3-бөлім **Раздел 3** **Section 3**

Информатика **Информатика** **Computer Science**

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MODEL FOR PROCESSING IMAGES OF ONLINE SOCIAL NETWORKS USED TO RECOGNIZE POLITICAL EXTREMISM

The scientific research is devoted to solving the important scientific and practical problem of recognizing calls for political extremism in online social networks, which today, due to their high popularity, are one of the main ways of spreading such calls. It is shown that modern means of detecting calls for political extremism in online social networks are mainly focused on the semantic analysis of text messages contained in them. At the same time, in modern online social networks, graphic resources have become widespread, which provide ample opportunities for the implementation of such calls. The possibility of detecting destructive content in images and video materials using neural network analysis is considered. The possibility of increasing the efficiency of neural network recognition has been determined due to the developed image pre-processing model, which makes it possible to adjust the brightness and contrast of images, as well as eliminate typical interference during video recording. The originality of the model lies in the use of a wavelet transform apparatus for filtering typical noise, as well as in the developed mathematical apparatus for adaptive contrast correction based on the local contrast of the neighborhood. It is shows that the use of the developed model for pre-processing images makes it possible to increase the accuracy of neural network recognition of calls for extremism in images and videos posted on online social networks by approximately 12 percent. It is advisable to correlate the paths for further research with the development of a neural network model adapted to the wide variation in the sizes of images and videos in online social networks.

Key words: social networks, detection of political extremism, images, contrast correction, wavelet analysis.

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Онлайн әлеуметтік желілері бейнелерін өңдеу арқылы саяси экстремизмді анықтау моделі

Ғылыми зерттеу интернет әлеуметтік желілердегі саяси экстремизмге шақыруларды танудың маңызды ғылыми-тәжірибелік мәселесін шешуге арналған, олар бүгінгі күні өзінің жоғары танымалдылығына байланысты осындай шақыруларды таратудың негізгі тәсілдерінің бірі болып табылады. Әлеуметтік желілердегі саяси экстремизмге шақыруларды анықтаудың заманауи құралдары негізінен олардағы мәтіндік хабарламаларды семантикалық талдауға бағытталғаны көрсетілген. Сонымен қатар, заманауи онлайн-әлеуметтік желілерде графикалық ресурстар кең таралып, мұндай шақырулар жасауға кең мүмкіндіктер берді. Нейрондық желіні талдау арқылы кескіндер мен бейнематериалдардағы деструктивті мазмұнды анықтау мүмкіндігі қарастырылады. Нейрондық желіні тану тиімділігін арттыру мүмкіндігі кескіндердің жарықтығы мен контрастын реттеуге, сондай-ақ бейне жазу кезінде әдеттегі шуды жоюға мүмкіндік беретін кескінді алдын ала өңдеудің әзірленген моделінің арқасында анықталды. Модельдің өзіндік ерекшелігі типтік шуды сүзу үшін толқындық түрлендіру аппаратын қолдануда, сондай-ақ көршілес аймақтың жергілікті контрастына негізделген адаптивті контрастты түзету үшін әзірленген математикалық аппаратта жатыр. Әзірленген кескінді алдын ала өңдеу моделін қолдану әлеуметтік желіде орналастырылған суреттер мен бейнематериалдардағы экстремизмге шақыруларды нейрондық желі арқылы тану дәлдігін шамамен 12 пайызға арттыруға мүмкіндік беретіні көрсетілген. Әрі қарай зерттеу жолдарын онлайн әлеуметтік желілердегі суреттер мен бейнелердің өлшемдерінің кең өзгеруіне бейімделген нейрондық желі моделін жасаумен байланыстырған жөн.

Түйін сөздер: әлеуметтік желілер, саяси экстремизмді анықтау, суреттер, контрастты түзету, вейвлеттік талдау.

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Модель обработки изображений онлайн социальных сетей, используемых для распознавания политического экстремизма

Научное исследование посвящено решению важной научно-практической проблемы распознавания призывов к политическому экстремизму в социальных сетях Интернет, которые сегодня в силу своей высокой популярности являются одним из основных способов распространения подобных призывов. Показано, что современные средства выявления призывов к политическому экстремизму в социальных сетях в основном ориентированы на семантический анализ содержащихся в них текстовых сообщений. В то же время в современных онлайн-социальных сетях получили широкое распространение графические ресурсы, предоставляющие широкие возможности для осуществления подобных звонков. Рассмотрена возможность обнаружения деструктивного контента в изображениях и видеоматериалах с помощью нейросетевого анализа. Определена возможность повышения эффективности нейросетевого распознавания за счет разработанной модели предварительной обработки изображений, позволяющей регулировать яркость и контрастность изображений, а также устранять типичные помехи при видеозаписи. Оригинальность модели заключается в использовании аппарата вейвлет-преобразования для фильтрации типичных шумов, а также в разработанном математическом аппарате адаптивной коррекции контраста на основе локального контраста окрестности. Показано, что использование разработанной модели предварительной обработки изображений позволяет повысить точность нейросетевого распознавания призывов к экстремизму в изображениях и видеороликах, размещенных в социальных сетях онлайн, примерно на 12 процентов. Пути дальнейших исследований целесообразно соотнести с разработкой нейросетевой модели, адаптированной к широкому варьированию размеров изображений и видео в социальных сетях онлайн.

Ключевые слова: социальные сети, выявление политического экстремизма, изображения, контрастная коррекция, вейвлет-анализ.

1 Introduction

Currently, online social networks are one of the main media, which a significant number of young people consider as the main source of authoritative and reliable information [1, 2]. In addition to the unconditional positive psycho-emotional effect, the spread of social networks also entails unconditional risks, including the spread of calls for political extremism [2, 13, and 22]. This explains the increased interest in developing tools for automatic monitoring of social networks. There are a number of existing technologies for monitoring social networks for the detection of various destructive information, which also includes calls for political extremism [1, 12, and 23]. It is worth noting that most known monitoring technologies are based on semantic analysis of text messages [3, 7, 16]. For example, paper [4] focuses on developing a multi-class sentiment classification based on social media comments in Bengali using machine learning. Article [5] discusses a procedure for determining how textual environmental cues and personal characteristics influence the expression of sentiments in social networks. Article [6] presents a method for processing text messages in social networks for ranking products, which is based on several classifiers and the interval intuitionistic fuzzy system TOPSIS. At the same time, the results [2, 12, and 16] and practical experience indicate that calls for political extremism can be implemented not only through text messages, but also through graphic materials (images and videos) posted on social networks. In line with modern research, it is advisable to analyze such graphic materials using neural network tools [10, 11]. Although quite a lot of work has been devoted to the general issues of developing such tools [8, 14, 15], the specifics of detecting calls for political extremism in images and video materials of online social networks have not been sufficiently covered, which explains the relevance of research in this direction.

In the vast majority of cases, graphic content on online social networks consists of monochrome or color images, as well as mono-channel video, also presented in monochrome or color format. For example in Fig. 1 shows an image that may be an illustration of a call for political extremism.

Fig. 1. A fight scene as a call to street riots

As practical experience and research results in the field of neural network analysis of static images and video information show [9, 11, 17], one of the promising ways to increase the efficiency of such analysis is to carry out pre-processing. Firstly, the purpose of such processing is to bring the parameters of images and video streams to the requirements put forward for the parameters of the input field of a neural network model of a given type. Thus, a significant difference between the size of the input field of the neural network model and the size of the analyzed image will require the use of a special image scaling procedure, since a trivial scaling procedure is likely are excessively distort the image. The distortion is especially noticeable in the case of possible disproportionate scaling of the image, the need for which may arise in the event of a mismatch between the aspect ratio of the input field of the neural network model and the aspect ratio of the analyzed image. As an example, Fig. 2 shows the image from Fig. 1, scaled non-uniformly using the well-known bicubic interpolation procedure. Fig. 2 illustrates that such a scaled image will be difficult to recognize by humans, and, therefore, neural network analysis will be difficult.

Fig. 2. Image scaling using the bicubic interpolation procedure

In addition, one should take into account the fact that in some online social networks, images and videos are posting in compressed form, which can cause difficulties when submitting them to the input of neural network analysis tools. Likewise, in many cases, preprocessing the input signal can significantly increase the accuracy of the output signal of the neural network model by leveling out noise and distortion that is difficult to display in training data. For example in Fig. 3 shows an image of a group of people captured in low light conditions caused by fog.

Fig. 3. Image of a group of people captured in low light conditions

Note that, in fact, the video stream consists of individual image frames. Therefore, processing a video stream can be considered as processing individual images, taking into account the need to implement this process in real time.

Thus, as a result of the conducted research, it can be assumed that pre-processing of images in online social networks correlates with solving the following problems:

1. Restoring a compressed image.
2. Scaling images to bring their size to the size of the input field of the neural network model.
3. Bringing images to a given color format.
4. Leveling out typical interferences and distortions characteristic of the field of political extremism in online social networks.

In accordance with [9, 11 and 24] it is necessary to develop an appropriate model, which will be the theoretical basis for solving these problems of pre-processing images and videos before submitting them to neural network tools for recognizing calls for political extremism.The purpose of this article is to develop a model for pre-processing images posted on online social networks to improve the efficiency of neural network tools for recognizing calls for political extremism.

2 Methods and materials

The first three problems of image preprocessing in online social networks are typical tasks of pre-processing images before feeding them into a neural network model of a given type. The fourth task takes into account the specifics of the applied research problem, i.e., tasks of detecting political extremism in online social networks through integral analysis of text and graphic information.

The research hypothesis is that the use of such a preprocessing model will improve the efficiency of neural network tools for recognizing calls for political extremism contained in images and videos of online social networks. To determine effective ways to solve the above problems, a study of some common online social networks was carried out regarding the features of placing images and video streams in them. Since there are currently quite a large number of online social networks, the article "Rating of social networks in Kazakhstan and what buyers expect from them", published on April 27, 2023 by the authoritative website Profit.kz, was used as a basis for determining the target list. It is notes that among those surveyed, 56% watch videos and listen to music on social networks, 44% of respondents read news, 26% communicate with people they already know, and 26% follow bloggers. At the same time, the main consumers of content are young people aged 14 to 18 years. The main indicators identified in the article characterizing the attendance of online social networks in the Republic of Kazakhstan indicate that the most popular social networks include: Instagram, TikTok, Telegram, YouTube, VKontakte, Facebook, Odnoklassniki, Twitter.

Taking into account practical experience, added to this list LinkedIn, Viber and WhatsApp. Social networks from the specified list were investigated from the standpoint of determining ways to solve the problems stated above related to the pre-processing of images and video streams.

A list of maximum and minimum resolution values for images and videos also defined, as well as an acceptable range of aspect ratios for images and videos. The corresponding data given in table 1 and table 2.

Table 1. Maximum and minimum resolution of images and videos on popular social networks

Social networks name	Maximum resolution, px	Recommended minimum resolution, px
Instagram	1080×1920	110×110
TikTok	1080×1920	20×20
Telegram	720×1080	320×480
Viber	1600×1200	640×480
WhatsApp	1600×1200	192×192
YouTube	3840×2160	426×240
ВКонтакте	1920×1080	145×85
LinkedIn	4096×2304	256×154
Одноклассники	1920×1080	190×190
Facebook	4096×2048	170×170
Twitter	1920×1200	32×32

Table 2. Aspect ratio range of images and videos on popular social networks

Social networks name	Acceptable aspect ratio of images and videos
Instagram	1:1; 1.9:1; 4:5
TikTok	1:1; 9:16
Telegram	1:1; 2:3;
Viber	1:1; 6:9; 4:3
WhatsApp	1:1; 4:3; 9:16
YouTube	4:3; 9:16
ВКонтакте	1:1; 2:3; 4:5; 9:16
LinkedIn	1:2,4; 9:16
Одноклассники	1:1; 1,78:1; 3:5; 6:5; 9:16
Facebook	1:1; 1,9:1; 2:1; 9:16
Twitter	1:1; 1:2,39; 9:16

Based on the methodology [11], taking into account the results of studies of well-known online social networks, the solution to the above first preprocessing problem associated with the restoration of compressed images and/or videos can be correlated with the use of publicly available codecs that are necessary to decompress the original image and/or or video. The list of required codecs determined by the lists of image and video formats that are used in online social networks formed in this section.

The solution to the second problem, associated with scaling images to bring their size to the size of the input field of the neural network model, is based on the statements proven in [11, 17] that modern neural network models are able to adequately analyze images proportionally enlarged by no more than 2 times or proportionally reduced by no more than 5 times. Therefore, the limits of expedient scaling of images and videos during their pre-processing before submission to the neural network model are limited by the coefficients $k_{max} = 2$ and $k_{min} = 0.2$, i.e., the range of variation of scale factors with proportional scaling is in the range from 0.2 to 2. With disproportionate scaling, it should be taken into account that neural network models are capable of analyzing images distorted by no more than 30% [18, 19].

At the same time, analysis of the data in Table 2.3 indicates that the range of variation in the size of images and videos on social networks in many cases significantly exceeds the specified acceptable limits of proportional scaling. In addition, the results of the analysis indicate significant variability in the aspect ratio of images and videos in popular social networks. For example, Instagram can post images with aspect ratios of 1:1 and 1.9:1, which also significantly complicates the procedure for scaling images if a general neural network model used for neural network analysis of these images.

Thus, the results of the studies show that in most cases, even within the same social network, it is very difficult to scale images to adapt them to the input field of a general neural network model designed to recognize political extremism. It should be noted that the use of several neural network models, which differ from each other primarily in the size of the input field, negatively affects the efficiency of the recognition system due to its technical complexity and the need to train several neural networks. In those cases when the image sizes vary by no more than 2.5 times (Telegram, Viber), in accordance with [20], the scaling procedure can be based on the bicubic interpolation apparatus.

The actual procedure for checking scalability can be defined using the following expressions:

$$k_x = Round(L_{NN}/L_{im}) \tag{1}$$

$$k_y = Round(H_{NN}/H_{im}) \tag{2}$$

$$\text{if } \; k_x \notin [k_{min}, k_{max}] \to stop \tag{3}$$

$$\text{if } \; k_y \notin [k_{min}, k_{max}] \to stop \tag{4}$$

$$\text{if } \; k_x/k_y > \partial \to stop \tag{5}$$

$$\text{if } \ k_y/k_x > \partial \rightarrow stop \tag{6}$$

where k_x, k_y are scale factors along the x and y axes; $Round$ – function of rounding to the smallest integer; L_{NN} – width of the input field of the neural network model, H_{NN} – height of the input field of the neural network model; L_{im} – width of the analyzed image; H_{NN} – height of the analyzed image; k_{min}, k_{max} – minimum and maximum allowable value of the scale factor; ∂ – maximum coefficient of variation of scaling along the axes.

Note that expressions (3, 4) determine the conditions for the possibility of proportional scaling, and expressions (5, 6) determine the conditions for the possibility of disproportionate scaling.

Solving the problem of bringing images to a given color format depends on the ratio of the color format of the analyzed image and the requirements for the color format of the input field of the neural network model. Possible options:

1. It is necessary to convert a color image in RGB format to RGBA format;
2. It is necessary to convert a color image in RGBA format to RGB format;
3. It is necessary to convert the color image to halftone;
4. It is necessary to convert the color image to binary.

The solution to the first two options implemented by trivially adding/removing the A-channel, which is responsible for the transparency of the image background.

The solution to the third option is implemented using expression (7).

$$C = 0,2125R + 0,7154G + 0,0721B \tag{7}$$

where C is the pixel color in halftone format; R, G, B – values that determine the color of the pixel in each of the RGB format channels.

The solution to the fourth option is implemented using expressions (7-9).

$$\begin{cases} \text{if } \ C \geq \alpha \rightarrow A = 1 \\ \text{if } \ C < \alpha \rightarrow A = 0 \end{cases} \tag{8}$$

$$\alpha = 0,5N \tag{9}$$

where α is the threshold value; N – pixel color depth in halftone format; A – pixel color in binary format.

It is advisable to divide the solution to the problem of leveling typical interference and distortion characteristic of the field of political extremism in online social networks into the stage of image quality correction and the stage of getting rid of interference.

By analogy with [11], at the stage of image quality correction, the procedure for normalizing color channels, brightness correction and image contrast correction implemented.

Note that normalizing the color channels of an image involves subtracting the average color value of this channel from the color of each pixel:

$$\overline{C} = C - C_{cp} \tag{10}$$

where $\overline{C}$ is the normalized pixel color, C is the original pixel color; C_{cp} – average color value in a given color channel.

The procedure for correcting the brightness of color channels is based on expressions (11, 12):

$$\Gamma(x,y)=\sum_{i=-a}^{0,5L}\sum_{j=-b}^{0,5H}(I(x+i,y+j)\times\Psi(x+i,y+j)), \tag{11}$$

$$\Psi=\begin{pmatrix}-2 & 0 & -2\\ 0 & 9 & 0\\ -2 & 0 & -2\end{pmatrix} \tag{12}$$

where Γ – filtered image; I – original image; Ψ – filter.

Note that expression (11) describes only one of the possible filter options.

The contrast correction procedure is described by expressions (13-16).

$$\begin{cases}\text{if} \ \ g<r\rightarrow q=r^{\frac{1-f}{1+f}}\\ \text{if} \ \ g=r\rightarrow q=g\\ \text{if} \ \ g>r\rightarrow q=r^{\frac{1+f}{1-f}}\end{cases} \tag{13}$$

$$f=\left(\frac{|g-r|}{g+r}\right)^{k} \tag{14}$$

$$k=k_{min}+(k_{max}-k_{min})a \tag{15}$$

$$r=\frac{1}{d^2}\sum_{i=x-0,5d}^{x+0,5d}\sum_{j=y-0,5d}^{y+0,5d}c_{i,j} \tag{16}$$

where q – adjusted pixel brightness value; g – initial pixel brightness value; r – the average brightness of a certain neighborhood of the pixel; f – function of nonlinear enhancement of local contrast; k – contrast enhancement factor; k_{max}, k_{min} – the maximum appropriate and minimum appropriate gain; a – adaptation coefficient, taking into account the characteristics of the pixel neighborhood; d – diameter of the pixel neighborhood; x, y – coordinates of the pixel for which contrast adjustment is implemented.

In accordance with the recommendations [18, 20] $k_{max}=0,7\ldots0,9$, $k_{min}=0,1\ldots0,3$, $d=15\ldots29$ pixels. As a first approximation, $k_{max}=0,9$, $k_{min}=0,2$, $a=0,6$, $d=20$. In the future, to clarify these parameters, it is possible to use the data from [11, 19].

To level out typical video recording interference, which manifests itself in the form of noticeable blurring of the image due to uneven lighting and/or video recording errors, an approach substantiated in [11] proposed, which is proposed to be used in distance education systems to filter biometric parameters. The essence of the approach is a pairwise comparison of wavelet coefficients of video frames with subsequent selection of a larger wavelet coefficient. The approach based on the practical statement that at different times of video recording, interference localized in different parts of the image. For example, in Fig. 4 and Fig. 5 show a scene of a street fight under the influence of interference localized in the upper left and lower right corners of the image, respectively.

Fig. 4. Blur localized to the top-left corner of the image

Fig. 5. Blur localized to the bottom-right corner of the image

The mathematical apparatus that defines the wavelet filtering model in the case of a square image of dimensions $N \times N$ is determined by the following expressions:

$$W_{m,k} = \frac{1}{\sqrt{2^m}} \sum_{n=0}^{N-1} (c(x_n)\varphi^*(2^m x_n - k)), \quad 1 \leq m, \quad k \leq N \tag{17}$$

$$W_{m,k}(i) = \frac{1}{\sqrt{2^m}} \sum_{n=0}^{N-1} (c(x_n, i)\varphi^*(2^m x_n - k)), \quad 1 \leq m, \quad k \leq N \tag{18}$$

$$q(x_n) = \frac{\pi}{\ln(2)} \sum_{n=0}^{N-1} \sum_{k=0}^{N-1} (\varphi^*(x_n) W_{m,k}), \tag{19}$$

$$q(x_n, i) = \frac{\pi}{\ln(2)} \sum_{n=0}^{N-1} \sum_{k=0}^{N-1} (\varphi^*(x_n) W_{m,k}(i)), \tag{20}$$

$$\text{if} \;\; w(1)_{m,k} \geq w(2)_{m,k} \rightarrow w(3)_{m,k} = w(1)_{m,k} \;\; \text{else} \;\; w(3)_{m,k} = w(2)_{m,k} \tag{21}$$

where W – matrix of wavelet coefficients; $c(x_n)$ – color brightness at point x_n for a halftone image; $c(x_n, i)$ – brightness of the $i-$th color channel at point x_n for a color image; m, k – shift and scale; x_n – coordinate of the $n-$th point of the image; $*$ – complex conjugation operation; φ – basis wavelet; $w(1)_{m,k}$ – $m, k-$th wavelet coefficient for the first image; $w(2)_{m,k}$ – $m, k-$th wavelet coefficient for the second image; $w(3)_{m,k}$ – $m, k-$th wavelet coefficient for the third filtered image;

It should be taken into account that expression (17) defines the matrix of wavelet coefficients of one row of points of a halftone image, and expression (18) defines the same matrix for the $i-$th color channel of a color image. The filtering process itself is implemented using expression (21). Restoration of the filtered halftone image is also realized using expression (22). To restore a color image, expression (23) is used.

$$q(x_n) = \frac{\pi}{\ln(a_0)} \sum_{n=0}^{N-1} \sum_{k=0}^{N-1} (\varphi^*(x_n) W_{m,k}), \tag{22}$$

$$q(x_n, i) = \frac{\pi}{\ln(a_0)} \sum_{n=0}^{N-1} \sum_{k=0}^{N-1} (\varphi^*(x_n) W_{m,k}(i)), \tag{23}$$

In contrast to the well-known basic solution of using wavelet transformations to level out noise [11], this dissertation work proposes the use of a filtering procedure based on expression (21), the use of the Haar wavelet as a base wavelet, defined by expression (24), as well as one level of detail wavelet transforms.

$$\varphi = \begin{cases} 1, 0 \leq x < 0,5 \\ -1, 0,5 \leq x < 1 \\ 0, x \notin [0,1[\end{cases} \quad (24)$$

Note that the justification for the feasibility of using an expression for filtering type (21) and wavelet-Haar implemented from the standpoint of minimizing computational resources at an acceptable level of filtering quality.

3 Results and discussion

Using the developed procedures defined by expressions (10-16), the processing shown in Fig. 3. Images of a group of people captured in low light conditions. The processing result is shown in Fig. 6. Expert comparison of Fig. 3 and Fig. 6 shows that from the point of view of recognizing the situation shown in the image, the implementation of the developed procedures increased the quality of the original image by 5-10%.

Fig. 6. Processed image of a group of people captured in low light condition

An example of using the filtering model specified by expressions (17-24) to eliminate blurs localized in different parts of the images shown in Fig. 4 and Fig. 5, shown in Fig. 7. In this case, the model was implemented using MatLab tools.

Computer experiments were carried out to confirm the hypothesis about the possibility of increasing the efficiency of neural network tools for analyzing graphic materials of online social networks through the use of the proposed preprocessing model (1-24).During the experiments was used a neural network model of the MobileNetV2 type supplemented with LSTM modules. The addition is implemented to increase the efficiency of neural network analysis of video sequences. The network was trained on training examples from the publicly available Real Life Violence Situations Dataset [21]. The database contains 1,000 violent videos and 1,000 non-violent videos collected from YouTube videos in a variety of media and settings. The sample is divided into training and validation in a ratio of 9:1. Graphs of the recognition accuracy of training (1) and validation (2) data are shown in Fig. 8.

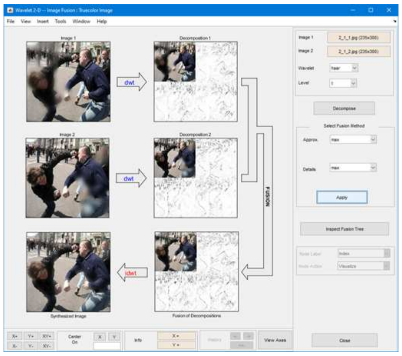

Fig. 7. Illustration of using the filtering model to eliminate blur localized in different parts of the image

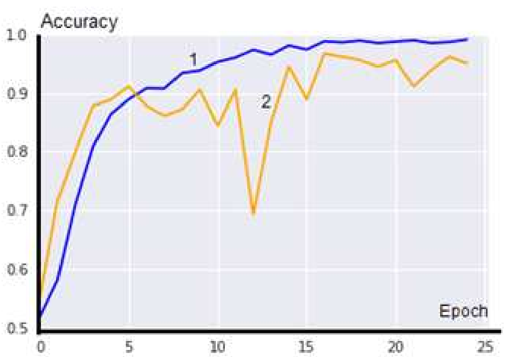

Fig. 8. Graphs of recognition accuracy of training and validation data

As shown in Fig. 8, after 25 training epochs, the recognition accuracy of training data is about 0.99, and that of validation data is about 0.97. To test the trained network, the 10 lowest-quality examples were selected from the validation set. The average recognition accuracy of these examples was about 0.88. These examples were further processed using the developed preprocessing model (1-24). The average recognition accuracy of the processed examples was 0.96. Thus, the use of the proposed preprocessing model made it possible to increase the recognition accuracy of video materials by approximately 1.09 times, which corresponds to the results of works [11, 18] in the field of increasing the efficiency of neural network analysis of graphic materials due to their preprocessing.

4 Conclusion

As a result of the research, an image pre-processing model was developed and verified to improve the efficiency of neural network tools for recognizing calls for political extremism in online social networks. The novelty of the proposed model lies in the use of an original wavelet transformation apparatus for filtering typical noise in images on online social networks, as well as a mathematical apparatus for correcting the brightness and contrast of images before submitting them to a neural network model for subsequent analysis. It is shown that the use of the proposed preprocessing model makes it possible to increase the accuracy of neural network recognition by approximately 1.1 times. It is also substantiated that the large variability of image sizes in popular online social networks does not allow these sizes to be reduced to a limited standard set, which predetermines the need for further research to take into account this feature in the architecture of a neural network model designed to detect political extremism.

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