Advances in Intelligent Systems and Computing 1350

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Gian-Antonio Susto *Editors*

Advances in Robotics, Automation and Data Analytics

Selected Papers from iCITES 2020

Springer

Advances in Intelligent Systems and Computing

Volume 1350

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Editors
Jessnor Arif Mat Jizat
Faculty of Manufacturing and Mechatronic
Engineering Technology
Universiti Malaysia Pahang
Pekan, Malaysia

Mohd Azraai Mohd Razman
Faculty of Manufacturing and Mechatronic
Engineering Technology
Universiti Malaysia Pahang
Pekan, Malaysia

Mohamad Shaiful Abdul Karim
College of Engineering
Universiti Malaysia Pahang
Gambang, Malaysia

Lim Wei Hong
UCSI University
Kuala Lumpur, Malaysia

Pengcheng Liu
University of York
York, UK

Han-Lim Choi
Department of Aerospace Engineering
Korea Advanced Institute of Science
and Technology
Daejeon, Korea (Republic of)

Ismail Mohd Khairuddin
Faculty of Manufacturing and Mechatronic
Engineering Technology
Universiti Malaysia Pahang
Pekan, Malaysia

Ahmad Fakhri Ab. Nasir
Faculty of Manufacturing and Mechatronic
Engineering Technology
Universiti Malaysia Pahang
Pekan, Malaysia

Abdul Aziz Jaafar
Faculty of Manufacturing and Mechatronic
Engineering Technology
Universiti Malaysia Pahang
Pekan, Malaysia

Anwar P. P. Abdul Majeed
Faculty of Manufacturing and Mechatronic
Engineering Technology
Universiti Malaysia Pahang
Pekan, Malaysia

Hyun Myung
School of Electrical Engineering
Korea Advanced Institute of Science
and Technology
Daejeon, Korea (Republic of)

Gian-Antonio Susto
Department of Information Engineering
University of Padua
Padova, Italy

ISSN 2194-5357 ISSN 2194-5365 (electronic)
Advances in Intelligent Systems and Computing
ISBN 978-3-030-70916-7 ISBN 978-3-030-70917-4 (eBook)
https://doi.org/10.1007/978-3-030-70917-4

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Preface

The International Conference on Innovative Technology, Engineering and Sciences 2020 (iCITES 2020), is the second edition of the conference series organized by Universiti Malaysia Pahang through its Alumni Society in an effort to promote key innovation in the following overarching themes and individual symposia, i.e. green and frontier materials, innovative robotics and automation, renewable and green energy, sustainable manufacturing as well as data analytics. The conference is aimed at building a platform that allows relevant stakeholders to share and discuss their latest researches, ideas and survey reports from theoretical to practical standpoint of the aforementioned fields.

ICITES2020 received more than 170 submissions. All submissions were reviewed in a single-blind manner, and the best 40 papers recommended by the reviewers are published in this volume. The editors would like to thank all the authors who submitted their papers as the papers are of good quality and represented good progress in industrial and robotic vision, motion control, autonomous mobile robots, intelligent sensors and actuators, multi-sensor fusion, deep learning and approaches and data processing.

The editors also would like to thank Assoc. Prof. Han-Lim Choi, Jamie Steel, Dr. Rabiu Muazu Musa, Dr. Miles Stopher, Assoc. Prof. Dr. Kazem Reza Kashyzadeh, Jee Kwan Ng for delivering their keynote speeches at the conference. They had to bring a new perspective on cutting-edge issues especially in the fields of robotics, automation and data analytics.

The editors hope that readers find this volume informative. We thank Springer for undertaking the publication of this volume. We also would like to thank the conference organization staff and the members of the international program committees for their hard work.

Contents

Editor Biographies

Dipl. Ing. (FH) Jessnor Arif Mat Jizat is a researcher at Innovative Manufacturing, Mechatronics & Sports Laboratory, Faculty of Manufacturing and Mechatronic Engineering Technology in Universiti Malaysia Pahang (UMP). He completed his master's degree at UMP and diploma (FH) at Hochschule Karlsruhe, Germany. His research interest includes machine learning, robotics, robotic vision and sports engineering.

Ismail Mohd Khairuddin is a lecturer at Universiti Malaysia Pahang. He received his bachelor's degree in Mechatronics Engineering from Universiti Teknikal Malaysia Melaka (UTeM) in 2010 and was awarded a master's degree in Mechatronics and Automatic Control from Universiti Teknologi Malaysia in 2012. His research interests include rehabilitation robotics, mechanical and mechatronics design, mechanisms, control and automation, bio-signal processing as well as machine learning.

Dr. Mohd Azraai Mohd Razman is a senior lecturer at Universiti Malaysia Pahang. He graduated from the University of Sheffield, UK, before he obtained his M.Eng. and Ph.D. from Universiti Malaysia Pahang (UMP) in Mechatronics Engineering. His research interest includes optimization techniques, control systems, signal processing, instrumentation in aquaculture, sports engineering as well as machine learning.

Ahmad Fakhri bin Ab. Nasir is a senior lecturer at Universiti Malaysia Pahang (UMP). He received his bachelor's degree in Information Technology from Universiti Malaya and a master's degree in Manufacturing Engineering from Universiti Malaysia Pahang. He pursued his Ph.D. at the Universiti Sultan Zainal Abidin. He has published several articles and actively doing research related to computer vision, pattern recognition, image processing, machine learning as well as parallel computing.

Mohamad Shaiful Abdul Karim received his B.Eng. (Electrical and Electronics), M. Eng. (Advanced Science and Engineering) degree and D. Eng. (Advanced Electrical, Electronic and Computer Systems) from Ritsumeikan University, Japan, in 2011, 2013 and 2016, respectively. In 2016, he joined Universiti Malaysia Pahang as a senior lecturer at College of Engineering. He is currently engaged in the research of microwave engineering, communication and biomedical medical devices.

Abdul Aziz bin Jaafar is an associate professor and researcher at the Faculty of Manufacturing and Mechatronic Engineering Technology, Universiti Malaysia Pahang. He received B.Eng (Mechanical/System) from Universiti Putra Malaysia and Ph.D. (Mechanical Engineering) from University of Bath, UK. His research interest is mainly on fluid flow and heat transfer, applications of light thin material on emergency and recreational shelters subjected to dynamic loading.

Dr. Wei Hong Lim is currently an assistant professor and a researcher at UCSI University. He obtained his B.Eng. (Hons) Mechatronic Engineering and Ph.D. in Computational Intelligence from Universiti Sains Malaysia, Penang, Malaysia. He was attached to the Intelligent Control Laboratory in National Taipei University of Technology, Taiwan, as the postdoctoral researcher from 2015 to 2017 and as the visiting researcher in 2019.

Anwar P. P. Abdul Majeed graduated with a first-class honours bachelor's degree from Universiti Teknologi MARA (UiTM), Malaysia. He obtained his master's degree Imperial College London, UK, before receiving his Ph.D. from Universiti Malaysia Pahang (UMP). He is a chartered engineer (C.Eng.) at the Institution of Mechanical Engineering (IMechE), UK.

Pengcheng Liu received the B.Eng. degree in measurement and control, the M.Sc. degree in control theory and control engineering from the Zhongyuan University of Technology, China, and the Ph.D. degree in robotics and control from Bournemouth University, UK. He is currently a lecturer (Tenured Assistant Professor) at the Department of Computer Science, University of York, UK. . He is an associate editor of IEEE Access, and he received the Global Peer Review Awards from Web of Science in 2019 and the Outstanding Contribution Awards from Elsevier in 2017.

Prof. Hyun Myung received the B.S., M.S. and PhD degrees in electrical engineering from the Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Korea. Since 2008, he has been a professor at the Department of Civil and Environmental Engineering, KAIST, and he is the head of the KAIST Robotics Program. From 2019, he is a professor at the School of Electrical Engineering. He led the development of the world-first robots such as jellyfish removal robot (JEROS) and CAROS (wall-climbing drones).

Han-Lim Choi received his M.S. in Aerospace Engineering from the Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Korea, in 2020. He then pursued his PhD in Aeronautics and Astronautics, Massachusetts Institute of Technology (MIT), USA. He is currently serving as an associate professor at the Department of Aerospace Engineering, KAIST, Daejeon. His research interest includes information-theoretic decision-making for cyber-physical systems, planning and control for multi-agent systems, air and space vehicle guidance and control as well as environmental sensing systems.

Dr. Gian Antonio Susto received the M.S. degree in control systems engineering and the Ph.D. degree in information engineering from the University of Padova, Italy, in 2009 and 2013, respectively. He is currently an assistant professor at the University of Padova and a chief data scientist and founder at Statwolf Limited, Dublin, Ireland. His research interests include manufacturing data analytics, machine learning, gesture recognition and partial differential equations control.

Development of Automatic Obscene Images Filtering using Deep Learning

Abdelrahman Mohamed Awad[1], Teddy Surya Gunawan[1,2][0000-0003-3345-4669], Mohamed Hadi Habaebi[1], Nanang Ismail[3]

[1] Electrical and Computer Engineering Department, International Islamic University Malaysia
[2] School of Electrical Engineering & Telecommunications, UNSW, Australia
[3] Electrical Engineering Department, UIN Sunan Gunung Djati, Bandung, Indonesia
tsgunawan@iium.edu.my

Abstract. Because of Internet availability in most societies, access to pornography has become a severe issue. On the other side, the pornography industry has grown steadily, and its websites are becoming increasingly popular by offering potential users free passes. Filtering obscene images and video frames is essential in the big data era, where all kinds of information are available for everyone. This paper proposes a fully automated method to filter any storage device from obscene videos and images using deep learning algorithms. The whole recognition process can be divided into two stages, including fine detection and focus detection. The fine detection includes skin color detection with YCbCr and HSV color spaces and accurate face detection using the Adaboost algorithm with Haar-like features. Moreover, focus detection uses AlexNet transfer learning to identify the obscene images which passed stage one. Results showed the effectiveness of our proposed algorithm in filtering obscene images or videos. The testing accuracy achieved is 95.26% when tested with 3969 testing images.

Keywords: convolutional neural networks, Adaboost algorithm, Haar-like features, skin detection, pornographic, image filtering, AlexNet.

1 Introduction

In the past decade, there were many filtering techniques used for the detection of pornography. In 1996, content-based filtering was proposed in [1]. Along with that, there are many blocking and filtering obscene content through media content (videos and images), Web indexing, and browsing. Keyword-based, blacklist-based, and content-based techniques are the categories of pornographic image filtering techniques [2]. Classification of pornographic images and videos is an unavoidable issue, but it is vaguely defined to some extent. Some define the pornographic frame or image as the images containing a full naked body, some define them as the images with massive skin exposed, and others categorize an image as a pornographic image if it has shown a human's private part.

Presently, pornography regulations exist in different countries, and accessing pornography websites is prohibited. Youth's entry into pornography is simple, leading to moral degradation and social problems [2]. In most countries, the lack of control and regulation on available information on the Internet has also become a significant concern for society. More than 4 million sexual content-based websites on the Internet are around 10% of all websites [3]. Moreover, Netflix, Twitter, and Amazon have fewer unique visitors than adult websites [4]. For that reason, anti-pornography filtering is essential to prevent the harmful impact of pornography content from reaching and affect our societies. Therefore, this paper aims to develop automatic obscene images and video filtering using deep learning algorithms. Two stages were proposed, including fine detection (skin and face detection) and focus detection. The aim is to develop an efficient obscene image or video filtering, which requires minimal computation but with high detection accuracy.

2 Obscene Image Filtering Techniques

Blocking and filtering obscene content through media content (videos and images) and Web indexing and browsing are crucial. Several techniques are currently used for filtering pornographic images and videos, including keyword-based, blacklist-based, and content-based techniques [2].

2.1 Keyword-based Technique

It is one of the static filtering techniques which is effectively used in Web page analysis and filtering. Keyword-based systems attempt to recognize pictures by analyzing the text names or the text surrounding them on the website. Keyword analysis can be used so that a web page can be classified into pages with pornographic content or not. The static nature language model is used for web page modeling [2]. If the applied keyword appears on a Web page, the Web page would be blocked. This method is quite challenging to implement on a large scale because of two significant problems, the sensitivity to keywords and the difficulty of adding more keywords in all languages [5].

2.2 Blacklist-based Technique

The URLs of pornography websites are collected and added to a blacklist. Once one of these URLs is accessed, an inspection software blocks this access. However, the number of pornography sites is increased unprecedented every day. Hence, manually includes in a static blacklist of all adult websites is impractical. The blacklist must be updated daily to overcome this problem, so this kind of software would be more efficient [6].

2.3 Content-based Technique

Content-based procedures assess pictures by coordinating picture content examination. The pioneering work was conducted by [1] when they used both texture properties and color to initiate a classifier for human skin location. After locating an image's human skin, these locations were passed to a geometric direct in light of body plans. Adult and non-adult pictures are used to set up a neural framework classifier of skin and non-skin classes [2].

By examining an image or a video (by extracting its key-frames) content-based technique can identify whether it contains obscene content or not. Several methods use this technique to identify nudity, which uses an approach based on the human structure model, but it is inefficient. They need to have completely naked people in the picture or the frame and simple background with simple colors. Nowadays, pornographic images have a variety in the background, scale, scenario, and human action [6]. The feature-based approach used a classifier based on the majority voting of a frame sample [7]. The convolutional neural networks (CNN) are used to classify the frames classified. The approach emphasizes the extraction of the feature from the picture [8]. Most of the feature-based approach uses bag-of-feature and CNN [9]. However, the bag-of-features approach has a high false-positive rate [10].

3 Proposed Obscene Image Filtering Algorithm

Skin tone is a crucial feature of pornographic image and video detection. A skin pixel can be classified based on the texture or color of the pixel. Assuming that the skin color belongs to a specific range of colors called (i.e., thresholds), this assumption allowed many techniques to use color-based techniques to classify pornographic images. In this method, the color thresholds for different skin colors are first learned from a series of marked training pictures. The pixel in the image is then compared to the criteria to figure out if the pixel is a skin pixel or not. Classifying whether the video connotations obscene frames or not start by extracting the keyframe, then the individual frame or an image has to be changed YCrCb and HSV color as a second step, YCrCb model is used because it is luma-independent [11].

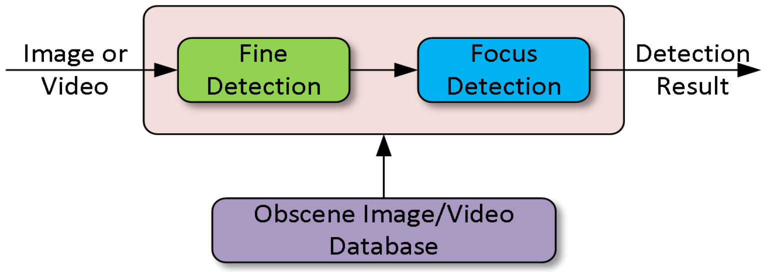


Fig. 1. Block diagram of the proposed system

In this research, we will use two levels of filtering, as shown in Fig. 1. The first one is *fine detection*, which uses a color-based technique to identify either the image or a video containing obscene videos. The second stage is *focus detection*, which passes the images with more skin regions into a trained neural network based on AlexNet transfer learning, identifying the images safely and efficiently.

3.1 Fine Detection Stage

This stage's primary focus is to identify the skin region and indicate if this skin is only on the face area or body area. The input for this stage is the images or videos (keyframe extracted as an image). The YCrCb mask will mask images, and the HSV mask then compiles the two masks to get the skin region. The segmented images with skin region will be passed to the face detection algorithm to check if there is a face or not. If there is no face, the skin region is a body region so that the image will be passed to the next stage, i.e., focus detection. If the image has a face, the face area will be removed from the calculation. If there is still a skin region representing more than 5% of the total area, the image will be passed to focus detection. If not, the image will be classified as a safe image, as shown in Fig. 2.

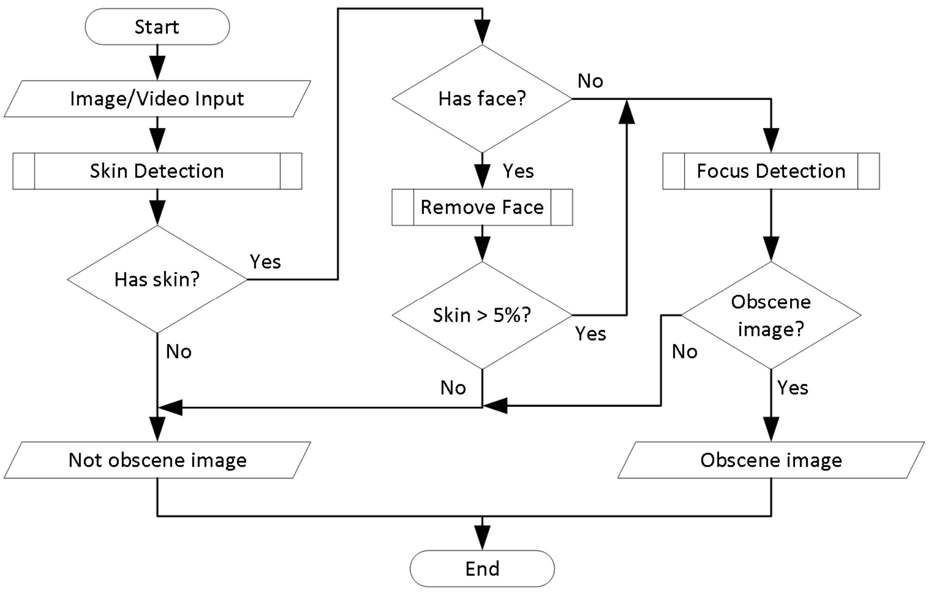


Fig. 2. Fine Detection Flowchart

In this paper, the keyframe extraction algorithm proposed in [12] will be modified and used. For implementation, FFmpeg-python was utilized to extract the keyframes. The second step of video-based pornographic detection and the first step of image-based pornographic detection is converting the frame or the image to the YCrCb color space. In this color space, Y represents luminance information, Cr and Cb are color-difference components that are storing the color information of an image [13]. YCbCr color model results in a better performance than RGB in skin detection because it is luma-independent. YCbCr values can be obtained from RGB color space using Eq. (1), as stated [11].

$$Y = 0.299R + 0.287G + 0.11B; \quad Cr = R - Y; \quad Cb = B. \tag{1}$$

There are large areas of naked skin in pornographic images. For this reason, skin color is the most stable attribute in pornographic images. Which makes the exact reason that skin color detection is indispensable for pornographic image recognition. This paper uses the skin-color model proposed in [14] to detect the skin-color regions of images, which will use both HSV and normalized RGB (YCbCr) models.

Detecting facial landmarks is a subset of the shape prediction problem. Taking the detection speed into account, the face detection algorithm that combines the Adaboost algorithm with Haar-like features is chosen, not affected by skin-color detection results. For the facial images, the skin-color areas are fundamentally composed of the faces. As for the pornographic images, skin-color areas are usually larger than the facial areas. Using this prior knowledge, we can determine if the image is a facial image or not. The facial areas are denoted as *Facial Region* (FR), and skin-color areas are denoted as *Skin Region* (SR). If $SR - FR < 5\%$, the image will be judged as the facial image, as shown in Fig. 3.

3.2 Focus Detection Stage

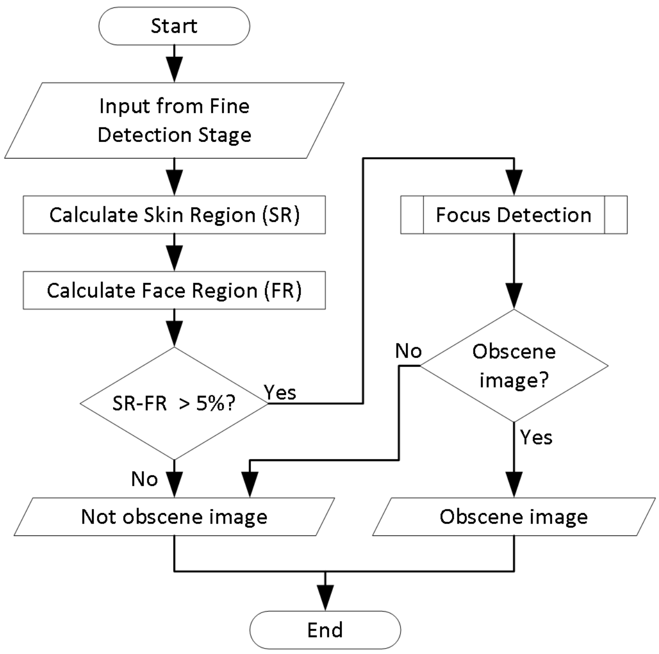


Fig. 3. Focus Detection Flowchart

After applying *fine detection,* the images will pass through a pre-trained convolutional neural network to identify if the image is safe or not, as shown in Fig. 3. This research is using transfer learning using the AlexNet neural network. AlexNet is a convolutional neural network with eight layers trained on more than a million images. In transfer learning, the original layers are used with a slight change in the number of output classes and then restrained with the new dataset.

4 Results and Discussion

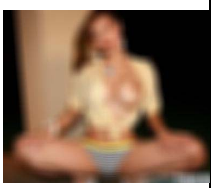
4.1 Dataset

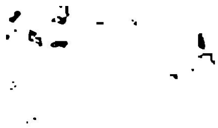
The primary dataset used was collected by [15], which contains nearly 80 hours of 400 pornographic and 400 non-pornographic videos. The keyframe of the videos was extracted to create 6500 porn frames and 7000 non-porn frames. For porn images, 3500 images were added to the dataset, and 3000 images were added to the safe images to create 10000 images for each category. The dataset was divided into 70% training data, 10% validation data, and 20% testing data.

4.2 Experiment on Fine Detection Stage: Skin Detection

In the skin detection stage, two masks were applied to each image. Then the two masks were compiled to get results with more accuracy. This stage results are under the effect of two main factors: image lighting and skin-like pixels.

Table 1. Example of Skin Detection

#	Original image	YCbCr mask	HSV mask	Compiled mask	% Skin
1					22.7 %
2					44.1 %

3					0.0%
4					17.5%
5					20.2 %

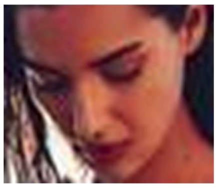
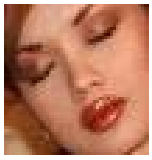
By looking at image numbers 1 and 2, we can see that these two images have complex backgrounds with skin-like pixels. The skin percentage is higher than what it is supposed to be. We can conclude that skin detection using both YCbCr and HSV masks give good detection with the pictures that do not have skin-like pixels. Nevertheless, it gives a high skin percentage in the pictures that have complex backgrounds or skin-like pixels. The image lighting also affects the number of skin pixels in the image. If the light is high, the skin color will be changed to another lighter color to be considered a normal pixel. All images will be passed to face detection except image number 3 because all images have some skin regions percentage.

4.3 Experiment on Fine Detection Stage: Face Detection

A Python library based on the Adaboost algorithm with Haar-like features is used to detect the pictures' face area in the face detection step. After detecting the face area in the image, the pixel number is reduced from the previous step's skin region. If the skin region represents more than 5% of the total skin area, the image will proceed to the next stage, i.e., focus detection. Otherwise, it will be considered a safe face image.

Table 2 shows the results of using face detection and showing the skin area without a face. Images 1, 2, and 3 will be passed to the next stage, i.e., focus detection, because they met the criterion, which has a skin region $> 5\%$ of the total image size. On the other hand, image 5 considered safe images because skin regions $< 5\%$.

Table 2. Example of Face Detection

#	Original image	Skin Region	% Skin	Face area	% Skin without Face
1			22.7 %		10.4%
2			44.1 %		41.4%
3			17.5%		12.5%
5			20.2 %		4.6 %

4.4 Testing on the Fine Detection Stage

For research purposes, the fine detection stage was tested with 1000 images categorized as Table 3. A safe image is an image that does not contain any pornographic features. The safe images were divided into two categories: hard and easy. Hard represents the images with skin-alike pixels, bad lighting, or large skin areas, but they are not obscene images, such as babies' images. The easy image did not have any skin pixels. The unsafe image is the image that showed exposed body skin. If the body's skin is in a large area, it is considered an easy unsafe image. Otherwise, it is a hard unsafe image. The hard safe image has a large number of false detection because of skin-alike pixels or lighting problems. For the hard unsafe images, five images are considered a safe picture because the exposed body skin exists in a small area.

Table 3. Testing data distribution and its detection results

	Safe Images		Unsafe Images	
	Hard	**Easy**	**Hard**	**Easy**
Number of Images	250	250	250	250
Detection Result				
Correct Identification	160 (64%)	240 (96%)	207 (82.8%)	235 (94%)
Incorrect Identification	90 (36%)	10 (4%)	43 (17.2%)	25 (10%)

4.5 Experiment on the Focus Detection Stage

After applying fine detection, the images will be classified by a convolutional neural network. This CNN is trained using the transfer learning method using the Alexnet that has eight layers. In transfer learning, the original layers are used with a change in the number of output classes and then retrained with the new dataset, as shown in Fig. 4. Only two classes are used as output: safe and unsafe images. Safe represents an image that is not pornographic. Unsafe represent an image that is pornographic.

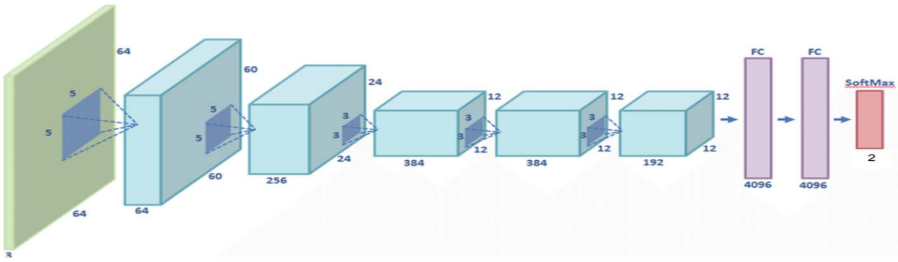


Fig. 4. Modified AlexNet structure for transfer learning of the focus detection stage

The dataset used for training contains 20000 images. Half of them are safe, and the other half contains unsafe images. For obscene image detection, the safe dataset selected from over 10000 images varied from human images, non-human images, babies' images, animals' images, images with complex backgrounds, and images with typical backgrounds. The dataset was divided into 70% training, 20% testing, and 10% validation.

Table 4. Confusion Matrix

		Predicted	
Actual		*Safe*	*Unsafe*
	Safe	TP: 1901 (94.6%)	FP: 109 (5.4%)
	Unsafe	FN: 79 (4.0%)	TN: 96.0%

The training is done using Matlab, which took 3 hours using a local machine with 540 iterations over the data. This training's resulting accuracy was 98.5 %, with a loss of less than 0.01, and validation accuracy of 98.19%, as depicted in Fig. 5. The testing data represent 20% of the total data, which equals 3969 images. The results of this testing are shown in the confusion matrix in Table 4. The overall accuracy of the testing was 95.26%.

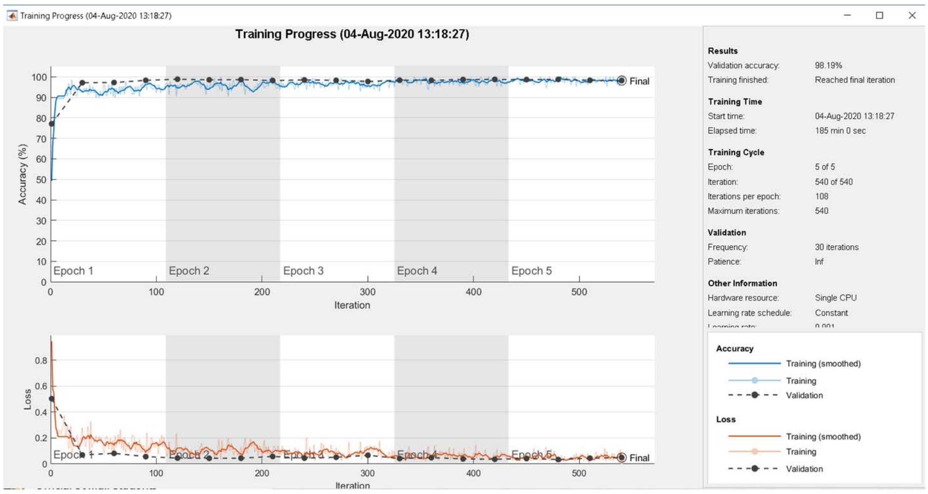


Fig. 5. Training progress report

5 Conclusions and Future Works

We have proposed an obscene image filtering system that can be fast and accurate. There are two stages in this algorithm, including fine and focus detection. Fine detection consists of two steps: skin detection followed by face detection. This stage's results were fast but not entirely accurate due to some lighting and skin-like pixels related problems. A transfer learning using AlexNet was done as the focus detection stage. The final accuracy achieved is around 95.25% when testing with 3969 images. Moreover, the false positive and false negative were 5.4% and 4.0%, respectively. Future works include improving the skin detection algorithm for skin-like pixels and bad lighting images, improving the face detection algorithm, and use other image datasets for training and testing.

Acknowledgments

The authors would like to express their gratitude to the Malaysian Ministry of Education (MOE), which has provided research funding through the Fundamental Research Grant, FRGS19-076-0684 (FRGS/1/2018/ICT02/UIAM/02/4). The authors would like to acknowledge the International Islamic University and the University of New South Wales's support.

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