UDC: 616-071+343.982.323+576.316

INTEGRATED APPROACH TO PERSONAL IDENTIFICATION USING DERMATOGLYPHS AND ARTIFICIAL NEURAL NETWORKS

Kotsyubynska Y.Z.¹, Gunas I.V.², Garazdiuk M.S.³, Fentsyk V.L.,⁴ Liampel V.I.⁵, Vadiuk A.V.¹

¹Ivano-Frankivsk National Medical University

² National Pirogov Memorial Medical University, Vinnytsya

³ Bukovinian State Medical Academy

⁴ Uzhhorod National University

⁵ Ivano-Frankivsk scientific research forensic center of the Ministry of Internal Affairs of Ukraine

Abstract. **Introduction.** Due to the full-scale military invasion of Ukraine by the aggressor state, the tendency to aggravate local armed conflicts in the world, which causes a large number of depersonalised, fragmented corpses, the problem of identifying the bodies of two or more persons arises

The aim of the study to develop expert criteria for the informativeness of dermatoglyphic fingerprints in the system of forensic medical identification of a person.

Materials and methods. The object of the study was fingerprint cards obtained from 460 people (200 women and 260 men) aged 18-59 years living in Ukraine. We used statistical analysis and neural network programming.

Results. Using neural network prediction, we have developed a methodology for reproducing unknown (lost) phenotypic traits based on the available ones (dermatoglyphs). Given the fact that many different neural networks can be built even on the same variables, depending on their combination, we managed to achieve a prediction accuracy of 73-90%, which suggests that a combination of different neural networks and an integrated approach show better results.

Conclusions.

Based on the above, it can be concluded that the reliability of the results obtained ranged from 73-90% (automatically calculated by the Dermatoglyphics For Prediction (DFP) software), which is significantly higher than the results of previous fingerprint examinations. The use of our proposed software in combination with other basic methods will improve the quality of forensic identification examinations.

Key words. Person identification, dermatoglyphic status, phenotype, criminalistics, fingerprinting, artificial neural network.

Problem statement and analysis of the latest research

In connection with the full-scale military invasion of the aggressor state into the territory of Ukraine, the tendency to aggravation of local armed conflicts in the world, which causes the appearance of a large number of impersonal, fragmented corpses, the problem of identifying the bodies of two or more persons arises [1,2].

In order to identify an unknown person according to the DVI-Interpol principle, a whole range of identification methods is used: DNA identification, dermatoglyphic identification, identification by dental status, drawing up a verbal portrait, anthropological identification, etc. However, none of the currently known methods is characterised by a one hundred per cent result. That is why several identification algorithms are used simultaneously, i.e. a multidisciplinary approach to identification: the use of all possible lines of evidence to confirm the identity between human remains and a missing person [3, 4].

The dermatoglyphic method, as a basic identification method, is widely used in identifying individuals in cases of mass casualties. However, due to the absence of a centralised database of dermatoglyphs in Ukraine, there is a need to develop predictive programs based on artificial neural networks (ANNs) that would allow predicting the lost phenotypic features of a person based on the available ones (in particular, dermatoglyphs) [5-7].

The aim of the study to develop expert criteria for the informativeness of dermatoglyphic fingerprints in the system of forensic medical identification of a person.

Materials and methods.

The object of the study was fingerprint cards obtained from 460 people (200 women and 260 men) aged 18-59 years living in Ukraine. We used statistical analysis and neural network programming.

Results and discussions

After we have decided on the working version of the neural network, STATISTICA allows you to save it as a programme code in the main programming languages: C and Java. In order to practically implement the resulting neural network, we used Java. After opening the STATISTICA-generated code in an integrated development environment (in our case, the popular Java IDE-IntelliJ IDEA [https://www.jetbrains.com/idea/ documentation/]), it is easy to see that the code is well structured and easy to understand (Fig. 1).

e l	<u>E</u> dit	<u>V</u> iew	<u>N</u> avigate	<u>C</u> ode	Analy <u>z</u> e	<u>R</u> efactor	Build	R <u>u</u> n	<u>T</u> ools	VC <u>S</u>	Window	<u>H</u> elp
N	eural	Nets	🖿 src 🔪	onets	>							
Ē	Pro	oject			• 🕀 💠	\$÷ ⊪	C n	nain.ja	va ×	C ne	ts.java ×	
V		Neural	Nets S:\Ja	va\statis	tica neura	al nets\Neu	R					
	▶.	.ide	a				19				double	<pre>e Wr = ContInputs[Cont idx++];</pre>
	►	src					20					e LWr = ContInputs[Cont idx++];
1		🔒 Ne	uralNets.im	ıl			21					e Atdl = ContInputs[Cont idx++]
v.		Externa	Libraries				22					e Adtl = ContInputs[Cont_idx++]
		< 1	.8 > C:\Pro	ogram Fi	iles\Java\i	dk1.8.0 111	23				double	e _Atbl = ContInputs[Cont_idx++]
		-	access-bri	-			24				double	e _Btcl = ContInputs[Cont_idx++]
			charsets.ja			1001	25				double	<pre>e _Ab1 = ContInputs[Cont_idx++];</pre>
				-			26					<pre>e _Bcl = ContInputs[Cont_idx++];</pre>
			cldrdata.ja				27					<pre>e _Cdl = ContInputs[Cont_idx++];</pre>
			deploy.jar	-			28					e <u>Atdr</u> = ContInputs[Cont_idx++]
		I	dnsns.jar	library ro	oot		29					e <u>Adtr</u> = ContInputs[Cont_idx++]
		▶ 🛯	jaccess.jar	library i	root		-30					e _Atbr = ContInputs[Cont_idx++]
		► II.	javaws.jar	library r	oot		31					e _Btcr = ContInputs[Cont_idx++]
			jce.jar libr				32					<pre>e _Abr = ContInputs[Cont_idx++];</pre>
			jfr.jar libra	-			33					<pre>e _Bcr = ContInputs[Cont_idx++];</pre>
				-			34					<pre>e _Cdr = ContInputs[Cont_idx++];</pre>
			j fxrt.jar lib				35					gstatist_PredCat="";
			jfxswt.jar	-			36					g []statist_DCats = new String[
		I	jsse.jar lib	rary root	t		37				_	tist_DCats[0] = "бойки";
		▶ 📙	localedata	.jar libra	ary root		38				_	tist_DCats[1]= "гуцули";
		► II.	managem	ent-ager	nt.jar libr	ary root	39				stat	tist_DCats[2]= "лемки";
		-	nashorn.ja	_	-		40				double	<pre>statist ConfLevel=3.0E-300;</pre>
			nlugin iar				41				double	ECONTREVEL=3.0E-300;

Figure 1. Java source code of the neural network created in STATISTICA and edited in IntelliJ IDEA

As can be seen from Fig. 1, in order to get the desired answer, the neural network needs to be given fractional values of the input data (Al, LUl, Atdl...), and then it will analyse them. The output is a text string (String) from the array of possible answers.

To expand the possibilities of analysis and forecasting, you need to increase the number of variables that the neural network will process. Above, we have briefly described how to create a network based on papillary pattern data and the characteristics of ethno-racial groups (Boyko, Hutsul, Lemko). If we add more variables to the above table (namely, features on the feet, features on the middle phalanges, etc.), the resulting neural network will be able to more accurately predict belonging to a particular category. Of course, this will increase the complexity of building and processing the results of the neural network calculations.

In order to implement a neural network with a sufficiently large number of input variables, you will either have to edit the resulting code (generated in STATISTICA) or enter all the relevant data of the person whose ethnicity we are determining into the network. (But how will such a neural network behave if we enter only the data of the angles on the right hand? Such a neural network will generate an error).

Given such a task, there is a simple and effective way to implement multitasking functions: divide the task into small parts, i.e., categorise the input data (e.g., category 1 - all data from the right hand, category 2 - all data from both hands, category 3 - data from both feet, etc.), create a separate neural network for each of the planned categories, and then combine them in a program that can determine the category(s) of input data and make a weighted prediction accordingly.

Thus, we have the core functionality of the application. To make full use of it, we developed a GUI

(graphical user interface) that facilitates data entry and makes it possible for other researchers to use it.

In general, the application we have developed (Dermatoglyphics For Prediction (DFP)) consists of a neural network-based core and a shell created mainly with the help of the javafx.application.*, javafx. stage.*, java.awt.* classes, as well as a large number of Java Development Kit 1.8 classes. [https://www.oracle.com/index. html]

The graphical interface was created using JavaFX 8. This framework allows you to quickly and efficiently implement a graphical shell of the main code, and it is also multi-platform (programs written in JavaFX run

on different operating systems). [https://docs.oracle.com/ javase/8/javafx/get-started-tutorial/jfx-overview.htm] We also used the JFoenix library to improve the design and to follow the generally accepted MaterialDesign standards. [http://www.jfoenix.com/documentation. html] Graphic objects created with this library meet all the modern trends in Desktop (in our case, Windows) programming.

To start our programme (DFP), you simply run the executable file DFP.jar (i.e. the programme does not need to be installed separately). In the main window of the programme, select the appropriate drop-down menus and enter the input data of the unknown person (if there is not enough data, the programme will indicate an input error). After entering the data, click «Submit». The program will process the data and display in a separate window the category (ethno-territorial affiliation, anthropometric, anthroposcopic parameters) to which the unknown person belongs, the probability of correct classification, etc.

As can be seen from the description, no special skills are required to work with the programme (DFP), and its operation is very fast (due to the fact that all classification is carried out during neural network training). The program takes up extremely little space (< 5 mb) and can be written to any modern storage device (or even sent in an email).

This neural network searches for the dependence of phenotypic traits on dermatoglyphic data from both hands, grouped together (summed) (A, LU, LR, W, LW), separately for women and men (Figs. 2, 3).

Fig. 4 shows the data on the created neural network for the female sample (name and number of neurons, percentage of correct classification, training function algorithms, neuron activation functions).

	Race (Classification summary) (DermFALL in WorkbookDermF) Samples: Train Race-Boiko Race-Control Race-Hutsul Race-Lemko									
5.MLP 5-15-4	Total	30,00000	32,00000	25,00000	25,00000	112,00				
	Correct	19,00000	21,00000	14,00000	16,00000	70,00				
	Incorrect	11,00000	11,00000	11,00000	9,00000	42,00				
	Correct (%)	63,33333	65,62500	56,00000	64,00000	62,50				
	Incorrect (%)	36,66667	34,37500	44,00000	36,00000	37,50				

Figure 2. Matrix of correct/incorrect classification for the female gender group

Predicted	Race (Confusion matrix) (DermFALL in WorkbookDermF) Samples: Train							
category	Race-Boiko	Race-Control	Race-Hutsul	Race-Lemko				
5.MLP 5-15-4-Boiko	19	8	5	2				
5.MLP 5-15-4-Control	1	21	4	6				
5.MLP 5-15-4-Hutsul	6	0	14	1				
5.MLP 5-15-4-Lemko	4	3	2	16				

Figure 3. Matrix of correct/incorrect predictions for the female gender group

Summar	Summary of active networks (DermFALL in WorkbookDermF)									
Index							Output activation			
5	MLP 5-15-4	62,50000	70,83333	54,16667	BFGS 18	SOS	Exponential	Sine		

Figure 4. General data about the built neural network

By analogy, we create a neural network for the male sample (Figs. 5-7).

A neural network is built on data. If we add (or remove) new variables, the neural network can demonstrate both better and worse prediction capabilities. Therefore, many different neural networks can be built even on the same variables depending on their combination. It is not worth saying that one of the neural networks is better than the other, but rather that a combination of different neural networks and an integrated approach shows better results.

Conclusions

Based on the above, it can be concluded that the reliability of the results obtained ranged from 73-90% (automatically calculated by the Dermatoglyphics For Prediction (DFP) software), which is significantly higher than the results of previous fingerprint examinations. The use of our proposed software in combination with other basic methods will improve the quality of forensic identification examinations.

Financial Disclosure.

The author declared no financial support.

Conflict of Interests.

The author declare that no confl ict of interests exist.

Referenses

1. Mishalov V. D., Gunas V. I. (2018) Discriminating

models of dermatoglyphic priority of practically healthy men to southern or other administrative-territorial regions of ukraine Судово-медична експертиза, (1), 17-21. https://doi.org/10.24061/2707-8728.1.2018.6

2. Gunas, V. I. (2018). Modeling using discrimination analysis, priority of practically healthy men to northern or other administrative-territorial regions of Ukraine on the basis of dermatoglyphic indicators features. Worlg of Medicine and Biology, 1(63), 9-14.

3. Possibility of using dermatoglyphic parameters of the medium and proximal finger falanges of the hands within the requirements of dvi-interpol Kotsiubynska, Yu Z.; Kozan, N. M.; (...); Vakar, T. V. Published 2020 |World of Medicine and Biology https://womab.com.ua/en/smb-2020-02/8451

4. KotsiubynskaYu., Kozan N. Use of dermatoglyphic parameters of the medium and proximal phalanges hand's fingers for integrated legal-medical identification of person. Медичні перспективи, 2020; XXV; 4 <u>https://medpers.dmu.edu.ua/issues/2020/N4/47-58.pdf т 8</u>.

5. Gunas IV, Dunayev OV, Popadynets OG, Kozoviy RV, Kindrativ EO. (2020) Study of ethnic and regional features of dermatoglyphic parameters of Hands and feet (lityrature review). Art of Medicine. 3(15): 216-221.

6. Mishalov V. D., Serebrennikova, O. A., Klimas, L. A. & Gunas, V. I. (2018). Regional trends indicators finger dermatoglyphics among modern Ukrainians. Biomedical and biosocial anthropology, (30), 5-12.

7. Ozor Nwafia Chinyere Pricilla, Emelobe Chidiebele

	Race (Classification summary) (DermMAll in WorkbookDermM) Samples: Train Race-Boiko Race-Control Race-Hutsul Race-Lemko								
2.MLP 5-15-4	Total	31,00000	30,00000	21,00000	30,0000	112,0000			
	Correct	24,00000	27,00000	15,00000	30,0000	96,0000			
	Incorrect	7,00000	3,00000	6,00000	0,0000	16,0000			
	Correct (%)	77,41935	90,00000	71,42857	100,0000	85,7143			
	Incorrect (%)	22,58065	10,00000	28,57143	0,0000	14,2857			

Figure 5. Matrix of correct/incorrect classification for the male gender group

Predicted	Race (Confusio Samples: Train	n matrix) (DermM	All in WorkbookD	0ermM)
category	Race-Boiko	Race-Control	Race-Hutsul	Race-Lemko
2.MLP 5-15-4-Boiko	24	2	2	0
2.MLP 5-15-4-Control	3	27	2	0
2.MLP 5-15-4-Hutsul	3	1	15	0
2.MLP 5-15-4-Lemko	1	0	2	30

Figure 6. Matrix of correct/incorrect predictions for the male gender group

Summa	Summary of active networks (DermMAII in WorkbookDermM)										
Index	dex Net. name Training Test perf. Validation Training Error Hidden Output										
		perf.		perf.	algorithm	function	activation	activation			
2	MLP 5-15-4	85,71429	79,16667	62,50000	BFGS 43	SOS	Logistic	Logistic			

Fig. 7. General data on the built neural network for the male gender group

Samuel,Igbigbi Patrick Sunday, Ozor Chigozie Kenneth Dermatoglyphic patterns of female convicted criminals in Anambra state Forensic Research & Criminology International Journal 2018;6(4):294–296.

8. Sudha IP, Singh J, Sodhi GS. Dermatoglyphics of Criminals and Effects of Social Environment: A Study. The Indian Police Journal. 2020. Available from: https:// bprd.nic. in/ WriteReadData/ userfiles/ file /202104200330035982091 ipj1.pdf#page=134.

9. Usman Shahid Butt, Anam Iqbal, Nasreen Akhtar, Sara Qazi, Zaryab Ali, Rahat Abdul Rahman

Dermatoglyphycs association with criminal intent. Pak J Physiol 2021;17(2): 35-37.

10. Kaur M, Kaur M, Kamal P, Kaur J. Sex Distinction in Digital Dermatoglyphic Patterns of Convicted Prisoners: A Comparative Cohort-Control Study. Arab Journal of Forensic Sciences & Forensic Medicine. 2019;1(10):1403– 1411. Available from: 10.26735/16586794.2019.030.

Received: 17.04.2024 Revised: 15.05.2024 Accepted: 17.05.2024