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Detecting Images with Adult Content Using SURF and Haar Wavelet

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Abstract. Detecting images with adult content is one of the necessary and challenging problems in the fields of machine learning and machine vision. It can be used for a variety of applications such as content filtering and censoring, and user tracking, and banning. In this work, a framework for detecting nudity and adult content in digital images by using the SURF algorithm and Haar wavelet is developed. The proposed method is divided into online and offline modules. Each process that has a high time consumption is implemented in the offline module. Therefore, it can increase the speed of implementation of the model. For the proposed method, 899 images are used, in that, 402 images contain adult content, and 497 images have no adult content. 300 features of each image are extracted to create a *bag of features* (BOF), and they were used for the training by using a *support vector machine* (SVM). The results showed that the proposed method achieved an accuracy of 89.3%, a sensitivity of 86.2%, and a specificity of 92.03% for the classifier. The proposed framework provides an effective solution for detecting images and/or videos containing adult content from the internet environment.

Key-words: Adult content; Haar wavelets; *machine learning* (ML); machine vision; nudity detection; *speeded up robust features* (SURF); support vector machines.

1. Introduction

Information on the Internet can hold useful knowledge, but it also can contain fake news, objectionable messages, criminal incitement, violence, pornography, and rumors. Many users of internet are children and underage persons. These persons are potential victims. Cyberporn is another name of pornographic content. The internet is the easiest way for finding cyberporn just with just a few clicks. The internet is an optimal market for producers and creators of pornographic content. In many countries, pornography is prohibited like Indonesia, Iran and etc., and the reason is its damages on the next generation morale of the nation. Based on some researches, porn addiction is more than psychotropic. Governments, families and education systems should have effective role on controling cyberporn. Thus, computer softwares for detecting pornographic images have so important role in this area [1, 2].

Information can exist in various shapes. One of the common forms is the image. The color, texture, shape, and structure of an image can contain useful information. For a two-dimensional image stored with 8 bits, it can contain 256 gray levels, and the gray values vary in the range of 0 to 255, in that, 0 is for black, and 255 is for white. Usually, a two-dimensional image will be presented in a matrix called to be a pixel matrix. The matrix can contain different contents such as landscape, nature, human, and other sensitive contents such as pornography.

Machine vision (MV) with specific algorithms can be used to process and analyze images/videos by extracting features. Object detection, object tracking, and pattern recognition are common applications of MV.

Pornography may appear in a variety of media, including books, magazines, postcards, photographs, sculpture, drawing, painting, animation, sound recording, film, video, and video games. In the literature, different nudity image filtering techniques are proposed. For images, color has an important role in processing and detecting adult content.

In the study of Chen and Lu [3], a color image segmentation method was proposed. In the first stage, histograms in color space are calculated and the histograms were clustered by fuzzy c-mean. In the second stage, the clusters are merged together to create a segmented image. In another research [4], the authors also proposed a method for image segmentation based on an *artificial neural network* (ANN). This method presents a color-based technique for object segmentation. In that, the ANN was used for the training. Lips, faces, hands, fingers, and tree leaves are used. Another study was proposed based on k-mean clustering for color image segmentation. The colors with the same brightness are clustered into several groups. The value of K was determined manually [5, 6]. Al-Mohair *et al.* [7] used a hybrid method for skin detection. In this study, they used a *multi-layer perceptron* (MLP) and k-mean based on YIQ color space and ECU dataset to detect humans with skin and non-skin pixels.

The structure and shape in nudity image processing are important features that can be extracted from the images. There are many methods that can extract these features [8, 9]. Histogram of oriented gradients (HOG) is a powerful and effective method. In another work [10, 11], the authors proposed a method with HOG to detect human faces. With HOG descriptor, a feature vector for each image is extracted and a *support vector machine* (SVM) is used for the training to classify the images into with-face and without-face groups. Some more popular classification models [12] include SVM [13–15], artificial neural network [4], decision tree [14], and deep learning [1, 16-21]. In another work [22], the use of multiple low-level image features and a support vector machine (SVM) was proposed to identify pornographic images. The color, texture, and shape features are extracted within the *region of interest* (ROI). Li *et al.* [21] proposed a novel method based on *spatial pyramid partition* (SPP) and *multi-instance learning* (MIL). The method has deployed a bag corresponding to an image and an instance matching to each partitioned sub-block described by low-level visual features. In the work [23], the authors proposed a method based on oriented FAST and *Rotated BRIEF* (ORB). The whole recognition process can be divided into coarse and fine detection. Coarse detection can identify the non-pornographic images, and the fine detection includes three steps: extract ORB descriptors from the skin-color regions and create a *bag of words* (BOW), construct the feature vector combining ORB feature, and train by an SVM. There are many other approaches as the high-level feature extractor like speed up robust features (SURF) [24], and *scale-invariant feature transform* (SIFT) [25] are the most preferred.

In this article, we focus on improving the ability to detect nudity contents on images based on a combination of SURF and Haar wavelet. Contributions in the current article focus on:

- Proposing a framework model for detecting images with pornography that can be implemented online and offline,
- Using SURF, spatial pyramid, and SVM methods to increase the accuracy,
- Creating a *bag of features* (BOF) to improve the performance.

The current article is organized as follows. In Section 2, a framework for detecting pornography images is developed. In Section 3, a short description of error metrics and the data is provided, and experimental results are presented and analyzed here. The last Section (Section 4) concludes the study.

2. Methods

Many nudity and pornography image detection methods only use skin detection methods based on color tones [26]. These methods usually detect adult content inaccurately. The proposed method uses several stages for detecting adult content on images. This workflow of the proposed framework is shown in Fig. 1.

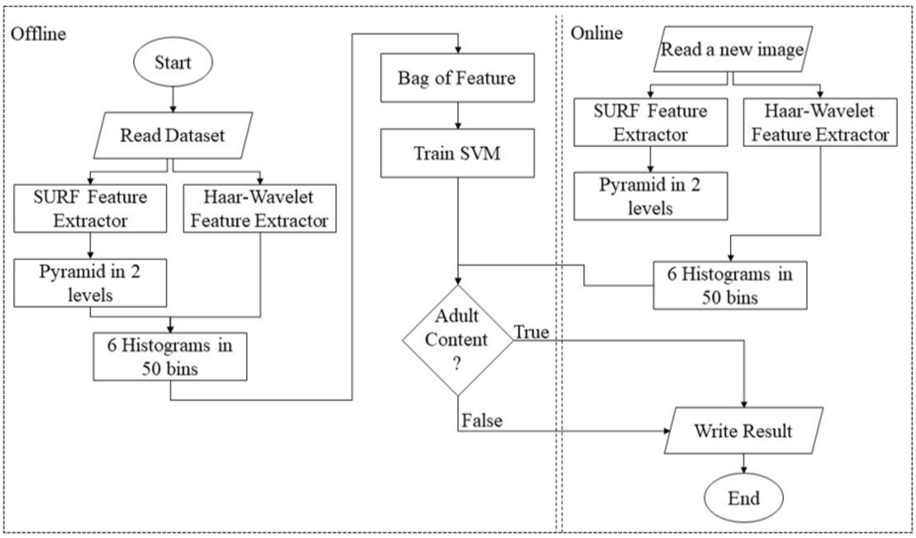

Fig. 1. Workflow of the proposed model.

In the first stage of the proposed framework, 899 images that contain nudity and normal contents are taken for analysis. There are not any datasets of pornography images, so the pornography images are taken from different websites. These images are used for feature extraction. To implement the framework, the proposed model is divided into online and offline modules. Extracting features from the dataset that has high-time consumption is implemented by using the offline module, and detecting the new image for classification is processed by the online module due to lower-time cost.

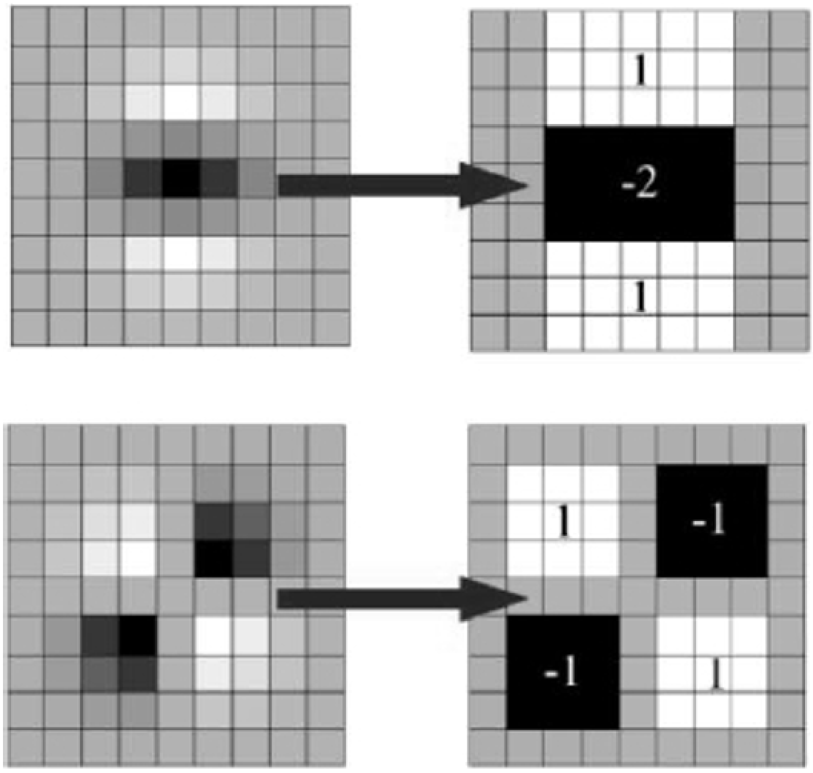

Fig. 2. A view of 9×9 (D_{yy} and D_{xy}) box filters.

In the SURF algorithm, interest points are detected by using Hessian. Given a point $x = (x, y)$ in an image I, Hessian $H(x, \sigma)$ at a point x with a scale σ is defined as follows:

$$H(x,\sigma) = \begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix}, \tag{1}$$

where $L_{xx}\ (x, \sigma), L_{xy}(x, \sigma)$, and $L_{yy}(x, \sigma)$ are the second-order derivatives of $L(x, \sigma)$, and $L(x, \sigma) = G(\sigma) * I$, $G(\sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/s\sigma^2}$ is a Gaussian kernel, and $\star$ is a convolution operator. In practice, sometimes, ones usually use box filter D to approximate Gaussian filter. In Fig. 2, 9×9 box filter is shown.

The interest points are set on different scales because searching for corresponding points often requires comparing images on the same distinct scale. Input images are often smoothed with a

Gaussian filter, and, then they are sub-sampled to reach the next higher level on the pyramid. In order to achieve rotational invariance, the orientation of the point of interest needs to be defined. The SURF algorithm will use a feature point as the center and draw 6 circles with 6 scales. After this, Haar wavelet is calculated for all feature points in x and y directions. In the last step of the SURF algorithm, it generates a feature point descriptor. The feature points select 2020 square region of the x-direction. The interest region is divided into 4×4 sub-regions (Fig. 3), and for every sub-region, the Haar wavelet responses are extracted at 5×5 areas that regularly spaced sample points. The descriptor vector contained all feature points of x and y directions. The 4D descriptor vector is defined as:

$$\vec{V} = \left(\sum d_x, \sum |d_x|, \sum d_y, \sum |d_y|\right), \tag{2}$$

where d_x and d_y are Haar wavelet response. $|d_x|$ And $|d_y|$ are absolute value of the response. Then $\vec{V}$ is a vector of $4 \times 4 \times 4 = 64$ dimensions [27, 28].

Fig. 3. (Left image) primal image, (right image) divided image to 2×2 sub-images.

After extracting the features, a histogram in 50 bins is used. In this step, we have $50 + (2 \times 2 \times 50) = 250$ features. To improve the accuracy, Haar wavelet in one level is used. Given a dataset contains elements. Therefore, there is $\frac{\rho}{2}$ averages and $\frac{\rho}{2}$ coefficients. In (3) and (4), the averages and the coefficients are calculated:

$$averages(i) = \frac{a_i + a_{i+1}}{2} \quad, i = 1, \ldots, \frac{\rho}{2}, \tag{3}$$

$$coefficients(j) = \frac{a_j - a_{j+1}}{2} \quad, j = 1, \ldots, \frac{\rho}{2}. \tag{4}$$

For calculating diagonal direction with Haar, the averages and the coefficients are calculated for all rows of the image pixels. Then, the average and the coefficient are calculated for all columns of the row-transformed pixels. For this work, 2×2 Haar matrix is used. The Haar wavelets mother wavelet function is computed in terms of:

$$\psi s = \begin{cases} 1 & 0 \le s < \frac{1}{2} \\ -1 & \frac{1}{2} \le s \le 1 \\ 0 & else \end{cases}. \tag{5}$$

Based on Haar wavelet's mother wavelet function, $H_{2\times 2} = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$ Haar matrix is obtained, And for N=2 the Haar transformed matrix is $H_{2\times 2} = \frac{1}{\sqrt{1}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$.

Values of coefficients are used. For every input image with a size of $m \times n$, we have $\frac{m}{2} \times \frac{n}{2}$ coefficients. Then, a histogram is calculated with $bin = 50$ for these features. At the last, the bag of features has $250 + 50 = 300$ features in this way. Fig. 4 presents a bag of features.

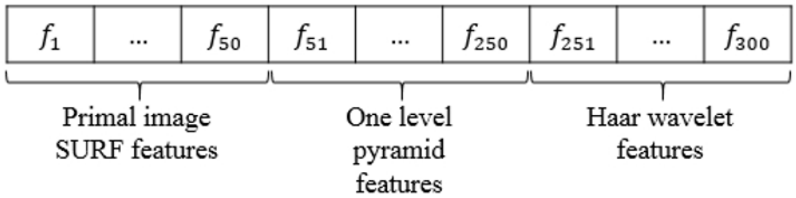

Fig. 4. A view of columns of BOF.

For classifying data, a seperation boundary is needed. In the linear classifier, finding a function like $f(x) = w^T x + b$ (SVM with the largest margin) is the main problem such that sign(f(x))=+1 for positive samples and $sign(f(x)) = -1$ for negative samples. Assume now that is defined as a margin of the classifier between two hyperplanes of the seperation (Fig. 5).

$$x = \begin{bmatrix} x_1 \\ \vdots \\ x_d \end{bmatrix}; w = \begin{bmatrix} w_1 \\ \vdots \\ w_d; \end{bmatrix}; b = \text{bias}. \tag{6}$$

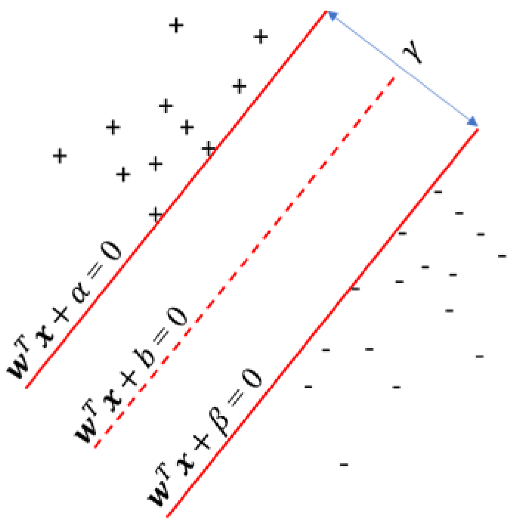

Fig. 5. A View of classifier.

With saving of generality, assume that $\alpha = b - 1$, and $\beta = b + 1$. So, the margin will be $\gamma = \frac{|\alpha - \beta|}{||w||} = \frac{2}{||w||}$. Finding the maximum margin between two boundries can be shown as

$\max_w \frac{2}{||w||} \equiv \min_w \frac{||w||}{2} \equiv \min_w \frac{w^T w}{2}$. At the end, it's the following equation which its name is Hard-Margin SVM:

$$\begin{array}{l} \min_{w,b} \frac{1}{2} w^T w \\ \text{s.t. } y_i(w^T x_i + b) \geq 1, \\ \forall i = 1, \ldots, p. \end{array} \tag{7}$$

For converting above constrained optimization problem into an unconstrained optimization problem, Lagrangian function of primal variables and dual variables will be defined as:

$$L(w, b, \alpha) = \frac{1}{2} w^T w - \sum_{i=1}^{p} \alpha_i \cdot [y_i \cdot (w^T x_i + b) - 1]. \tag{8}$$

Differentiate the Lagrangian function of SVM is shown in the following equations:

$$\nabla_w L(w, b, \alpha) = 0 : w = \sum_{i=1}^{p} \alpha_i y_i x_i. \tag{9}$$

$$\nabla_b L(w, b, \alpha) = 0 : w = \sum_{i=1}^{p} \alpha_i y_i = 0. \tag{10}$$

Finally, the dual problem of SVM will be defined as:

$$\begin{array}{l} max - \frac{1}{2} \sum_{i=1}^{p} \sum_{j=1}^{p} \alpha_i \alpha_j y_i y_j x_i^T x_j + \sum_{j=1}^{p} \alpha_i, \\ \text{s.t.} \sum_{j=1}^{p} \alpha_i y_i = 0, \\ \alpha_i \geq 0, \forall i = 1, \ldots, p. \end{array} \tag{11}$$

In the proposed model a non-linear soft margin SVM is trained on a dataset for classification that has regularization parameters $C > 0$ and misclassification parameters too. The dataset includes a set of input samples $(x_i, y_i)_{i=1,\ldots,p}$ where $x_i \in \mathbb{R}^q$are the inputs and $y_i \in \{-1, +1\}$ are the outputs. The regularization term is $\frac{1}{2}||w||^2$ and error variable ξ satisfies $\xi = (\xi_1, ..., \xi_p)^t$ based on $\xi_1 = L(f(x_i), y_i) = max\{0, 1 - y_i.(w^T x_i + b)\}$. The optimization problem is defined as:

$$\begin{array}{l} min_{w,e} \frac{1}{2} w^T w + C e^T \xi, \\ \text{s.t., } y_i(w^T \phi(x_i + b)) \geq 1 - \xi_i, \\ \xi \geq 0 \; \forall i = 1, \ldots, p, \end{array} \tag{12}$$

where $C > 0$ is the regularization parameter, p is a number of training data, e is a vector of error weights, ϕ is a kernel function which satisfies $K(u_i, u_j) = \phi(u_i).\phi(u_j)$, and classification vector w satisfies $\vec{w} = \sum_{i=1}^{p} \alpha_i v_i \phi(\vec{u}_i)$. For this primal problem, by using SVM, a dual problem is presents as follow:

$$\begin{array}{l} min_\alpha \frac{1}{2} \sum_{i=1}^{p} \sum_{j=1}^{p} \alpha_i v_i \big(\phi(u_i).\phi(u_j)\big) \alpha_j v_j - \sum_{j=1}^{p} \alpha_i, \\ \text{s.t.} \sum_{i=1}^{m} v_i \alpha_i > 0, \\ 0 < \alpha_i < C. \end{array} \tag{13}$$

where $K(.,.)$ is a polynomial kernel function that we can choose as $K(\vec{x}_i, \vec{x}_j) = \phi(x_i).\phi(x_j) = (\vec{x}_i.\vec{x}_j + 1)^3$, [29–31]. In the next Section, all defined parts will be implemented on dataset and results are shown in it.

3. Results

We implement the framework with a computing system with Windows OS, MATLAB R2017a, CPU Core i7-7500U, and 16GB RAM.

3.1. Accuracy assessment metrics

To assess the accuracy of detecting images with pornography content, we use metrics as follows:

$$\begin{array}{l} Accuracy\ (ACC) = \frac{TP+TN}{TP+TN+FP+FN}, \\ Sensitivity\ (TPR) = \frac{TP}{TP+FN}, \\ Specitivity\ (TNR) = \frac{TN}{TN+FP}, \\ Fall-out\ (FPR) = \frac{FP}{TN+FP}, \\ Misclassification = \frac{FP+FN}{TP+TN+FP+FN}, \end{array} \tag{14}$$

where TP,TN,FN,FP are True Positive, True Negative, False Negative, and False Positive, respectively.

3.2. Data

In this article, 763 images from various resources on the Internet (Google images) and 101 images from Caltech [32] are used. Among them, 402 images with adult content and 497 images without adult content are also used. The size of each image is roughly 300×200 pixels. Figs. 6, 7, and 8 present some image samples.

Fig. 6. A view of 101 Caltech images dataset (negative images).

Fig. 7. A view of images without pornographic content (negative images).

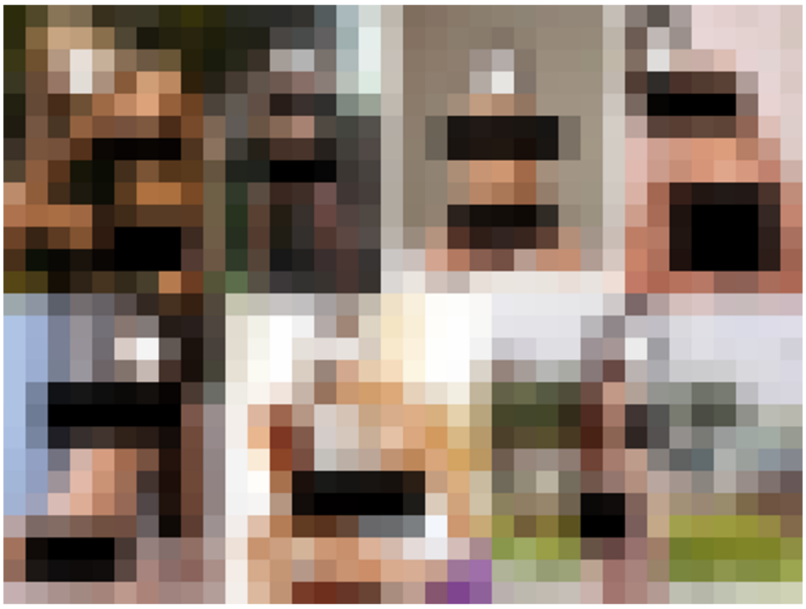

Fig. 8. A view of nudity images (positive images).

3.3. Experiments and discussions

SURF features and Haar wavelet diagonal transform on these datasets and histograms in 50 bins are calculated. A view of histograms is shown in Fig. 9 and Haar transformed is shown in Fig. 10.

For each image, SURF method is calculated in 2 levels. At level one, the features of the whole of images are extracted. At level 2, the primal images are divided into 4 sub-images and features

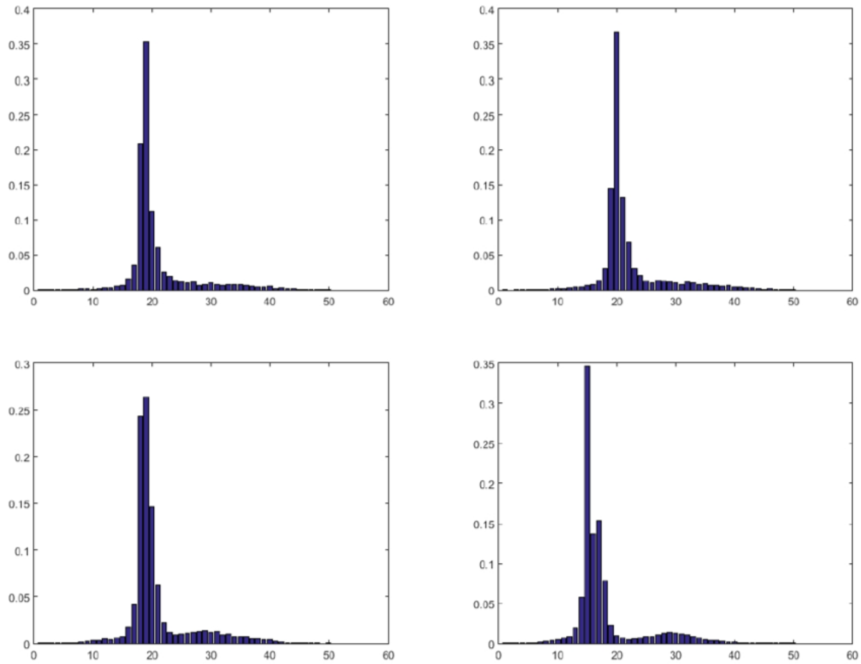

Fig. 9. Histograms of SURF interest points of negative images (First row) and negative row (second row).

Fig. 10. A view of Haar transformed.

Table 1. Contingency table of the proposed method

	Nudity (Positive)	**Non-Nudity (Negative)**	
Nudity (Positive)	TP=364	FP=38	
Non-Nudity (Negative)	FN=58	TN=439	
Total	422	477	

Table 2. A comparison between methods performance

Method	**Year**	**TPR**	**FPR**	**TNR**	**ACC**
Automatic detection of human nudes [33]	1999	–	4.2%	–	43%
Adult image detection method base-on skin color model and support vector machine [34]	2002	–	–	–	80.7%
Classifying offensive sites based on image content [8]	2004	–	9.8%	–	89%
An Algorithm for Nudity Detection [26]	2005	96.29%	6.76%	–	–
Two phases neural network-based system for pornographic image classification [35]	2009	85.9%	9.8%	–	–
Fast and Effectively Identify Pornographic Images [22]	2011	96.05%	–	96.17%	–
Detecting pornographic images by localizing skin ROIs [36]	2013	–	–	88%	83%
A classification of internet pornographic images [37]	2016	–	4.2%	–	85.2%
Pornographic Image Recognition via Weighted Multiple Instance Learning [16]	2018	97.52%	1%	–	–
Prototype of Pornographic Image Detection with YCbCr and Color Space (RGB) Methods of Computer Vision [38]	2019	76.66%	–	–	76%
Proposed Method	–	86.2%	7.9%	92.03%	89.3%

of each sub-image are extracted. For these levels, histograms are calculated. In the last step, Haar wavelet transform in the diagonal direction for each image is calculated. Because the image sizes are different, another histogram is calculated with 50 bins for Haar wavelet transform.

After training by SVM with the polynomial kernel, the results of the accuracy of the proposed method are presented in Table 1.

As we can see that the proposed method achieved an accuracy of 89.3%, a sensitivity of 86.2%, a misclassification (error) of 10.6%, and a specificity of 92.03% specificity for the classifier. Also, the mean square error (MSE) is 0.1068. The results of the experiments showed that the proposed framework can detect images with pornography content with high accuracy.

Creating Haar wavelet feature Bag takes up about 17.13 seconds and creating SURF feature Bag needs around 40.25 seconds for mentioned images. Also, training with SVM on 899×300 matrices needs around 10 seconds. For 899 images, the time cost is about 67.38 seconds. With increasing the numbers of pictures, this time will increase too. With implementing creating feature Bag and training SVM in the offline phase, time will be saved in each detection on new samples.

Next, we compare the performance of the proposed framework with other similar methods. The results were shown in Table 2. As can be seen that the proposed method works effectively and can compete with other similar state-of-the-art methods.

4. Conclusions

With the proliferation of adult content on the Internet, protecting children from this harmful content is a necessary task for researchers. In this article, we have proposed a framework for detecting images with adult content. The framework utilized the SURF algorithm and Haar wavelet to extract the necessary features. After that, the features were put into BOF to deploy the training with SVM. The framework is implemented through two modules: online and offline. The proposed framework was tested on a large dataset with adult-content-free images and sensitive images with adult content. The experimental results showed that the proposed model achieved an accuracy of 89.3%, a sensitivity of 86.2%, and a specificity of 92.03% in classifying images into the regular image group and pornography image group.

For future work, the proposed model will incorporate ANN, memetic, or genetic algorithms to increase the overall accuracy of detecting pornography content.

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