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Modeling of Psychomotor Reactions of a Person Based on Modification of the Tapping Test

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ABSTRACT The paper considers the method for analysis of a psychophysical state of a person on psychomotor indicators – finger tapping test. The app for mobile phone that generalizes the classic tapping test is developed for experiments. Developed tool allows collecting samples and analyzing them like individual experiments and like dataset as a whole. The data based on statistical methods and optimization of hyperparameters is investigated for anomalies, and an algorithm for reducing their number is developed. The machine learning model is used to predict different features of the dataset. These experiments demonstrate the data structure obtained using finger tapping test. As a result, we gained knowledge of how to conduct experiments for better generalization of the model in future. A method for removing anomalies is developed and it can be used in further research to increase an accuracy of the model. Developed model is a multilayer recurrent neural network that works well with the classification of time series. Error of model learning on a synthetic dataset is 1.5% and on a real data from similar distribution is 5%.

KEYWORDS tapping test; mathematical modeling; psychomotor reactions; time series; recurrent neural network.

I. INTRODUCTION

DETERMINING the basic properties of the nervous system is directly related to both theoretical and applied research [1-2]. The finger-tapping test (FTT) has been used for almost a century to evaluate muscle control and motor ability in the upper extremities [3]. FTT is frequently used to quantitatively evaluate patients with Parkinson's disease [4], ataxia [5], Alzheimer's disease [6], and Korsakoff syndrome [7], as well as in individuals who have suffered an acute stroke [8]. Also, FTT is widely used to evaluate motor function in the upper limbs [9-11]. At the moment, with this type of testing, the results are checked by experienced doctors and conclusions are made about the psychophysical state of the person. But with the rapid development of machine learning (ML) algorithms, they rapidly began to be used in medicine. There are a number of different quantitative models that can be used in a medical diagnostic decision support system including parametric methods, non-parametric methods and several neural network models [12, 13].

In medicine, modeling the human psychophysical state can help to better understand the nature of some mental illness. This helps in determining a more accurate diagnosis of the patient. Also, after difficult operations, it is possible to monitor the change in the psychophysical state of a person that allows preventing the occurrence of stress, which will adversely affect the state of health. APSP helps in selecting candidates for the position who need a stable nervous system. In other words, having some tools of APSP in the form of a set of mathematical models can improve the quality of selection of individuals by the level of stability of the nervous system.

There are rapid methods for determining the stability of the nervous system and the balance of nervous processes on psychomotor parameters, which were developed by E.P. Ilyn. One of the most well-known methods of determining the stability of the nervous system is the tapping test. Based on it, five types of dynamics of the maximum pace of work can be distinguished: convex type (indicates the presence of a strong nervous system); straight type (nervous system of medium strength); intermediate and concave types (middle or weak nervous system); degressive type (weak nervous system) [14]. This division is designed for testing using simple tools like a pen and a sheet of paper. The process of passing the classic tapping test is quick and simple, but it has a negative side: most of the useful information is lost.

The object of the research is the psychomotor learning (the relationship between cognitive functions and physical movement). The subject of the research – the relationship between psychomotor indicators obtained as a result of FTT and other psychological indicators. The purpose of this work is to develop a model for the classification of the psychophysical state of a person (based on the FTT) in the form of a set of layers of different neural network (NN) architectures with certain hyperparameters, develop a software product for conducting FTT as an application and develop a method for reducing anomalies that will be used before NN.

The model in the context of this work is a set of mathematical equations and algorithms that generally form an architecture, in which, by inputting data of a certain structure (in our case it is a vector that describes the time series), we obtain other data that can also be categorical. This model must be flexible enough (it must contain a number of hyperparameters) so that it can be used for different samples. This architecture consists of two parts and will be considered in this paper as a description of its high-level components.

The experiments demonstrate the structure of the data obtained using the tapping test. As a result of the study, we gained knowledge of how to conduct experiments so that the model is better generalized in the future. A method for eliminating some anomalies is developed, which can be used in further research to increase the accuracy of the model. The method has two hyperparameters that are selected when model training. A model is developed – a multilayer neural network that works well with the classification of time series. This is an important aspect of the analysis of the psychophysical state of a person.

The range of applied tasks is very wide. The model can be used, first of all, in the process of candidate selection for a position that requires a stable nervous system, for example, in selecting a candidate head of some governmental institution. Also considered mathematical modeling can be used in medicine, for example, to determine how a particular method of treatment affects the psychophysical state of a person.

The remainder of this paper is organized as follows: the analysis of modern literature is presented in Section 2. Materials and methods are presented in Section 3. Subsection 3.1 is about an app that we used for conducting a test. Subsection 3.2 is about data preparation and Subsection 3.3 describes the modeling. Section 4 is a result of experiments and model training. Section 5 reveals a discussion about different methods of data collecting. Section 6 concludes the paper and determines the prospects for further research.

II. LITERATURE ANALYSIS

A fairly accurate way to analyze data from different areas of medicine is the use of machine learning models [15]. In particular, computer vision has become widely popular [16]. Often, if the dimension of the input data is the same, it is possible to do with conventional models, for example, as regression or support vector machine [17]. But recurrent neural networks have a great potential in medicine [17, 25]. This is a class of neural networks in which connections between nodes make a time-oriented graph. Due to this, they work well with sequences of different dimensions. If we used classical models of machine learning (Support Vector Machine, Random Forest, etc.), then we would need to describe the time series by some numerical characteristics. In this modeling, is first needed to consider *n* (number of clicks). It is also needed to describe the time series with the following numerical characteristics: average value, median, modus, standard deviation, minimum, maximum, etc.

On the other hand, the use of appropriate models for the problems of classification, clustering, regression [19-21] requires a fairly large amount of data [15]. This amount of data is difficult to obtain because experiments usually require special equipment. With the development of technology, some methods can be simplified and easily used on conventional devices like personal computer or mobile phone. One such method is – FTT [22]. Of course, they give a fairly large error [23], but due to the fact that they are mobile, it is possible to collect a lot of data, which makes it possible to use machine learning models for various problems [24].

III. MATERIAL AND METHODS

A. FORMULATION OF THE PROBLEM

A person clicks the index finger of the right hand on some location of the device as many times as possible over a period of time (one minute). Since the device records the time of each press, the result can be represented as a vector like this:

$$X = (t_2, ..., t_n), \quad (1)$$

where *i*-th element t_i – time (in seconds), when the user clicks on the device for the *i*-th time. More important is the length of time between clicks. Number of clicks will always be one more than number of time intervals between those clicks. This is the reason that (1) does not have t_1 in order for the dimension X to be equivalent to the dimension Y. The latter is defined as follows:

$$Y = (t_2 - t_1, t_3 - t_2, ..., t_n - t_{n-1}) . \tag{2}$$

The content of this vector is as follows: *i*-th element – time between i+1-th and i-th clicks. The same dimension (1) and (2) are required to visualize time series. Elimination of anomalies is important in further analysis, which uses models that are sensitive to anomalies.

It is necessary to consider models that work with different dimensions of input data, because for each experiment the number of presses n on the device will be not the same. As for part of modeling, consider the problem of classification. Suppose there are N classes of various mental illnesses C_1, C_2, …, C_N and testing is performed on M individuals. In fact, it does not have to be a disease. This can be, for example, a type of psychophysical state of a person. Then, after all experiments, we will have a data Table 1 with a series and a target value.

Table 1. View data after collecting them for the problem of classifying time series

(X, Y)	C_1	C_2	…	C_N
(X_1, Y_1)	c_{11}	c_{12}	…	c_{1N}
(X_2, Y_2)	c_{21}	c_{22}	…	c_{2N}
…	…	…	…	…
(X_M, Y_M)	c_{M1}	c_{M2}	…	c_{MN}

Where $c_{ij} = 1$, $i = \overline{1, M}$; $j = \overline{1, N}$ when person i has C_j disease. In other cases, $c_{ij} = 0$. Once we have trained the model on this data, we can perform an FTT test on a patient whose diagnosis is unknown and get a vector (X, Y). Submit this vector like input to the trained model and at the output get the next vector: $C_k = (c_{k1}, c_{k2}, ..., c_{kN})$, $k = \overline{1, M}$; $I_k = \arg\max_i C_{ki}$, $i = \overline{1, N}$, that is, the person who passed the test most likely belongs to the i-th class according to Table 1. We can say that the closer the c_{ki} to 1, the more likely the patient has C_i disease. C_k can be classified as a categorical distribution. The vector C_k shows that according to some data the probability of belonging to a series of one class is greater than the probability of belonging to another class.

B. FTT

FTT is one of the most common tests for a person's psychophysical condition, which is quite mobile and does not require specialized equipment. For our series of experiments, a program was developed that summarizes the classic FTT. Its essence is that a person for 60 seconds clicks the index finger of his right hand on a special place of the device. We chose a smartphone as a device.

Fig. 1 presents the main page of the application, which was developed by us for the experiment. The application contains one button, clicking on which testing begins. The view of the main page of the application after pressing the button is shown in Fig. 2. Then the timer is started for 60 seconds and the time of each subsequent press and their total number is recorded. It is also important that the person taking the test follows certain rules: the palm should lie on the table, and the index finger, which should press on the device under it, should be straightened. It is also important to have as few people as possible in the room. It is necessary to isolate as much as possible from various external factors to the person who passes the experiment.

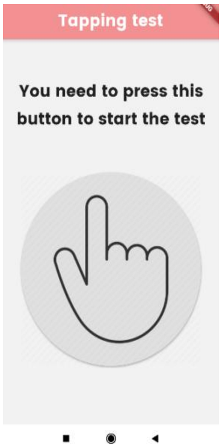

Figure 1. The main page of the application

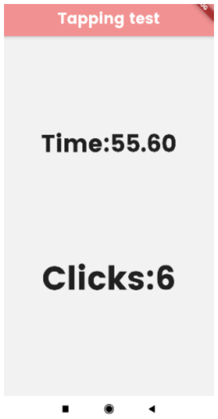

Figure 2. The main page of the application is activated

C. DATA PREPARATION

Since the model to be used is quite sensitive to anomalies and due to the large number of these anomalies can be poorly generalized. It is necessary to develop a method to reduce the number of these anomalies. Obviously, in this case, the anomalies can be considered too large values y_i that deviate greatly from the standard deviation or are much larger than it. To do this, we use the following formula:

$$y_i := \min(y_i, aM(Y) + b\sigma(Y)), i = \overline{1, n}, \quad (3)$$

where, the hyperparameters *a*, *b* will be determined in the process of conducting numerical experiments. $M(Y)$ – mean value of *Y*. $\boldsymbol{\sigma}(Y)$ – standard deviation of *Y*.

D. MODELING

Unlike direct propagation neural networks, in which the signal propagates strictly from the output of one layer to another, RNNs (recurrent neural networks) use their internal memory to process arbitrary sequences of inputs [25], and therefore can be used in solving our problem. The target label can be different: in the case of regression – a number, in the case of classification – a class. This article will consider the problem of classification, because it has more nuances when working with weight optimization, error function, accuracy metrics, etc. The first step is to choose the specific architecture of the recurrent neural network that will be used in the model. There are several, but we will consider two: the classical recurrent neural network and the long short-term memory (LSTM) architecture, which we will use in our research.

Fig. 3 shows a fragment of a neural network. The relationship between neurons in time and the method of calculating their output is given by the following relations:

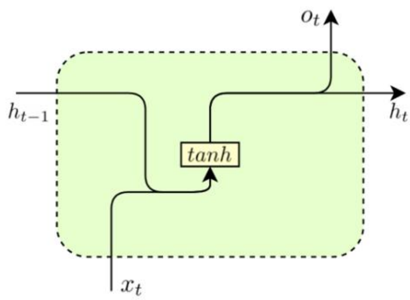

Figure 3. Schematic representation of a fragment of a classical recurrent neural network

$$h_t = \tanh(W_h x_t + U_h h_{t-1} + b_h)$$
$$o_t = \tanh(W_o h_t + b_o),$$

where h_t – vector of the hidden layer of the neural network; o_t – vector of the output layer; W, U, b – matrix and vector of weights; x_t – vector of the input layer.

This architecture can use recursive communication to store previous information. This makes it adapted to the input data of different dimensions, which is required for our task. However, the data presented initially in the last iterations have very little effect on the definition of the class. In our case, the number of elements is quite large, and for correct prediction is needed to remember a lot of data. Classical RNN may perform poorly in data of this type due to the problem of long-term dependencies [26]. One of the solutions is to use its modification – LSTM with which there are no similar problems. LSTM is a type of RNN architecture that works well with long-term dependencies. It was proposed by Sepp Hochreiter and Jürgen Schmidhuber in 1997. The LSTM structure also unfolds in time like the classical RNN, but has a slightly different architecture of layers that interact in a special way. Schematically, the structure of the neuron at time *t* is shown in Fig. 4.

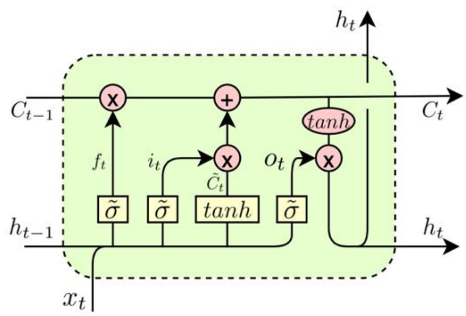

Figure 4. Schematic representation of the LSTM architecture

The relationship between neurons in time and the method of calculating their output is given by the following relations:

$$h_t = o_t * \tanh(C_t), \text{ where}$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o),$$
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t, \text{ where}$$
$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c),$$
$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f),$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i),$$

where σ, tanh – activation functions. Square brackets mean that values will be converted to a single vector.

We can get acquainted with this architecture in more detail by following the references [17, 25, 27]. Therefore, LSTM will be used in this model as the first layer of the neural network. This is done in order to first use LSTM to reduce the data to a fixed dimension, and only then apply the data to subsequent layers of neurons of another type (such as fully connected).

The LSTM architecture is typically used to predict the behavior of the time series in subsequent moments of time. That is, h_t is the prediction of y_t. But in our case, it is necessary to characterize the time series. To do this, we will supply the LSTM outputs to a fully connected neural network with a fixed number of neurons. Select the activation function *relu*.

$$relu(z) = \max(0, z),$$

where z – input value of the neuron.

We can put several layers of fully connected neural networks and apply the outputs of the previous one to the input of the next layer. The last layer, namely the number of its neurons and the activation function will depend on the problem:

1. In the classification problem, this layer will have the number of neurons equal to the number of existing classes and the softmax activation function:

$$softmax(\boldsymbol{p})_j = \frac{e^{p_j}}{\sum_{k=1}^{K} e^{p_k}}, j = \overline{1, K},$$

where K – the dimension of the output of the previous layer, p – K-dimensional vector with arbitrary component values. Component of vector $softmax(p)$ belongs to the area [0, 1] and gives a total of one.

2. In the regression problem, the last layer must have a dimension equal to the number of values that we want to predict. The activation function can be both *relu* and linear, depending on the numerical range on which the value that we predict may exist. In the case of *relu*, these are only positive numbers, and linear is the entire numerical axis.

We consider the problem of classification. As in our case, without reducing the generality, we will have two classes, then to determine the accuracy of the model we will use the area under receiver operating characteristic (ROC) curve (AUC) – the area bounded by the ROC – curve and the axis of the error rate of positive classifications. The AUC metric was chosen to show the accuracy of the model in more intuitive format. The AUC shows accuracy well on asymmetric datasets [28] (when objects of one class are much more frequent than objects of another class). AUC is used for binary classification, but there is a variation for many classes. Again, it is worth emphasizing why classical algorithms were not used for this, such as Bayes, logistic regression, support vector machine, random forest for classification, etc. The main reason is that these algorithms do not work with data of indefinite dimension, as in our case. Therefore, the only way out is to use models that assume this, which was proposed in the paper.

To optimize the weights (for both LSTM and feed forward neural network), a gradient descent was used in the work, namely its modification – Adam [29]. Partial derivatives are calculated using the backpropagation method [30]. So, we have a model that consists of the following submodels: anomaly liquidation and neural network [30].

First, all data is partially cleared using (3), and then fed to the neural network. The number of neurons in each layer was selected by us using cross-validation [31]. If the accuracy on the validation data began to decrease sharply when the accuracy on the training increased, then we decreased the number of neurons in one of the layers. If the model showed a poor result on both training and validation data, we increased the number of neurons. In total, the neural network looks like this:

1) LSTM – 128 neurons;
2) FNN (Feedforward neural network) with relu
3) activation – 64 neurons;
4) FNN with relu activation – 32 neurons;
5) FNN with softmax. The output dimension is N, where N is the number of classes.

Cross entropy will be used as a function of error:

$$L = H(y, \hat{y}) = -\sum_{i=1}^{N}(y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)).$$

Here $\hat{y}_i$ is the probability of obtaining a class, and y_i is the real probability. y_i will be equal to 1 only in one case: when i is a valid class. In other words, this function shows the degree of similarity of the two categorical distributions y_i, $\hat{y}_i$ and the smaller the value, the more the output of the model is similar to the actual correspondence of classes and time series. The complete model for the analysis with all its components can be represented as it is seen in Fig. 5.

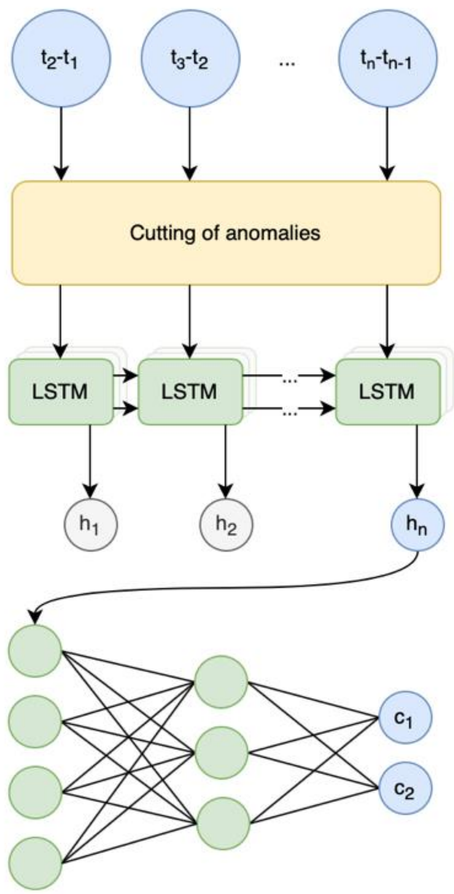

Figure 5. Schematic representation of architecture

After the anomalies in the vector Y are cut off, it is fed to a layer of neurons of the LSTM (long short-term memory) type. After the series passes through this layer, the last value is taken (it stores information about the previous behavior of the time series).

The resulting vector is fed to the first layer of FNN with the function of activation *relu*. The last layer should be the softmax activation function in order to classify the resulting vector as a categorical probability distribution. When learning, the outputs of the last layer will take into account the calculation of the error L, which is differentiated, which allows to apply the backpropagation method.

IV. RESULTS

A. RESULTS OF FTT EXPERIMENTS

The study involved 30 people with a mean age of 30 years and a standard deviation from it – 15 years. Participants were asked to perform the test with the index finger of their right hand for 60 seconds. Before dealing directly with the model (its testing), it is worth looking at the visualization of the time series (X, Y) of some individual experiments to better understand the structure of the data. In Fig. 6–9 red lines show the cut boundaries of the anomalies, which are based on formula (3).

The hyperparameters a and b are equal to 1, 3, respectively, and were selected using a grid search and rounded to the nearest whole number. It is important to note these hyperparameters received during the training of the model on the simulated data. In fact, when conducting large experiments (with a large amount of data) we need to look again for these hyperparameters under the collected dataset in order to increase the accuracy of the obtained data.

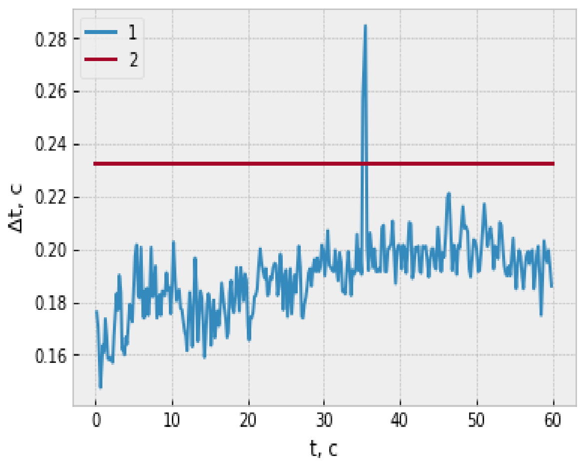

Figure 6. 1 – time series of the first experiment; 2 – value of the cut anomalies

In the case presented in Fig. 6, we see one anomaly (peak on the upper side of line 2 at t = 35.876), which stands out against the background of other data. After application (3), it will be equal to 0.233. In this case (3) works correctly, because during the experiment the person was really distracted for a split second.

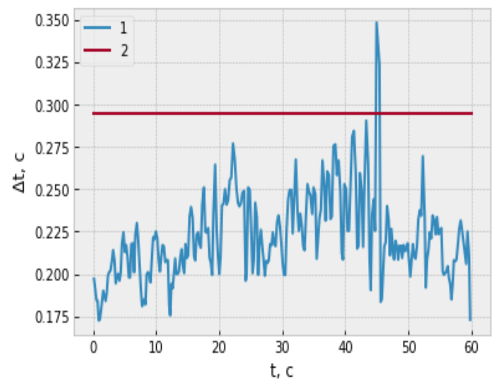

Figure 7. 1 – time series of the second experiment; 2 – value of the cut anomalies

In Fig. 7 we also see the anomaly, which will be cut before applying to the input of the model. This case is similar to the previous one.

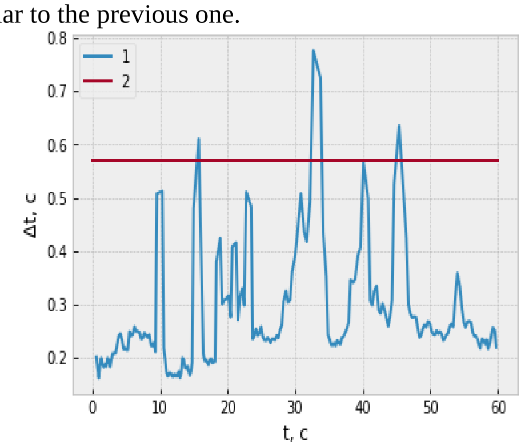

Figure 8. 1 – time series of the third experiment; 2 – value of the cut anomalies

The case presented in Fig. 8 differs from the previous two because it has a much larger variance. The person who was taking the test was almost not distracted, and the presence of such peaks indicates a psychophysical state, so most of them will not be cut.

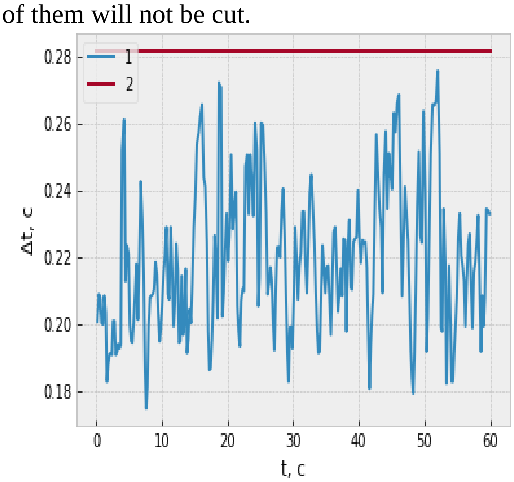

Figure 9. 1 – time series of the fourth experiment; 2 – value of the cut anomalies

The case of Fig. 9 has a minimum variance (it is worth paying attention to the scale of the vertical axis), so there are no anomalies in it. In the same form it will be submitted to the model. The result of application (3) is true, the person was not distracted by external factors when undergoing testing.

The results of all thirty experiments are given below in the form of histograms – a method of presenting tabular data (see Fig. 10-12). This is done in order to get acquainted with the distributions of some numerical characteristics of the time series of experiments.

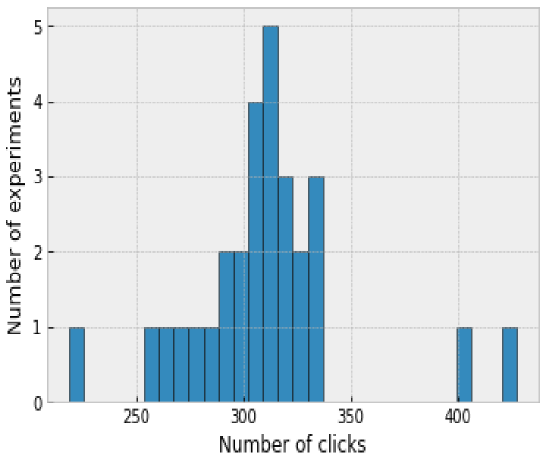

Figure 10. Histogram of the distribution of the number of clicks N

The width of the column indicates the range, and the height indicates the number of experiments that belong to that range. Analyzing the histogram in Figure 10 it can be concluded that the average value of the number of clicks of the thirty experiments is concentrated in the vicinity of 310 clicks. We can also see that in two experiments, people were able to click more than 400 times on the device.

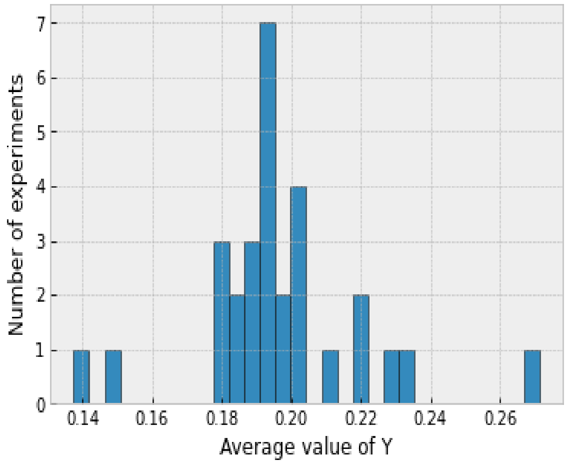

Figure 11. Distribution diagram of the average value of Y

As the number of experiments increases (with large-scale data collection), it is likely that the distribution of the number of clicks will be very similar to that shown in Fig. 11, and this can be quite helpful in subsequent studies. An overview of what data to expect and which models to use appears. Below is another histogram of the distribution of the standard deviation of each experiment (see Fig. 12).

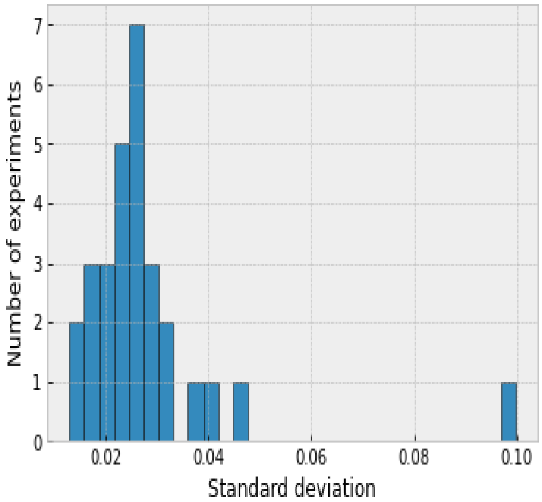

Figure 12. The distribution diagram of the standard deviation

B. RESULT OF MODEL LEARNING

Unfortunately, little research has been done on data collection based on the tapping test, as this requires knowledge in the development and design of information systems, and therefore there are not enough data sets to test the developed model. Of course, with the development of technology this will change, but now, to test the developed model on data of this type, it is necessary to test it first on synthetic data, and then on data from another distribution, but similar to the data of the tapping test (one-dimensional time series). So we proposed a synthetic data generator, the operation of which is explained below.

B.1 RESULT OF MODEL LEARNING ON A SYNTHETIC DATASET

The synthetic data generator works as follows:

1. One of the functions is randomly selected (uniform distribution):

   a. $g_1(x) = 0.005(x-30)^2 + 0.3;$

   b. $g_2(x) = -0.005(x-30)^2 + 0.5.$

2. m numbers are generated on the interval [0, 60] (uniform distribution). m is also chosen randomly from the interval [200, 400].
3. Each of the numbers is fed into a randomly selected function g_i and r is added – a normally distributed quantity with a mathematical expectation of zero and a variance of two (for each number in the

series it is generated again): $r \sim \mathcal{N}(\mu = 0, \sigma^2 = 2)$ The target label is a randomly selected function, and the data is the resulting vector.

The model was trained in 40 epochs. Optimization was performed using a mini-batch gradient descent. The dataset was generated in 100,000 rows and divided into 2 subsets in the ratio 1/3: 2/3 – training and validation. The model was trained on the training subset, and the final accuracy was displayed on the validation subset. Also on the validation subset the model is checked for overfitting [14].

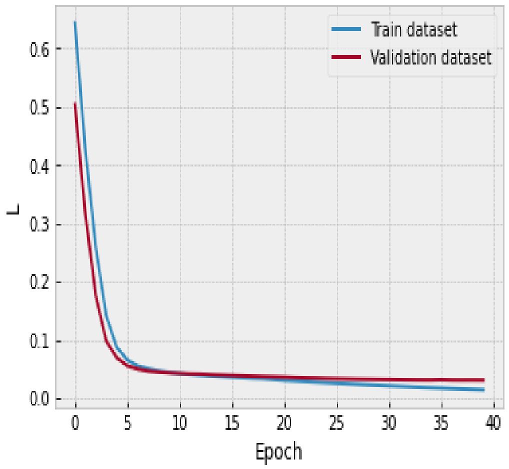

Figure 13. Changing the error function on the training and validation subset, where L is the value of the error function

In order to show the learning speed of the model, the following graphs are used: change in AUC (see Fig. 14) and error functions with each epoch (see Fig. 13).

In the fifteenth epoch, the model showed an AUC of 0.9913, and in the last fortieth – 0.9976 (AUC is measured from zero to one, and the higher the value, the more accurate the model). The error L in the fortieth epoch was 0.0146.

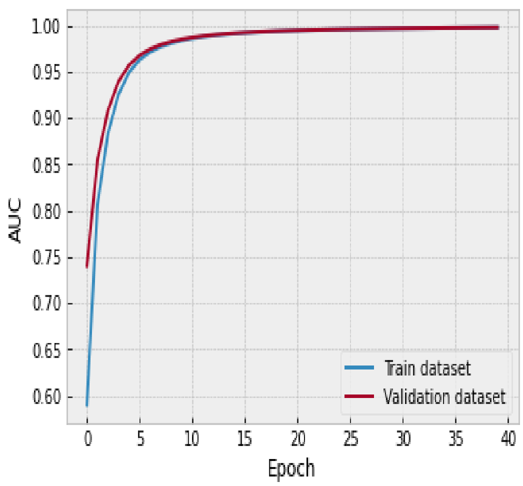

Figure 14. Changing the accuracy of the AUC on the training and validation subset

Below, Fig. 15 shows the results of solving the problem of classification on synthetic data on specific examples.

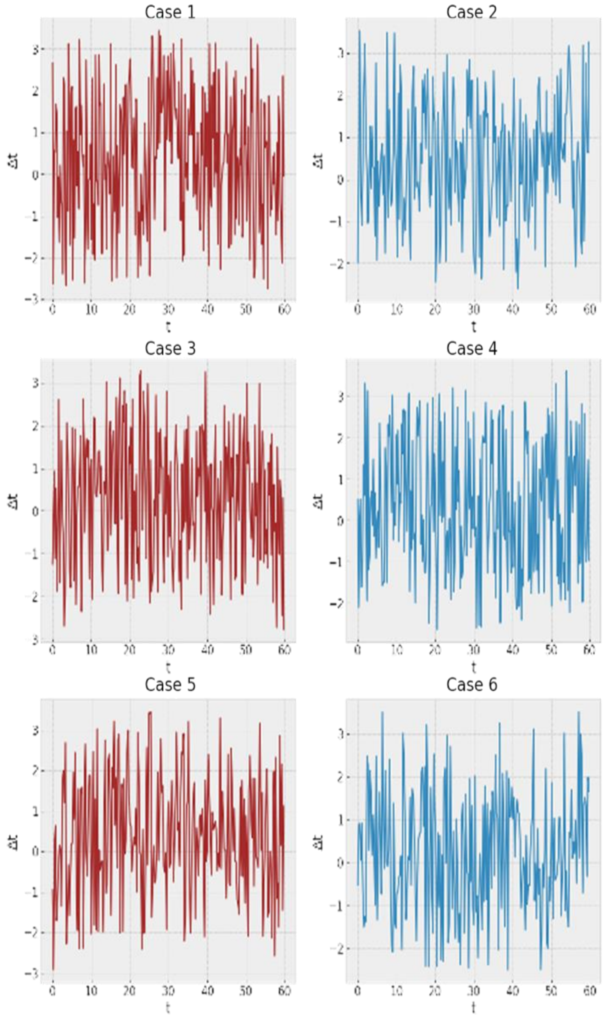

Figure 15. The results of solving the classification problem on specific examples (blue graphs – classes of function a, red – classes of function b)

Table 2. Probability of time series belonging to the class

Case	g_1	g_2
1	**0.9996**	0.0004
2	0.0010	**0.9990**
3	**0.9991**	0.0009
4	0.0050	**0.9950**
5	**0.9989**	0.0011
6	0.0013	**0.9987**

In Table 2 a bold font indicates valid classes (of which there were two for this test). Columns g_1, g_2 are responsible for predicting the probability with which the series belongs to a certain class. As we can see, the model predicts the correct classes with high accuracy.

B.2 RESULTS OF MODEL LEARNING ON A REAL DATA WITH SIMILAR STRUCTURE

Also, by encoding words, the problem of text classification can be reduced to this task. There are many datasets on this issue. We selected an imdb dataset from the keras library [33]. Its dimension is 50,000 rows divided into 3 classes. This dataset was also divided into 2 subsets, but in another proportion in order to provide more data for training: 35,000 elements for training and 15,000 elements for validation. Also, in order to show the learning speed of the model, the following graphs were used: change in AUC (Fig. 16) and error functions with each epoch (Fig. 17).

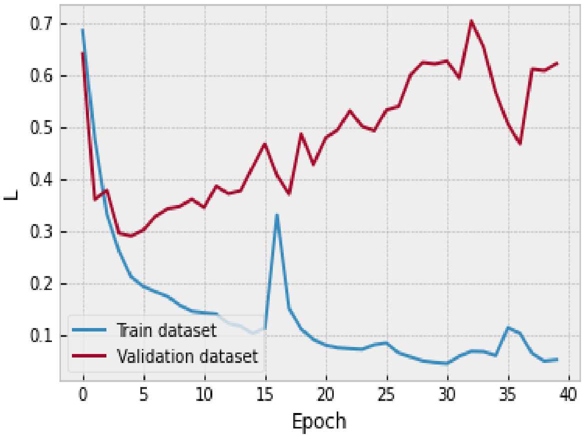

Figure 16. Changing the error function on the training and validation subset, where L is the value of the error function

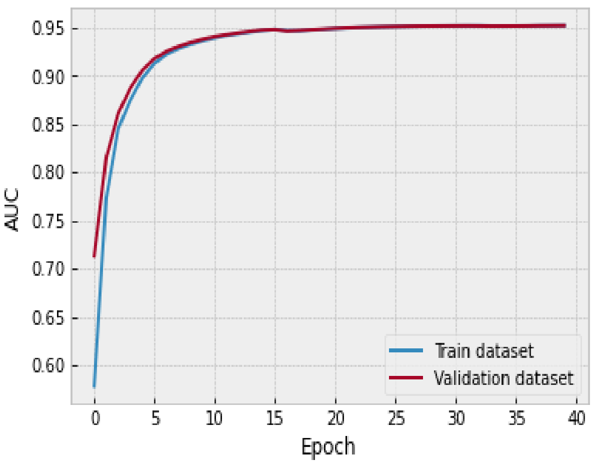

Figure 17. Changing the accuracy of the AUC on the training and validation subset

In the fifteenth epoch, the model showed an AUC of 0.9472, and in the last fortieth – 0.9518. This indicates that the model is quite powerful and copes with such complex data as text. The error L in the last epoch was equal to 0.0530. The best error is between the fifth and tenth epoch with respect to the validation dataset. The error on the validation dataset indicates that after 20 epochs, the model is overfitted.

V. DISCUSSION

Another method of reading data to analyze the psychophysical state of a person is the keyboard typing test (KTT) [34]. The essence of KTT is that a person enters arbitrary text on the keyboard for a certain period of time. The time when she/he pressed the key and when she/he released the key is recorded. The key pressed is also recorded. So, as a result, we have two vectors and an array with the keys pressed:

$$X_1 = (t_{11}, t_{12}, ..., t_{1n}),$$
$$X_2 = (t_{21}, t_{22}, ..., t_{2n}),$$
$$K = [k_1, k_2, ..., k_n].$$

Vector ΔX: $\Delta X = X_2 - X_1$ indicates how long the key has been pressed.

For comparison, consider the results of an experiment involving 85 people [23] (see Fig. 18). Participants were asked to enter any text on the computer keyboard.

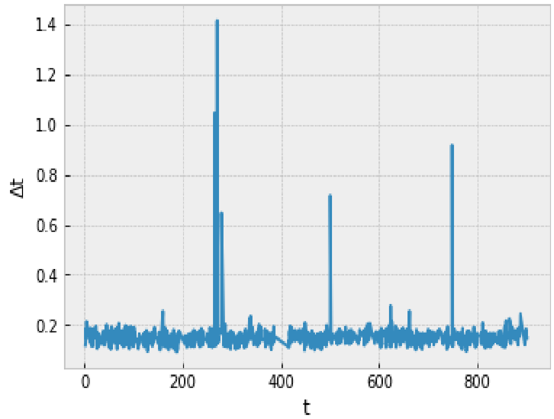

Figure 18. Time series before reducing anomalies

As we can see in Fig. 18, KTT results also show anomalies. They can be removed using equation (3) to increase the accuracy of the model. Fig. 19 shows that after reducing the anomalies, the points that are far from the average value became equal to 0.341.

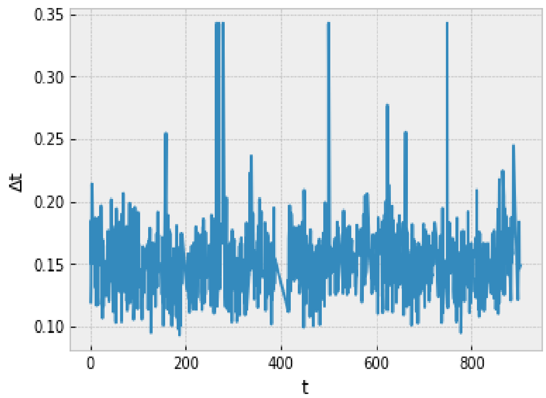

Figure 19 – Time series after reduction of anomalies

Both methods (FTT, KTT) demonstrate well the motility of the fingers of persons who were tested. When conducting the experiment, we noted exactly how in the case of FTT we need to click on the device: we need to put our hand on the table and with our index finger, without bending it, click on a certain place on the device. But often people broke these rules. In general, both in FTT and in KTT, external factors strongly influenced the result.

There are many methods for reading data similar to a tapping test or a keyboard typing test. With the right approach in terms of analysis, we can achieve good results in identifying special patterns and relationships between motor skills and psychophysical state of a person. This can be applied in many of the areas mentioned earlier. One such approach is proposed and analyzed in this article. It is with the use of neural networks, in particular LSTM, and with the correct collection of data, that one can find these connections and patterns that one might never find by relying on intuition.

VI. CONCLUSION

In this paper, a model for classification of a psychophysical state of a person on psychomotor indicators based on recurrent neural networks is developed. The model is implemented programmatically and tested on synthetic and real data from similar distribution. For forty learning epochs, the model showed 99% AUC on synthetic data, and 95% AUC on data from another distribution. A software product is developed that accurately records the moments of clicks and with which data is collected. Based on the investigation, it is analyzed how to conduct experiments for better model generalization in future. More specifically, external factors should be eliminated as much as possible, and the person being tested should be monitored so that he or she does not break the rules. In general, the conducted research can serve as an excellent basis for other investigations in different directions, such as:

1. Selection of candidates for a position that requires a stable nervous system;
2. Detection and investigation of different diseases related to psychophysical state of a person;
3. Monitoring of psychophysical state of a person after medical operations using deep learning models.

It also could be something related to optimization of model for getting better accuracy.

Our approach combines robust machine learning architectures and statistical methods. We hope that the proposed approach will be useful for future investigations of psychophysical state.

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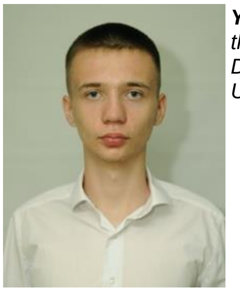

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