Determination of Significant Behavioral Parameters on COVID-19 Diagnosis by Artificial Neural Networks Modeling

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Abstract: *Investigated various options for constructed artificial neural networks (ANNs) used to discriminate databases of behavioral parameters captured by vibraimage technology for patients with confirmed diagnosis of COVID-19 and reference group with confirmed absence of COVID-19 disease. The developed ANNs were learned using ADAM and Nesterov methods. The dependences of method accuracy and the number of errors (discriminating ability of the test) on the structure of ANN and the set of behavioral parameters are presented. Statistical analysis of the same groups of patients and the control group was carried out using standard statistical methods (mat expectation, SD, variability) and groups discrimination by ANN methods. The structure of ANN and input data of behavioral parameters was optimized. Achieved zero error of existing databases discriminating for the patients with a confirmed diagnosis of COVID-19 and the control group. Identified significant behavioral parameters for the diagnosis of COVID-19.*

Keywords: *vibraimage, artificial neural networks, neural network learning, behavioral parameters, neural network structure, AI, ANN, diagnostic accuracy, error.*

Introduction

Technical solutions related to artificial neural networks (Haykin, 2008; Burakov, 2013; Goodfellow et al., 2017) are increasingly important in the development of various technologies and practical applications. The challenge posed to the world by the COVID-19 pandemic has led to the development of many solutions (Laguarta et al., 2020; Soares et al., 2020; Erdem & Aydın, 2020; Hussain et al., 2020; Jin et al., 2020; Wynants et al., 2020; Jimenez-Solem et al., 2021) based on artificial neural networks (ANNs) and artificial intelligence (AI) designed to diagnose COVID-19. Based on vibraimage technology, methods of medical diagnostics were previously developed and substantiated (Blank et al., 2012; Minkin, 2007; 2020; Minkin & Nikolaenko, 2008), therefore, the use of vibraimage technology for the diagnosis of COVID-19 becomes one of developers task. A number of technical solutions have been developed to diagnose COVID-19 (Minkin & Bobrov, 2020), including using ANN and AI (Minkin et al., 2020).

The main advantages of neural networks are the ability to parallelize the flow of information (high speed) and the ability to self-learn and generalize information (Haykin, 2008). At the same time, the final decision made by the trained neural network is not obvious, it is almost impossible to verify (confirm or refute) other known methods. The ability to obtain a valid result based on information that was not encountered in the learning process is, on the one hand, a clear advantage of neural networks (Haykin, 2008), which is especially important for modeling complex biological processes (Novoseltsev,

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1978). On the other hand, the practical closeness of decision making by a neural network or artificial intelligence creates a certain distrust in the perception of an unobvious result of contactless diagnosis of a certain disease.

The objectives of this work are to determine the significant behavioral parameters used in the diagnosis of COVID-19, to modeling the optimal structure of the ANN for sorting out the results of studies of patients and the control group, as well as to improve the accuracy of the method used and reduce errors in the diagnosis of COVID-19.

Materials and Method

The results of both groups studies including patients and control group are behavioral parameters measured using vibraimage technology by VibraHT and HealthTest programs (Minkin et al., 2020). Vibraimage technology detects the behavioral parameters of a person based on various equations for analyzing the micromovements of a human head (Minkin, 2020). The physiological basis connecting head movements and behavioral parameters is vestibular-emotional reflex (Minkin&Nikolaenko, 2008; Minkin, 2020). Measurements of behavioral parameters by these programs were carried out for 1 or 3 minutes, and during the measurement, the program performs 5 readings per second for each behavioral parameter P1–P16 (Minkin, 2020). The resulting data are the mean M for each of the 16 behavioral parameters, as well as the root mean square value of the change in this parameter during the measurement period (SD1–SD16) and the variability of each parameter during the measurement V = M/SD.

The results of patients group study include 268 measurements data captured by VibraHT or HealthTest programs (Minkin et al., 2020) based on head micromovements parameters of patients with a confirmed diagnosis of COVID-19 (of which 250 patients with confirmation of COVID-19 by CT and PCR in the active phase and 18 patients at the asymptomatic stage of the disease COVID-19). The measurements were taken between May and October 2020. The age of patients was from 25 to 75 years, the ratio of men — women (60–40)%. Ethnic composition — 100% Caucasian. The demographic parameters of the control group were matched identically to the patient group.

VibraHT and HealthTest programs are identical in processing algorithms and differ in the level of professional settings. Measurements of the behavioral parameters of patients were carried out using MS LifeCam Cinema and MS LifeCam Studio webcams. The camera resolution was set to 640×480, the frame rate was 30 fps, the black and white mode was enabled in the settings. The examined person was located at a distance of (50–100) cm from the webcam, the horizontal size of the head was more than 200 pixels. The image quality level when tested with VibraHT and HealthTest programs was above 80% for all accepted test results. The computers used to measure behavioral parameters had Windows 10 operating systems and processors of at least Intel i5.

The results of the control group study include 268 measurements by VibraHT program of head micromovement parameters of patients with confirmed absence of COVID-19 symptoms and negative PCR test for COVID-19. The control group included 20 measurements of patients with confirmed ARVI disease in order to exclude the possibility of detecting the symptoms of pathology-normal when comparing patients and the control group, directing behavioral diagnostics specifically to identify the symptoms of COVID-19.

The research methodology is based on ANN learning of various structures using a training program written by one of the authors (Valery Akimov) to discriminate the results of patients and the control groups and determine the number of errors in the specified data discrimination. The structure of trained ANN were two and three layers; the sigmoidal neuron was chosen as the main ANN element, since the sigmoidal function is the most popular in ANN construction (Haykin, 2008).

The selection of significance coefficients in the neural network was carried out using the standard optimization algorithms ADAM and Nesterov (Nesterov, 1983; Goodfellow et al., 2017), used in ANN training and learning. The developed program trains ANN to have 0 on the output neuron for the control group and 1 for the group of patients with a confirmed COVID-19 diagnosis.

Block diagrams of the constructed ANNs for discriminating group databases are shown in Figure 1.

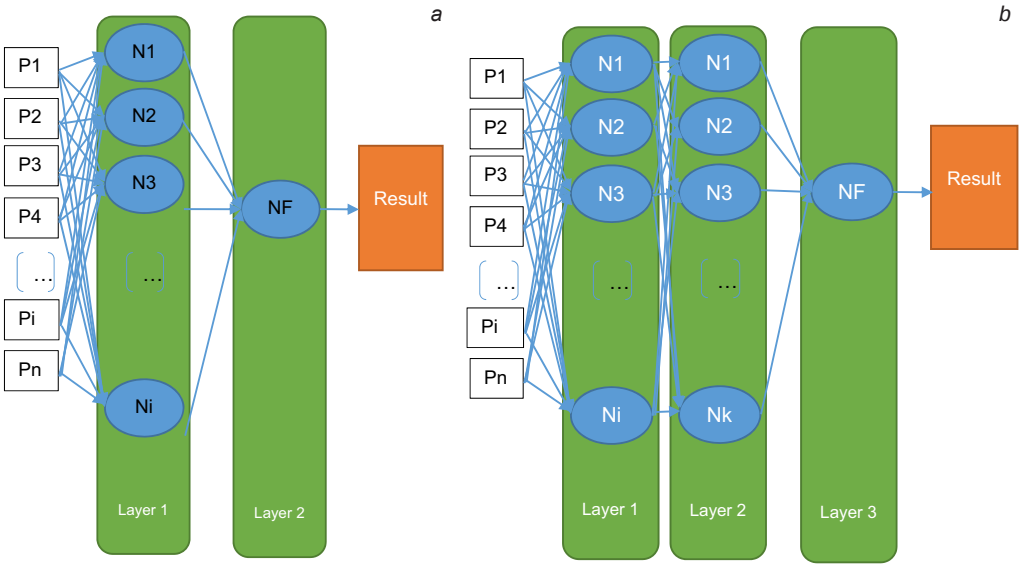

Fig. 1. *Block diagrams of linear neural networks with feedforward for discrimination of databases in two groups: patients and control, a — the simplest feedforward network; b — a feedforward network with one hidden layer of neurons*

Results

First, compare and consider the study results of the behavioral parameters of patients and the control group using standard Excel tools and VibraStat program (Minkin, 2019). Figure 2 shows the mean values of behavioral parameters for patients (M1) and control (M2) group.

The behavioral parameter E7 (energy) has the maximum difference in the groups, the mean E7 in the control group exceeds the mean E7 in the group of patients by 30%.

Figure 3 shows the standard deviations (SD) of the behavioral parameters for patient (S1) and control (S2) groups.

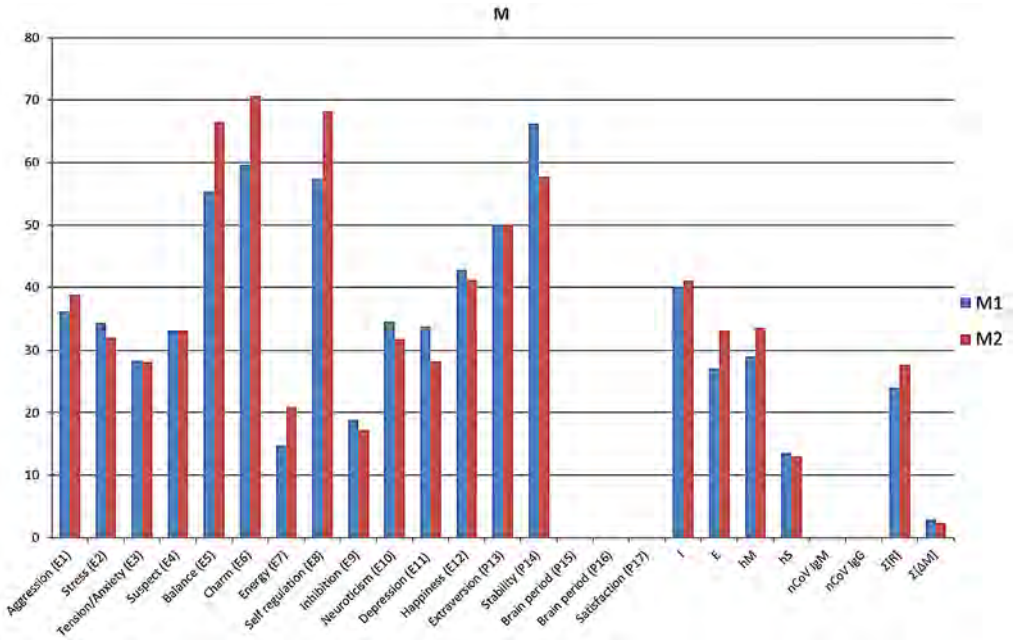

Fig. 2. *Mean values of behavioral parameters for patient (M1) and control (M2) groups*

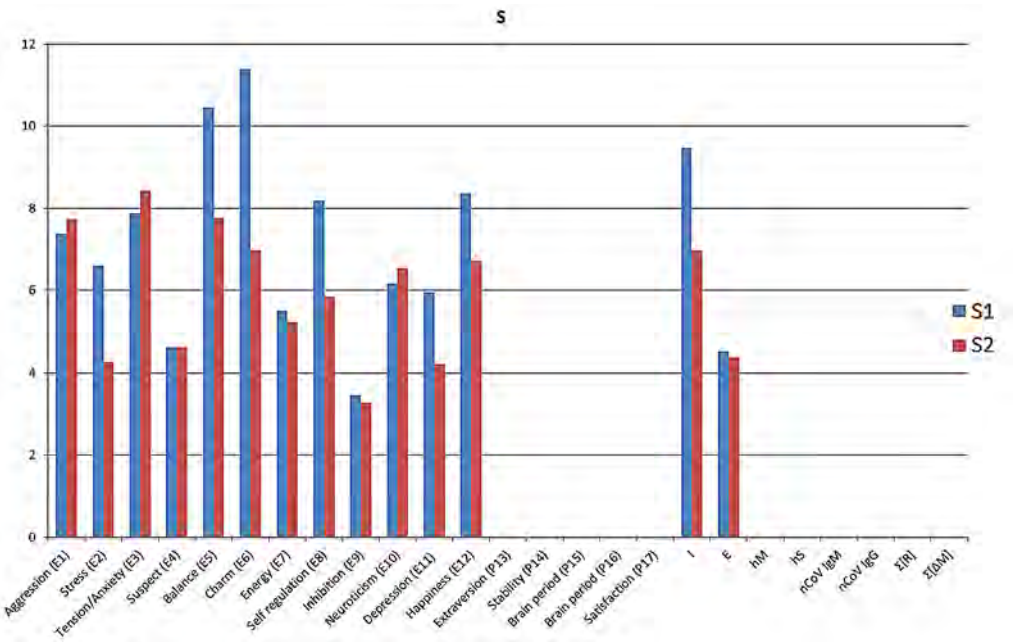

Fig. 3. *Mean of behavioral parameters standard deviation (SD) for patient (S1) and control (S2) groups*

The difference of more than 30% in the groups of patients and the control group has the standard deviation of six behavioral parameters: E2 (Stress), E5 (Poise), E6 (Charisma), E8 (Self-regulation), E11 (Depression) and I (Information efficiency).

Figure 4 shows the standard deviation (RMSD) of the behavioral parameters of the patient groups (V1) and the control group (V2).

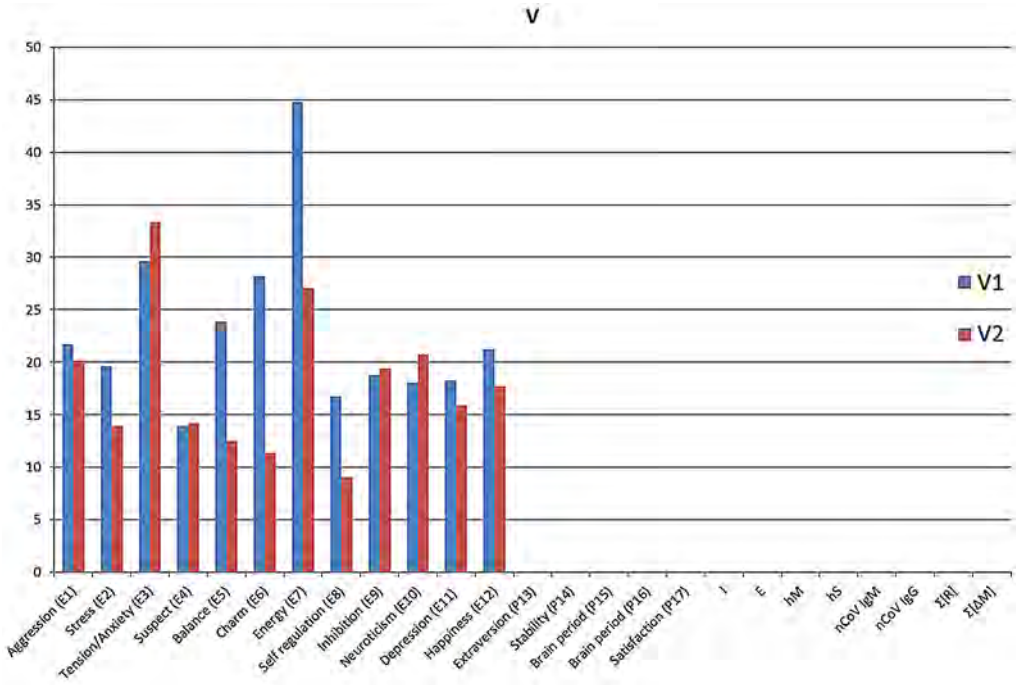

Fig. 4. *Mean of behavioral parameters variability for patients (V1) and control (V2) groups*

The difference of more than 30% in the groups of patients and the control group has variability of five behavioral parameters: E2 (Stress), E5 (Poise), E6 (Charisma), E7 (energy), E8 (Self-regulation), and the variability of the Charisma parameter differs in more than 2 times.

Table 1 shows the results of 12 different experiments to determine the dependence of the number of errors when sorting the results in groups of patients and the control on the structure of the neural network and the number of input behavioral parameters fed to the input layer of neurons.

The results shown in Table 1 show that the number of data parse errors is a complex function, determined by a set of settings, and cannot be directly reduced by increasing the input neurons or input parameters.

Table 1

Dependence of the number of errors number for databases discrimination of patient and control groups on ANNs structure and the number of input behavioral parameters fed to the input layer of neurons at different training times

N	ANN structure	Number of input quantities	Accuracy and Errors (with a training time of 1.5.10 minutes)	Note
1	5 × 1	36 (P12 × 3)	1 min — 491/566 5 min — 496/566 10 min — 497/566 69	Initially new ANN
2	10 × 1	87 (A1F-P4)	1 min — 553/566 5 min — 553/566 10 min — 553/566 13	Initially new ANN
3	10 × 1	40 (T10 + IE + A2 + A3 + + Sat + S(R)	1 min — 558/566 5 min — 559/566 10 min — 559/566 7	Initially new ANN Test with normalization of input data
4	18 × 1	36 (P12 × 3)	1 min — 549/566 5 min — 549/566 10 min — 549/566 17	Initially new ANN
5	30 × 1	30 (P10 × 3)	1 min — 553/566 5 min — 554/566 10 min — 554/566 12	Initially new ANN
6	36 × 1	36 (P12 × 3)	1 min — 553/566 5 min — 553/566 10 min — 554/566 12	Initially new ANN
7	38 × 1	38 (P12 + IE)	1 min — 554/566 5 min — 554/566 10 min — 554/566 12	Initially new ANN
8	72 × 1	36 (P12 × 3)	1 min — 279/566 5 min — 279/566 10 min — 279/566 287	Initially new ANN
9	40 × 20 × 1	12SD Others = 0	1 min — 536/566 5 min — 552/566 10 min — 554/556 12	Initially-trained ANN 26 (M + SD)
10	40 × 20 × 1	12V Others = 0	1 min — 554/566 5 min — 557/566 10 min — 557/566 9	Initially-trained ANN 26 (M + SD)
11	40 × 20 × 1	12M Others = 0	1 min — 547/566 5 min — 560/566 10 min — 560/566 6	Initially-trained ANN 26 (M + SD)
12	40 × 20 × 1	40 (T10 + IE + A2 + A3 + + Sat + S(R)	1 min — 552/566 5 min — 566/566 10 min — 566/566 0!!!	Initially new ANN

Table 2 shows the significance of the behavioral parameters obtained for the first layer of neurons in structure 12 (Table 1). The highlighted line shows the maximum weights of the significance coefficients; they do not differ much for all the given behavioral parameters.

Table 2

Input coefficients significance of behavioral parameters for the first layer of neurons in ANN structure 12. The highlighted line shows the maximum weights of significant coefficients

	Aggression (P7)/M	Aggression (P7)/S	Aggression (P7)/V	Stress (P6)/M	Stress (P6)/S	Stress (P6)/V	Tension/Anxiety (F5X)/M	Tension/Anxiety (F5X)/S	Tension/Anxiety (F5X)/V	Suspect (P19)/M
max(w)	319	123	352	404	132	331	270	115	470	209
	1	2	3	4	5	6	7	8	9	10
	Suspect (P19)/S	Suspect (P19)/V	Balance (P16)/M	Balance (P16)/S	Balance (P16)/V	Charm (P17)/M	Charm (P17)/S	Charm (P17)/V	Energy (P8)/M	Energy (P8)/S
max(w)	101	289	501	220	271	750	270	438	204	139
	11	12	13	14	15	16	17	18	19	20
	Energy (P8)/V	Self regulation (P18)/M	Self regulation (P18)/S	Self regulation (P18)/V	Inhibition (F6)/M	Inhibition (F6)/S	Inhibition (F6)/V	Neuroticism (F9)/M	Neuroticism (F9)/S	Neuroticism (F9)/V
max(w)	616	424	99	144	363	40	268	548	102	297
	21	22	23	24	25	26	27	28	29	30
	A2/M	A2/S	A2/V	A3/M	A3/S	A3/V	I	E	sat	refCor
max(w)	272	303	9	130	363	22	454	359	546	350
	31	32	33	34	35	36	37	38	39	40

The relatively small scatter in the significance (200–500) of most of the behavioral parameters when sorting the data can be explained by the principle of minimum correlation used to calculate behavioral parameters in vibraimage technology (Minkin, 2020). A small number of parameters, including the variability A2 and A3 (significance 9 and 22), are of minimal significance, which can be replaced by more informative ones in further studies.

Discussion

The results presented in Table 1 for the same settings of the linear ANN with an increase in the first line of neurons (structures 1 (5 × 1); 4 (18 × 1); 6 (36 × 1); 8 (72 × 1)) show that the number of sorting errors decreases significantly (from 69 to 12) only until the number of input neurons exceeds the number of input parameters. A significant excess in the number of input neurons (72 by 36 for structure 8) leads to a sharp increase in the sorting errors from 12 to 287.

The number increase of input behavioral parameters (compare the structures of networks 2 and 3) in itself does not lead to an increase in the sorting accuracy for one ANN structure. The number of input parameters 87, the number of errors is 13, and decrease in the number of input parameters to 40 leads to errors decrease to 7.

The results presented in Table 1 for simple linear ANN with only two layers of neurons (input and output layers, structures 1–8) show a sufficiently high informative value of input behavioral parameters for databases discrimination. Therefore, diagnosing COVID-19, since in the best-case structure 3 give discrimination accuracy close to 99% with additional normalization of the input parameters.

The preliminary long-term training of the neural network (more than 24 hours) with incomplete data (variants of network structures 9–11) is inferior in accuracy to the optimized fast learning of the variant of structure 12, in which the data sorting error is reduced to zero.

Of course, the presented databases discrimination results can most likely be even more optimized with an increase in the patient and control group databases, since it is impossible to further improve the sorting algorithm when an error of 0 is reached in the last 12 variant of the NN structure and the optimized flow of input behavioral parameters.

The data from the first layer of ANN (Table 2) can be conditionally considered the real significance of the input parameters, since their significance can change on the hidden layer of structure 12. However, one should not expect a significant change in significance for such a simple ANN structure, which was used in this study.

Statistical processing of the results of studies of the behavioral parameters of the groups of patients and the control, presented in Figures 2–4, also show a high informativity of behavioral parameters for the diagnosis of COVID-19. There are significant differences in the average values of behavioral parameters (6 parameters: E5; E6; E7; E8; P14; E differ by more than 6% between groups), and the threshold of 6% was previously set as a certain limit of the accuracy of the measured parameters of the vibraimage (Minkin, 2019).

SD and variability (Figures 3 and 4) of the behavioral parameters turned out to be even more informative for the standard statistical breakdown of the studied data groups, since the differences in the groups of 6 RMS parameters and 5 variability parameters

exceeded 30%, and the variability of the E6 parameter differs in groups of patients and control more than 2 times.

Most of this article is devoted to the processing of mathematical data, but behind each digit of the behavioral parameters determined by vibraimage technology, there is an objective symptomatology of the disease. The multiple symptoms of COVID-19 (Struyf et al., 2020) find unconditional confirmation in human behavioral responses (increased levels of stress, depression and neuroticism with a decrease in energy, balance, self-regulation and information efficiency) and in significant temporary instability of behavioral parameters.

These changes in behavioral parameters make it possible to diagnose COVID-19 by analyzing reflex head movements due to the vestibular-emotional reflex. The high diagnostic information content of human behavioral parameters makes it possible to sort data on relatively simple structures of the NS, and therefore to diagnose COVID-19 on simple user devices, personal computers and mobile phones.

In future studies, a significant increase in the size of the patient and control group databases is required to transfer the obtained accuracy to a random sample of subjects. The resulting zero error and, accordingly, 100% accuracy, sensitivity, and specificity when sorting data in the above ANN structures are likely to change somewhat with a significant increase in databases.

However, we think that the proposed method for diagnosing COVID-19 when monitoring behavioral parameters using vibraimage technology seems to be quite promising, since the expected drop in accuracy with an increase in the database can be compensated for by an increase in accuracy with an increase in the complexity of the ANN structure and an increase in input behavioral parameters.

In addition, it can be assumed that the proposed method can be universal for the diagnosis of many, if not any, diseases. The transition from biochemical testing to the control of informative reflex movements and behavioral parameters is similar to the transition to green energy compared to fuel, since it is environmentally friendly and does not require significant costs.

Separate consideration should be given to the work on the effectiveness of vaccination against COVID-19 study using the developed technology for diagnosing COVID-19 based on behavioral parameters measured by vibraimage technology. Our preliminary results on several people testing show the appearance of behavioral signs of COVID-19 on 3 days after the first vaccination Sputnik V (Logunov et al., 2021) when no biochemical methods show significant biochemical changes in the human body. In our opinion, this indicates the highest sensitivity of reflex micromovements of a human head and the vestibular-emotional reflex to any pathological processes and insignificant changes in the physiological state. The set of measured behavioral parameters fixed by AI may be more informative than traditional medical and biochemical diagnostic methods.

In addition, a separate consideration is necessary for post-covid-19 rehabilitation processes (Barker-Davies et al., 2020), since the results obtained using the diagnosis of behavioral parameters by AI and vibraimage technology allow to see the behavioral trace from COVID-19 after half a year or more after the disease. The COVID-19 diagnostic method proposed in this publication can be an effective means of monitoring post-covid rehabilitation processes.

Conclusion

The studies have shown the significant significance of most of the behavioral parameters measured by vibraimage technology for the diagnosis of COVID-19. The conducted studies of various ANN structures allowed us to optimize the set of input behavioral parameters and minimize the error to zero when sorting out databases of patients with a confirmed diagnosis of COVID-19 relative to the available control data group.

The set goal of identifying significant behavioral parameters in the diagnosis of COVID-19 can be considered achieved, since 38 out of 40 used mean behavioral parameters showed acceptable significance when sorting databases using synthesized ANN structures. The tasks of optimizing the ANN for sorting out the databases of patient groups and the control group were completed, and 100% accuracy of COVID-19 diagnostics was achieved based on the available results of 536 measurements.

Obtained results make possible to use the developed methodology not only for diagnosing COVID-19, but also for monitoring the effectiveness of vaccination processes against COVID-19 and post-covid-19 rehabilitation of patients.

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