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NEURAL NETWORK MODEL OF ARTIFICIAL INTELLIGENCE FOR HANDWRITING RECOGNITION

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ABSTRACT

The problem of handwritten symbols recognition has been investigated in the paper. The main aim of this paper is to present a new neural network model (NNM) of artificial intelligence (AI) for handwriting recognition. The handwriting includes only Cyrillic capital and small letters of the Russian language. The recognition system consists of two subsystems: first neural network and second neural network. The neural networks we used for recognition of handwriting and in particular for gender classification (man or woman). The method (neural network technologies) has been applied successfully to design biometrical system for Automated Factographic Information Retrieval System (AFIRS). The neural network algorithm for handwriting recognition in AFIRS was developed. The experimental results were obtained. Experimental test of used techniques and the accuracy of recognition of a sex of the executor of the hand-written text received as a result of the test are described briefly.

Keywords: *Neural Network Model, Handwriting Recognition, Feature Extraction, Classification, Artificial Intelligence, Writer Verification*

1. INTRODUCTION

Artificial neural networks (ANNs) [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11] have been used [10] for handwriting recognition. The ANNs were invented many years ago back in the previous century. Warren S. McCulloch and Walter Pitts [8] created a very important model for neural network (NN) in 1943. For example a simple artificial neuron was the Threshold Logic Unit (TLU). The interest of scientists in such networks appeared in the 1960s after the publication of the classical book by F. Rosenblatt [9]. In this book [9] F. Rosenblatt investigated multilayer systems with layers consisting of special links of elements.

In 1957 F. Rosenblatt invented a linear classifier called the perceptron. This perceptron is the simplest type of feed-forward ANN. The perceptrons of F. Rosenblatt [9] were very popular in the latest '50s and '60s of the previous century. He studied a perceptron. Perceptrons are a special type of neural network. He developed and extended this approach in his book [9]. It is well known that F. Rosenblatt received international recognition for the perceptron. In some cases [11] the perceptron of F. Rosenblatt (PofFR) is considered as a one-layer perceptron. A three-layered PofFR is usually mentioned [11] in historical context (Note: F. Rosenblatt investigated three-layered perceptrons). A three-layer PofFR contains [9, 11] a sensor layer S, an associative layer A and a reaction layer R (Fig. 1). A neural network represents a highly parallelised dynamic system [1].

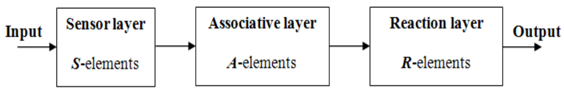

Figure. 1: Three-layer perceptron of F. Rosenblatt

Today in some papers [11] the Rosenblatt perceptron is used for handwritten digit recognition (special database was used: 60,000 samples of handwritten digits were used for perceptron training, and 10,000 samples for testing). In [11] the recognition rate of 99.2% was obtained. It is important to note that [11] fast training convergence and a simple device structure made this perceptron attractive for researchers. However, some important problems remain unsolved – for example:

– recognition age of a person by handwriting;
– recognition of sex (man or woman) by handwriting;
– recognition of psychological characteristics of a person by handwriting.

There are typical scientific areas of applications for ANNs:

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- approximation of functions;
- prediction/forecasting;
- clustering;
- classification (pattern recognition);
- associative memory;
- control;
- optimisation;
- and many other areas.

Today neural networks [1, 2, 3, 4, 5, 6] are very popular in the world and particularly in the field of neurocomputers [1]. For example, in article [3] a decision-making rule of the neural networks committee for ill-posed approximation problems was considered. A probabilistic neural network model and a deterministic neural network model are used in article [1]. The method from [7] was used for the given neural network modeling. Probabilistic neural networks (PNN) [2, 6] are an important case of neural networks. PNN can be used for the recognition of psychological features. These psychological features were extracted from handwriting. Automated Factographic Information Retrieval System (AFIRS) [4] are a special case of question-answer systems (QA systems) [12, 13] or database fact retrieval systems [14]. This AFIRS [4] in its structure contains biometrical systems to enable recognition of a person. To develop this biometrical system we used neural networks [4].

Handwriting [4, 5, 15, 16, 17, 18, 19] is a very interesting and difficult object for recognition. For example: handwriting recognition [15], writer identification (handwriting identification) [5, 15, 16, 17], writer verification [16, 17, 19] or even writer classification [4].

Forensic [5] methods consist of multi-disciplinary approaches to perform important tasks. For example: handwriting recognition, writer classification and writer verification, as well as statistical pattern recognition [20]. Methods of machine intelligence [21] and artificial intelligence [22, 23] offer the possibility of being able to recognise handwriting. The methods of quantum computing [24] are the most prospective for such recognition.

There are many disadvantages to existing methods of pattern recognition, for example:

There is no NNM of AI to recognize the age of the person by handwriting.

There is no NNM of AI to recognize the sex (man or woman) by handwriting.

There is no estimation method for the probability of error classification for Cyrillic capital letters of the Russian language.

We have established the following objectives. We want to get the answers to these important and up-to-date questions:

Is there a neural network model of AI able to recognise the sex by handwriting?

What is the estimation of probability of error classification for the Cyrillic capital letters of the Russian language?

Therefore in this paper we suggest a new algorithm of pattern recognition and NNM of AI to recognize the sex of a person by their handwriting.

2. FEATURE EXTRACTION

Usually handwriting attributes (features) are extracted from handwriting by means of automatic unit or with the help of an expert (i.e. manually). These features are input data for our neural network model of artificial intelligence. One example of handwriting is shown in Fig. 2. The modern Russian alphabet is shown in Fig. 3. The reduced Russian alphabet is shown in Fig. 4. Some important problems were considered in the indicated articles [4, 5, 15, 16].

This paper [4] deals with the problem of biometric systems of identification for automated factographic information retrieval systems.

This paper [5] concerns the problem of the neural networks for the forensic handwriting Russian expert.

These papers [15, 16] are concerned with the problem of on-line and off-line handwriting recognition in [15] and writer identification for Chinese handwriting in [16].

3. HANDWRITING FEATURES

All features of lower case letters were combined in one abstract letter (some symbol). Let us denote it as **S**. The modified Russian alphabet is shown in Fig. 5. We used one logical letter **S** for all features of lower case letters. The final Russian alphabet is shown in Fig. 6.

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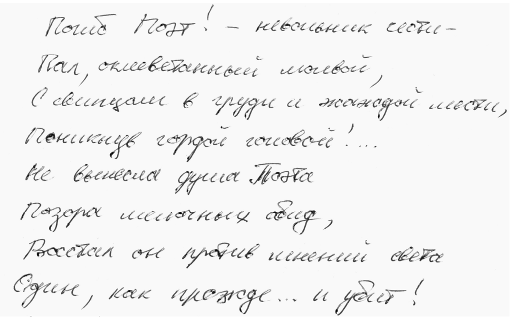


Figure 2: Example of handwritten text [5]

А а	Б б	В в	Г г	Д д	Е е	Ё ё
Ж ж	З з	И и	Й й	К к	Л л	М м
Н н	О о	П п	Р р	С с	Т т	У у
Ф ф	Х х	Ц ц	Ч ч	Ш ш	Щ щ	Ъ ъ
Ы ы	Ь ь	Э э	Ю ю	Я я		

Figure 3. Russian alphabet (33 letters)

А а	Б б	В в	Г г	Д д	Е е	
Ж ж	З з	И и		К к	Л л	М м
Н н	О о	П п	Р р	С с	Т т	У у
Ф ф	Х х	Ц ц	Ч ч	Ш ш	Щ щ	
		Э э	Ю ю	Я я		

Figure 4. The reduced alphabet of Russian (28 letters)

А	Б	В	Г	Д	Е	
Ж	З	И		К	Л	М
Н	О	П	Р	С	Т	У
Ф	Х	Ц	Ч	Ш	Щ	
		Э	Ю	Я	S={а,б,в,г,д,е,ж,з,и,к,л,м,н,о,п,р,с,т,у,ф,х,ц,ч,ш,щ,э,ю,я}	

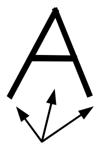
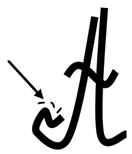
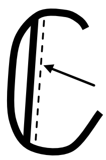
Figure 5. The modified Russian alphabet (28 letters and 1 more letter)

А	Б	В	Г	Д	Е	Ж
З	И	К	Л	М	Н	О
П	Р	С	Т	У	Ф	Х
Ц	Ч	Ш	Щ	Э	Ю	Я
S						

Figure 6. The final Russian alphabet (29 letters)

We used our neural networks for recognition of handwriting and in particular for gender classification (man or woman). This handwritten text includes only Cyrillic capital and lower case letters. Some examples of handwriting attributes (special features) are shown in Table1.

TABLE 1: THE QUANTITY OF MEN AND WOMEN IN THE GROUPS [4]

№	Capital letter (image)	Description of feature of this capital letter	Weight of feature	Number of gradation of feature
1		***Structural complexity of movements when performing*:** **The letter as a whole – a simplified, similar to printed** (marked by the arrows)	A_i=+1.99	i=2
2		***Movement form when performing***: *The final part of the first element – twisting* (marked by the arrow and dashed line)	A_i=-2.42	i=8
3		Movement form when performing: The **third element – twisting** (marked by the arrow and a dashed line)	$П_i$=-0.39	i=18
4		***Relative extent of movement across when performing*:** **It is increased at the expense of an additional stroke to the right of the main part of a letter** (marked by the arrow and a dashed line)	C_i=+1.54	i=22

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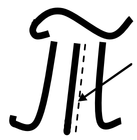
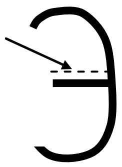
5		Movement form when performing: **The second element – rectilinear** (marked by the arrow and a dashed line)	$Т_i$=+0.76	i=10
6		Movement form when performing: **The second element – rectilinear** (marked by the arrow and a dashed line)	$Э_i$=-0.44	i=11
7		***Movement form when performing*:** **The final part of the first element – loopback** (marked by the arrow and a dashed line)	$Ю_i$=+1.13	i=11
8		Movement form when performing: **The initial part of the first element – helix** (marked by the arrow and a dashed line)	$Я_i$=-0.39	i=6

4. NEURAL NETWORK MODEL OF ARTIFICIAL INTELLIGENCE

When numbering equations, enclose numbers in parentheses and place flush with right-hand margin of the column. Equations must be typed, not inserted.

(If nonstandard fonts are used its better to put equations as images instead of text)

We used an approximate total of m=2000 for the special feature of letters. We took decisions according to a minimum assessment in the average probability of a mistake for the discriminator on statistically independent binary entrances.

Common rule:

$$\text{writer} = \begin{cases} \text{man}, & \text{if } g(\overline{x}) \geq 0 \\ \text{woman}, & \text{if } g(\overline{x}) < 0 \end{cases}, \quad (1)$$

where $g(\overline{x})$ – discriminant function in neural networks [5, 25]:

$$g(\overline{x}) = \sum_{i=1}^{m} w_i x_i + T, \quad (2)$$

where w_i – weights and T – threshold [5, 7, 25]:

$$w_i = \log \frac{q_i(1-p_i)}{p_i(1-q_i)}, \; T = \sum_{i=1}^{m} \log \frac{(1-q_i)}{(1-p_i)} + \delta, \quad (3)$$

where $q_i = p(x_i = 1/\omega_1)$ – for the i-th feature estimation (on training set) conditional probability on condition of a writer-man ($q_i \notin \{0,1\}$); $p_i = p(x_i = 1/\omega_2)$ – for the i-th feature estimation (on training set) conditional probability on condition of writer-woman ($p_i \notin \{0,1\}$). We only considered special case $\delta = 0$. We used only l inputs (number of features of handwritten text), i.e. we used only $x_i = 1$.

In this case the discriminant function in our neural networks will be [5]:

$$g'(\overline{x}) = \sum_{i=1}^{l} w_i' x_i, \; w' = \log \frac{q_i}{p_i}, \quad \text{where } p_i \neq 0. \quad (4)$$

It is possible that in this case the efficiency of discrimination changes slightly.

In this article [5] it has been noted that when using l inputs instead of $m = 1275$ inputs (i.e. 1275-bit binary feature vector), then the efficiency of discrimination changes insignificantly.

The neural networks for recognition of a writer's sex were tested: male or female. One of the two neural networks is shown in Fig. 7.

Two neural networks were developed. The first neural network only recognised male writers. The

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second neural network only recognised female writers. Let us define some simple variables (parameters) L and D.

Let us suggest that for the first neural network L=1 and L=0, where: L=1 – the writer is male and L=0 – the sex of the writer is unknown, while for the second neural network D=1 and D=0, where: D=1 – the writer is female and D=0 – sex of the writer is unknown.

Then all these cases can be combined in the following rule:

If L=1&D=0, the writer is male;

If L=0&D=1, the writer is female;

If (L=1&D=1) or (L=0&L=0), the sex of the writer is unknown.

Note: this neural network model is a very simple model of artificial intelligence.

Two-layer neural networks were developed. The first layer (input layer) includes 29 neurons (binary discriminators). The second layer (output layer) includes only 1 neuron. The output of this neuron is an output for the neural network. We used a threshold activation function for neurons (i.e. for linear discriminators [25]). Let us suggest that fi(g) and fZ(g) are the threshold for activation of the function. Every neuron is the discriminant function in the neural networks.

The Back-Propagation algorithm is very popular. However, we used another algorithm. The training rule for learning neural networks is quite well known.

The algorithm for training is suitable for the neural network model of artificial intelligence. Main elements of this algorithm was described in [7, 25]. Weights of symptoms for letters and thresholds match the criterion of minimum for error of discrimination (classification).

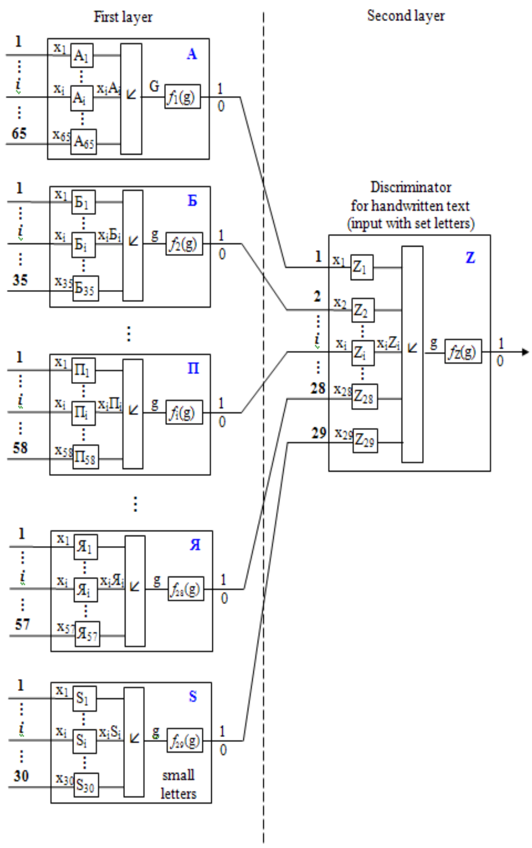

Figure 7. Artificial neural network to classify into two classes: man or no man, woman or no woman.

5. RESEARCH

Experiments for estimation of error recognition are a very important for us.

In this paper, we shall consider two experiments.

Experiment 1

A set of handwritten texts were prepared for the first experiment. Some examples of groups for men and women are shown in Table 2.

TABLE 2: THE QUANTITY OF MEN AND WOMEN IN THE GROUPS [4]

Writer	Groups		Total
	Capital letters	Lower case letters	
Man	215	100	315
Woman	105	100	205
Total	320	200	520

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An estimation of the probability of error discrimination (classification) for capital and lower case letters was conducted, as well as an estimation of the probability of error classification for the set of letters on the experimental set. Tables 3, 4 summarise the experimental results referring to these two estimates.

Let us suggest that Pr is the estimation of probability of error discrimination (classification). Table 3 summarises the experimental results referring to the probability Pr for some Cyrillic capital letters.

TABLE 3: ESTIMATION OF PROBABILITY OF ERROR CLASSIFICATION FOR SOME LETTERS

Letter	A	B	E	K	M	H	O	P	C	T	**X**
Pr	0.28	0.31	0.30	0.25	0.28	0.28	0.32	0.29	0.32	0.29	0.30

Set Y of all Cyrillic capital letters (see Table 3) was sorted (ordered) according to the criterion of maximum probability Pr: Y={O, C,…}.

Let us suggest that R(***i***) is the estimation of probability of error discrimination (classification) for set from ***i*** letters. Table 4 summarizes the experimental results referring to the probability R(***i***) for a set of Cyrillic capital letters.

TABLE 4: ESTIMATION OF PROBABILITY OF ERROR CLASSIFICATION FOR SET OF LETTERS

Amount (***i***) of first letters in set **Y**	1	2	3	4	5	6	7	8
Probability **R(*i*)**	0.33	0.28	0.22	0.18	0.11	0.1	0.1	0.1

Table 4 demonstrated, that R(***i***)≥0.1 i.e. this means that min{***i***}≥6 (therefore six or more letters are enough for subset Y). We used a testing set of 100 handwritten texts, 50 written by women and 50 by men.

The following data was obtained from the experiment for the neural network model of artificial intelligence:

mistaken conclusion — 1%;

writer is unknown — 12%;

right conclusion — 87%.

We consider these results good enough.

Experiment 2

Let us define the next variables and designations:

M – is a quantity of handwritten features (i.e. features are extracted by the forensic expert for handwriting recognition);

H – is a quantity (percentage) of occasions upon which the sex of the writer was recognised correctly;

U – is a quantity (percentage) of un-decisive results (i.e. the sex of the writer remains unknown);

E – is a quantity (percentage) of occasions upon which the sex of the writer was recognised mistakenly.

Experimental sets of handwritten texts were prepared for the second experiment. Some examples of quantity groups for men and women are shown in Table 5.

TABLE 5: THE QUANTITY OF MEN AND WOMEN IN THE AGE GROUPS [26]

Writer	Age					Total
	18–22	23–30	31–37	38–47	48–76	
Man	62	80	66	60	53	321
Woman	78	62	68	84	78	370
Total	140	142	134	144	131	691

The estimation of ***H***, ***U*** and ***E*** was made for the experimental set. Table 6 summarizes the experimental results referring to ***H***, ***U*** and ***E***.

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TABLE 6: ESTIMATION OF H, U AND E [26]

M	%			
	H	*U*	*H + U*	*E*
60	58.47	22.43	80.9	19.1
50	57.16	23.44	80.6	19.4
20	53.68	26.92	80.6	19.4
16	53.84	25.62	79.46	20.54
14	52.82	25.83	78.65	21.35
13	53.11	25.18	78.29	21.71
7	50.07	27.50	77.57	22.43
6	49.93	27.21	77.14	22.86
5	48.77	26.48	75.25	24.75
4	48.34	25.83	74.17	25.83
3	44.28	26.92	71.2	28.8

Table 6 shows that:

– if M increases, then E decreases and vice versa;

– if M increases, then E decreases and there is a limit for decrease of E;

– if M>13, then H>50;

– $19\% < E < 30\%$;

– $90\% > (H+U) > 70\%$.

Details and additional information about this research can be found in [26].

<u>Use the Neural network model of artificial intelligence and the program 'man-WO-man'</u>

AFIRS was successfully developed for police. Software of special AFIRS includes a program 'man-WO-man' including the neural networks. The ***C*** programming language was used for this program.

The program code of these systems contains thousands strings of source text. Many programming languages were used to create these AFIRS, e.g. ***C***/***C***++, Fortran, Basic, Visual Basic for Applications, Assembler.

Police and experts need to make the right decisions. There are a lot of possible applications [10]:

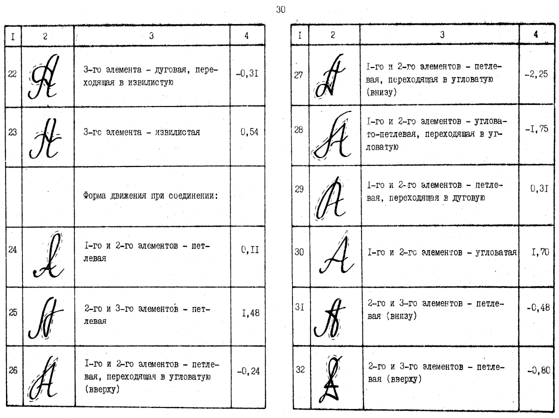
– victims receive anonymous letters and threats in letters;

– at the crime scene experts find: notes, financial documents, records with fictitious addresses – for example, in cases of fraudulent or similar actions;

– other cases which are associated with handwriting.

Note that all of these cases require handwriting research. The police are interested in age, gender and other characteristics of the offender.

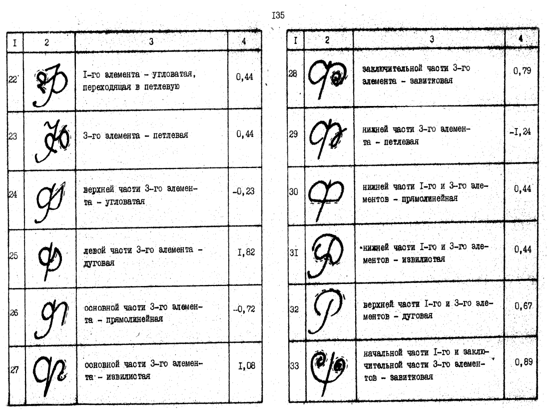
This NN model of AI and the program 'man-WO-man' help experts to make correct decisions. AFIRS 'MASTER' was successfully developed [10]. The program 'man-WO-man' uses this NNM of AI. Many of the required tables have been prepared for forensic experts. These forensic experts extract features for handwriting recognition. Some examples of these tables (special features of handwriting) are shown in Fig. 8, 9, 10.


30

I	2	3	4
22		3-го элемента – дуговая, переходящая в извилистую	-0,3I
23		3-гс элемента – извилистая	0,54
		Форма движения при соединении:	
24		I-го и 2-го элементов – петлевая	0,II
25		2-го и 3-го элементов – петлевая	I,48
26		I-го и 2-го элементов – петлевая, переходящая в угловатую (вверху)	-0,24

I	2	3	4
27		I-го и 2-го элементов – петлевая, переходящая в угловатую (внизу)	-2,25
28		I-го и 2-го элементов – угловато-петлевая, переходящая в угловатую	-I,75
29		I-го и 2-го элементов – петлевая, переходящая в дуговую	0,3I
30		I-го и 2-гс элементов – угловатая	I,70
3I		2-го и 3-го элементов – петлевая (внизу)	-0,48
32		2-го и 3-го элементов – петлевая (вверху)	-0,80

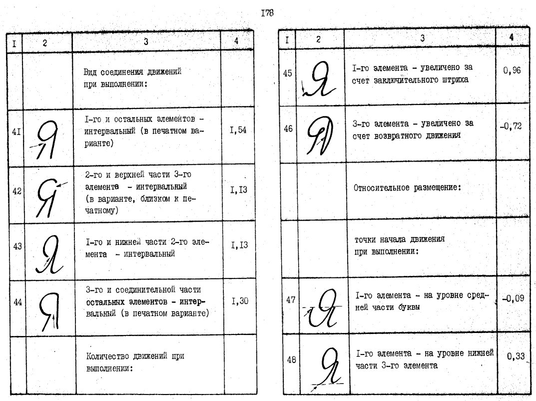
Figure 8. Table 30 in [10]


I35

I	2	3	4
22		I-го элемента – угловатая, переходящая в петлевую	0,44
23		3-го элемента – петлевая	0,44
24		верхней части 3-го элемента – угловатая	-0,23
25		левой части 3-го элемента – дуговая	I,82
26		основной части 3-го элемента – прямолинейная	-0,72
27		основной части 3-го элемента – извилистая	I,08

I	2	3	4
28		заключительной части 3-го элемента – завитковая	0,79
29		нижней части 3-го элемента – петлевая	-I,24
30		нижней части I-го и 3-го элементов – прямолинейная	0,44
3I		нижней части I-го и 3-го элементов – извилистая	0,44
32		верхней части I-го и 3-го элементов – дуговая	0,67
33		начальной части I-го и заключительной части 3-го элементов – завитковая	0,89

Figure 9. Table 135 in [10]


I78

I	2	3	4
		Вид соединения движений при выполнении:	
4I		I-го и остальных элементов – интервальный (в печатном варианте)	I,54
42		2-го и верхней части 3-го элемента – интервальный (в варианте, близком к печатному)	I,I3
43		I-го и нижней части 2-го элемента – интервальный	I,I3
44		3-го и соединительной части остальных элементов – интервальный (в печатном варианте)	I,30
		Количество движений при выполнении:	

I	2	3	4
45		I-го элемента – увеличено за счет заключительного штриха	0,96
46		3-го элемента – увеличено за счет возвратного движения	-0,72
		Относительное размещение:	
		точки начала движения при выполнении:	
47		I-го элемента – на уровне средней части буквы	-0,09
48		I-го элемента – на уровне нижней части 3-го элемента	0,33

Figure 10. Table 178 in [10]

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After the expert has extracted features, he uses the program 'man-WO-man'. Then the expert passed the features as input to this program. Further, this program gives the data about the writer (i.e. man or woman or unknown) to the expert. More important details on features can be found in [4, 5, 10].

6. DISCUSSION AND FUTURE WORKS

This section presents the results obtained from the experimentation and briefly discussion about the results.

In papers [13, 17] a probabilistic models, statistical model for writer verification, likelihood ratio, error rates (percent misclassification), macro and micro features, experimental results were discussed, but macro and micro features were not considered in detail, at the same time the neural network model of artificial intelligence for handwriting recognition were not touched at all. In papers [18, 19] a off-line handwriting identification, writer verification and hidden Markov models were discussed, but handwriting features were not considered in detail, at the same time the neural network model for handwriting recognition, alphabet and features of capital letters were not touched at all. In papers [3, 6] a probabilistic neural networks and decision making rule of the neural networks committee, results of modeling experiments were discussed, at the same time the neural network model for handwriting recognition and handwriting features were not touched at all. In paper [11] recognition of handwritten digits was discussed, but recognition of handwritten capital letters was not touched at all. In set of monographs [1, 2, 7, 20] a neural networks, learning machines and statistical pattern recognition were discussed in detail, but problem of handwriting recognition were not considered in detail, at the same time the neural network model for handwriting recognition and features of capital letters were not touched at all. And our research partly eliminates the deficiencies given above.

Important results were obtained, for example (our merits):

• The problem of handwritten symbol recognition was investigated.
• A neural network model of artificial intelligence was developed.
• A neural network algorithm for handwriting recognition in AFIRS was developed. The basis for developing of AFIRS was laid out.
• The program «man-WO-man» was developed.
• Experimental confirmation of the neural network model of artificial intelligence was obtained. In particular it is shown, that an estimation of error of misclassification is only 1% and right conclusion — 87%.

Other results were not obtained, for example (our demerits):

• This error of misclassification cannot be less than 10-4.
• Special features cannot be extracted automatically.
• No experiments on the features of the English language were carried out.

Future steps include getting the answers to the following important questions:

1. How do parameters of the algorithm of pattern recognition influence information retrieval?
2. Could one recognize special symbols of handwriting automatically?
3. Which structure of neural network is most suitable for recognizing handwriting?
4. Could one recognize psychological characteristics of the writer of handwriting?
5. Could one recognize age of the writer of handwritten text?
6. How do parameters of neural network model of artificial intelligence influence error discrimination (classification)?
7. Could one extract features special of handwritten text automatically?
8. What activation function is most suitable for recognizing handwriting?

The neural network algorithm will be the subject of our future work in which we are aiming to improve tools for forensic experts and police. That is why our plans are:

- Developing the neural network algorithm for recognizing psychological characteristics of the author of handwriting.
- Experiment with structures of neural networks.
- Developing the neural network algorithm for recognizing the age of the writer.

Some details on features of tools for forensic experts and police can be found in [4, 5].

7. CONCLUSION

This paper proposes a method for neural network model of artificial intelligence for handwriting recognition and investigates this model. The main purpose of this research work is to propose tools for scientists and developers of pattern recognition systems. For the feature extraction, the important parameters such as features of handwriting capital letters were extracted and were studied in detail. The new algorithm of pattern recognition and NNM of AI to recognize the man or woman how the

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writer of handwritten text were developed. The performance of this algorithm is evaluated in terms of H, U, E and (H+U). The results show that the algorithm is more efficient to recognize gender of the writer. The proposed algorithm gives better results than other well known algorithms. The neural network technology has been applied successfully to design biometrical system for AFIRS. The neural network algorithm for handwriting recognition in AFIRS «MASTER» was developed. The program «man-WO-man» uses this NNM of AI. Our experimental results demonstrate that the proposed neural network model of artificial intelligence has higher precision of recognition than other model, for example mistaken conclusion — 1%. Overall, the neural network model can help the industry to learn about the trends of changes in the artificial intelligence. Here, we suggest the NNM of AI that can be applied in the future to develop biometrical systems to person's recognition. Also we suggest the features of handwriting for capital letters to wide use in pattern recognition systems. For example we recommend to use six or more letters in biometrical system for AFIRS, that is enough for efficient of recognition gender of the writer. The neural network algorithm can to recognize only gender of the writer. This limitation, in addition to the traditional limitations of a recognition system, will be the subject of our future work in which we are aiming to improve the NNM of AI. We believe that our model is useful for forensic experts to recognize gender of the writer.

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