machine learning methods for the detection of pathology of internal human organs based on the results of bioelectrography

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Abstract— **The possibility of using the bioelectrography method for detecting pathology of internal organs is considered. Sets of data sets for machine learning are formed on the basis of ultrasonic diagnostics readings. Machine learning methods were analyzed with an assessment of the feasibility of their use. The results of detection of pathology of internal organs with the use of classifiers are presented: Decision tree; KNN; Logistic regression; Random forest; SVC; XGBoost.**

Keywords— bioelectrography, machine learning, ultrasound diagnostics, pathology of internal organs, GRV-grams

I INTRODUCTION

The modern growth of computing power makes it possible to apply mathematical models in conjunction with human physiological indicators. This makes it possible to develop and implement methods for rapid analysis of human conditions, one of which is the production and analysis of GRV-grams based on bioelectrography [1]. The possibility of using such an approach is confirmed by studies [1-14]. The pathology of the cardiovascular system is analyzed in [1-4]. It was shown in [2] that the dynamics of heart rate variability and bioelectrography varies depending on the season. In the study [3], it was revealed that the parameters of GDV in patients with arterial hypertension and healthy subjects differ (this is especially noticeable on the left hand). In [4], damage to the main arteries of the head was observed at the extracranial level using GRV grams. The classification of patients into groups has been formed: healthy; patients with identified cerebral artery stenoses <50% of the vessel diameter or convolutions of these vessels with a local hemodynamic shift and patients with identified vascular lumen stenoses >50% or pronounced convolutions of these vessels with a hemodynamically significant shift. Based on the GRV-grams, a search was made for sectors that can be used in the future to build diagnostic rules. It is concluded that the GDV-bioelectrography method allows to diagnose the presence and degree of pathological vascular changes at the extracranial level with a sufficiently high accuracy.

The study of the pathology of the respiratory organs is devoted to works [5, 12], in which the relationship between chronic obstructive pulmonary disease of stages 1-2 and GRV-gram was noted. The structure and severity of psychovegetative disorders in patients were revealed using the Wayne questionnaire and the hospital scale of anxiety and depression in [5]. Based on these data, the correlation between the GDV-gram and the course of the underlying disease was evaluated.

An assessment of the influence of meteorological factors on the parameters of bioelectrograms in patients can be attributed to a separate direction [2, 6-7]. In [7] it is shown how the GRV-gram changes depending on the heliogeomagnetic factors on the derived parameters of the GRV-gram. In the study [8] the influence of the biofeedback method using bioelectrography.

Bioelectrography methods are also used in the tasks of evaluating the functioning of athletes' activities [1, 9]. In [1] it is shown that the assessment of the GRV-grams allows for a sufficiently accurate rapid assessment of the parameters of the psychophysiological state of athletes at all stages of preparation and participation in responsible competitions, it is revealed that there is a decrease in the area of the glow of the GRV-grams, as well as an increase in the activation coefficient in the group with low adaptive capabilities. The work shows that the GRV-grams of athletes at rest are relatively more structured compared to healthy subjects of the appropriate age from the control group. Summarizing these studies, we can say that the method of GDV-bioelectrography is advisable to use in the screening assessment of the functional state of the body of athletes-athletes. Both studies confirm the assumptions that bioelectrography methods allow timely corrective measures aimed at their optimization, including by means of psychophysiological and psychological support for training and competitive activities.

Methods for assessing resistance to stress are considered in [11, 12].

Features of bioelectrography in patients with diabetes mellitus were revealed in [13, 14]. A significant change in a number of indicators of gas discharge imaging in patients with type 1 diabetes mellitus has been established, which makes it possible to use the method on an outpatient basis for diagnosis in patients with type 1 diabetes mellitus [13], and in [14] for diagnosis in patients with type 2 diabetes mellitus.

The analysis of the obtained research results showed that the use of GRV-grams of patients, in comparison with traditional methods of detecting organ pathology, makes it possible to train the model under study for further use only of the results of bioelectrography.

II IDENTIFICATION OF PATHOLOGY OF HUMAN INTERNAL ORGANS BASED ON THE RESULTS OF BIOELECTROGRAPHY

To obtain a set of initial data, datasets formed by bioelectrography were used, which were compared with the results obtained by ultrasound diagnostics. The information was collected by taking the results of bioelectrography from the fingers placed in the Bio-Well device, as well as from the results of ultrasound diagnostics of human organs obtained from a common repository of files with observations and conclusions on various violations. This made it possible to identify the correlation of pathology of internal organs with the results of bioelectrography.

Based on the results of this stage, a data warehouse was formed, in which there are more than 4,000 ultrasound diagnostic results and a repository for datasets containing bioelectrography data. However, the systematization of the received data, in practice, faced problems of interoperability and format conversion, since the data for processing is presented in an inconvenient format for subsequent processing. Thus, the analysis of the selected results of ultrasound diagnostics revealed a problem in which one file may contain several conclusions on different organs, or there may be several files in which the results of ultrasound diagnostics of different systems of the organism under study are stored. In this regard, in order to obtain a combined data set, the task arose of collecting all the studies for each patient individually. In this connection, to automate the matching process, software was developed that sorted through the files with the selection of the necessary data. The complex of the developed software is shown in Fig. 1. The next stage was the formation of a generalized dataset aimed at sampling conclusions on the necessary organs, in the form of a generated table, where each patient is compared with the conclusion on each disease separately.

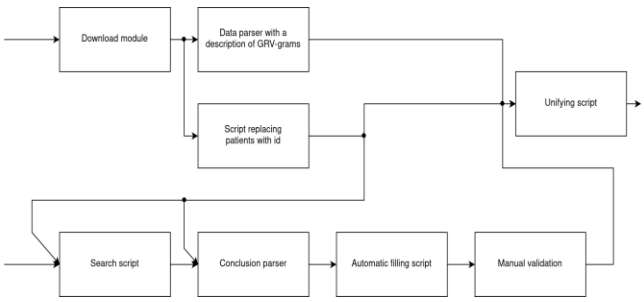

Fig. 1. The complex of the developed software

On the basis of the obtained table, with the help of the developed software and a formed set of data for each subject, based on the diagnoses or observations, the fact of the presence of pathology of the organ under study is taken out. For example, the following diagnoses may indicate the presence of problems with the gastrointestinal tract and genitourinary system: hepatomegaly, steatohepatosis, hepatosplenomegaly, biliary dyskinesia (JVP), diffuse changes in the structure of the kidneys. And, if the software meets the conclusion: "An echographic picture of diffuse changes in the structure of the pancreas, hepatomegaly, enlargement of the heart, microliths of the left kidney", then a conclusion is formed that the patient is supposed to have problems: with the pancreas; enlargement of the liver, as well as diffuse changes in the structure of the kidneys (kidneys in general). According to the results of the software, at this stage, a document is formed in which each patient is put in accordance with the assumption of the presence of pathology with the organ in the form shown in Figure 2, where 1 means the presence of pathology of the organ under study, 0 – the absence of pathology. A dash or a dark column is equivalent to the absence of information on this organ in all files of ultrasound diagnostic results that are available for this patient.

To validate the conclusions that were generated by the software, an expert doctor in the field of medical diagnostics was involved in order to verify the correctness of conclusions about the presence of organ pathology. This made it possible to form a final dataset, according to which machine learning was carried out and to build histograms of the distribution of pathology by selected organs (an example of a histogram is shown in Fig. 2). The obtained histograms show the distribution of the number of healthy (0) and those with pathology (1) of the organ under study, as well as the number of patients who do not have pathology data for the organ under study (-).

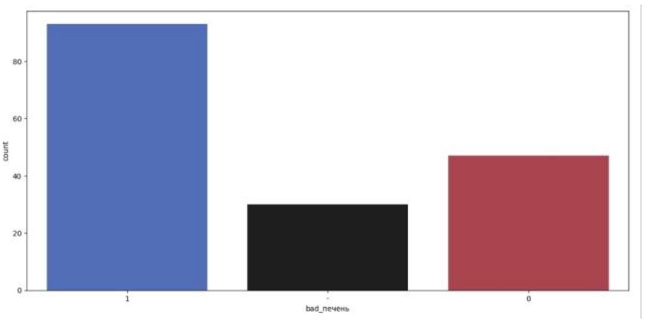

Fig. 2. Example of the distribution of persons with liver pathology

Analysis of the histograms obtained showed that the most common disorders include pathology of such organs as: gallbladder; liver; pancreas; kidneys; spleen; thyroid gland. At the same time, the analysis of the shape of histograms indicates that in most cases there is no uniform distribution for them, and the fact of the presence of organ pathology or its absence prevails. In this regard, it became necessary to use different approaches to the classification of pathology, therefore, at the stage of training the model, the following classifiers were selected: Decision tree; KNN; Logistic regression; Random forest; SVC; XGBoost in two variants: directed to the f1 metric; directed to the recall metric.

Under these conditions, the task arose of finding a classifier with the best values of the predictions presented. The separation of XGBoost was chosen in two variants in order to train the model to assume organ pathology as accurately as possible (target metric - f1), or to detect data belonging to the smallest class (target metric - recall). For the rest of the classifiers, GridSearch was used, which allows you to select the best parameters for each of the classifiers.

During the training, the detection task was divided into 6 subtasks, each of which had a binary classification: organ pathologies were considered separately from each other, i.e. the result for each case was 1 or 0, where 1 is the fact of pathology from the organ and 4 approaches were used:

- the data was compiled in its original form;
- the training data was supplemented using SMOTE;
- the features were standardized using Standard Scale r;
- the signs were standardized, and the training data was also supplemented with the help of SMOTE.

Each model for each organ under study was considered separately, and then a comparison was carried out to select a certain classifier that demonstrates the best results.

III. Results of practical application

Based on the results of training and predicting facts about a problem with a particular organ, the following results were obtained. For the gallbladder, randomForest turned out to be the best classifier, the training data passed through the addition using SMOTE. The error matrix and metrics for it are shown in Fig. 3.

```
[[ 9  5]
 [10 23]]
              precision    recall  f1-score   support

           0       0.47      0.64      0.55        14
           1       0.82      0.70      0.75        33

    accuracy                           0.68        47
   macro avg       0.65      0.67      0.65        47
weighted avg       0.72      0.68      0.69        47
```

Fig. 3 Results of using the randomForest model to detect gallbladder pathology

To detect liver pathology, it is advisable to use both logistic regression and XGBoost, which has a recall target metric. For both models, the training data passed through the addition using SMOTE. The error matrix and metrics are shown in Fig. 4 and 5.

```
[[ 7  4]
 [12 24]]
              precision    recall  f1-score   support

           0       0.37      0.64      0.47        11
           1       0.86      0.67      0.75        36

    accuracy                           0.66        47
   macro avg       0.61      0.65      0.61        47
weighted avg       0.74      0.66      0.68        47
```

Fig. 4. Results of the application of logistic regression for the detection of liver pathology

```
[[ 9  2]
 [15 21]]
              precision    recall  f1-score   support

           0       0.38      0.82      0.51        11
           1       0.91      0.58      0.71        36

    accuracy                           0.64        47
   macro avg       0.64      0.70      0.61        47
weighted avg       0.79      0.64      0.67        47
```

Fig. 5. Results of using the XGBoost model to detect liver pathology

Logistic regression and random forest models showed the best results for the pancreas. For these classifiers, the error matrix and metrics are shown in Fig. 6.

```
[[ 6  3]
 [10 28]]
              precision    recall  f1-score   support

           0       0.38      0.67      0.48         9
           1       0.90      0.74      0.81        38

    accuracy                           0.72        47
   macro avg       0.64      0.70      0.65        47
weighted avg       0.80      0.72      0.75        47
```

Fig. 6. Results of the application of logistic regression and random forest for the detection of pancreatic pathology

To identify kidney pathology, the best result was demonstrated by the Decision Tree classifier, the result of which is shown in Fig. 7.

```
[[ 3  4]
 [13 27]]
              precision    recall  f1-score   support

           0       0.19      0.43      0.26         7
           1       0.87      0.68      0.76        40

    accuracy                           0.64        47
   macro avg       0.53      0.55      0.51        47
weighted avg       0.77      0.64      0.69        47
```

Fig. 7. Results of using the Decision Tree classifier to detect kidney pathology

However, the use of these methods in order to detect the pathology of the spleen showed that none of the classifiers could properly cope with their task, since the results are very different from those mentioned above. The best results in this class were obtained using random forest models and logistic regression, shown in Figure 8.

```
[[41  1]
 [ 5  0]]
              precision    recall  f1-score   support

           0       0.89      0.98      0.93        42
           1       0.00      0.00      0.00         5

    accuracy                           0.87        47
   macro avg       0.45      0.49      0.47        47
weighted avg       0.80      0.87      0.83        47
```

Рис. 8. Результаты применения логистической регрессии и случайного леса для выявления патологии селезенки

To determine the pathology of the thyroid gland, the best classifier turned out to be KNN, which demonstrated the result shown in Fig. 9.

```
[[ 5  2]
 [19 20]]
              precision    recall  f1-score   support

           0       0.21      0.71      0.32         7
           1       0.91      0.51      0.66        39

    accuracy                           0.54        46
   macro avg       0.56      0.61      0.49        46
weighted avg       0.80      0.54      0.61        46
```

Fig. 9. Results of using the KNN model to detect thyroid pathology

Summing up the results of the study, the following features of the application of these methods can be distinguished:

- for the gallbladder, random Forest turned out to be the best, which correctly recognized the result with an accuracy of 68%;
- logistic regression and XGBoost with the recall target metric turned out to be the best for the liver, which showed an accuracy of 66%, with almost equal degree of detection of both pathology and normal functioning of the organ;
- logistic regression and random forest showed 72% accuracy for the pancreas, the lowest percentage of recognition of one of the classes was 67%;
- for the kidneys, the best result is the accuracy of predictions of 64%, however, a healthy organ was correctly determined with an accuracy of less than 50%
- . The spleen is an organ whose disease could not be correctly predicted: the best accuracy, although 87%, was due to the predominance of one of the classes.
- the chosen classifier for the thyroid gland – KNN – best determined a healthy organ (71%), but the overall accuracy of predictions is close to 50% – 54%. The percentage of a correctly identified thyroid patient is only 51%.

Analyzing the results obtained, we can say that the percentage of errors is lower in those models where the distribution of the number of sick and healthy people is approaching normal. The extension of the method with the further use of neural networks is possible, but is hampered by the complexity of the process, with results equal in comparison with machine learning models.

IV. Conclusion

To the further direction of research, it is advisable to include the expansion of classes of machine learning models with respect to body systems to which these methods can be applied. Separately, it is possible to consider a combination of methods for more accurate detection of a particular pathology.

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