ENHANCED AGEHOLONET ALGORITHM USING AGE ESTIMATION AND OBJECTIONABLE IMAGE FOR PORNOGRAPHIC IMAGE DETECTION

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DEDICATION

This thesis is dedicated to my lovely wife for her endless love, support, and patients. She was supporting me in up and downs of my journey which without her support I was not able to survive the pressures and challenges that I faced. Also, I would like to dedicate tis thesis to my beloved parents which they were my first teachers and their constant encouragement, prayers and trust was helping me to finish this journey.

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ABSTRACT

With the rapid growth of the internet and emerging technologies, developing media content, and sharing them globally have become simple and fast. Despite the abundance of advantages this phenomenon has brought, it has led to some concerns in exposing people to unwanted and offensive media content. Among unwanted images, objectionable images are the most offensive ones which people are trying to avoid viewing. Although a number of research have been conducted in this area, this field is still scarce and there are challenges that should be addressed. One major challenge in this field is the lack of a well-defined definition for objectionable images. Therefore, different scholars with varied perceptions of the objectionable image came up with algorithms to tackle the problem of detecting objectionable images. In this research, the objectionable image detection model which is called Holistic Local Aware Deep Network or in short HoLoNet has the following novel characteristic: the local and global features are seamlessly integrated into the network and mutually affect each other during training. Moreover, in order to include the age of humans in the image of final decision, Gender Aware Age Estimation Net or in short GeAeNet was proposed. GeAeNet estimates age under condition of identified facial attribute of gender which makes the estimation more accurate. Moreover, the loss function is proposed to supervise the GeAeNet. Using this loss function, the network tends to generate a more reasonable probability distribution of age classes, where the predicted probability of each age class should be inversely proportional to the deviation from the ground truth age class in general. The combination of HoLoNet and GeAeNet formed the proposed AgeHoLoNet excluding the False Positive (FP) cases wherein detected objectionable images would only be humans who are under adulthood borderline age. GeAeNet outperformed state-of-the-art techniques in both controlled and wild environments by achieving Mean Absolute Error (MAE) 2.43 in facial age estimation dataset (MORPHII) and 2.64 in facial aging dataset (FG-NET) and 5.12 in Age Database (AgeDB) datasets. Finally, comparing the objectionable model with state-of-the-art techniques proves that HoLoNet alone outperforms related works with accuracy of 0.956 and AgeHoLoNet with accuracy of 0.964 over Pornography Dataset (NPDI).

ABSTRAK

Dengan perkembangan internet yang pesat dan teknologi yang baru muncul, membangunkan kandungan media dan membagikannya di seluruh dunia menjadi mudah dan pantas. Walaupun terdapat banyak kelebihan yang dibawa oleh fenomena ini, ia menimbulkan beberapa kebimbangan dalam mendedahkan individu kepada kandungan media yang tidak diingini dan menyinggung perasaan. Di antara imej yang tidak diingini, imej yang tidak menyenangkan merupakan imej yang paling menyinggung yang cuba dielakkan oleh orang ramai untuk tidak melihatnya. Walaupun sejumlah kajian telah dilakukan dalam bidang ini, ia masih kurang dikaji dan terdapat cabaran yang harus ditangani. Satu cabaran utama dalam bidang ini adalah kurangnya definisi yang tepat untuk imej yang tidak menyenangkan. Oleh itu, para sarjana yang mempunyai persepsi yang berbeza-beza terhadap imej yang tidak menyenangkan muncul dengan algoritma untuk mengatasi masalah mengesan imej yang tidak menyenangkan. Dalam penyelidikan ini, model pengesanan imej yang tidak menyenangkan yang disebut Holistic Local Aware Deep Network atau ringkasnya HoLoNet mempunyai ciri-ciri berikut: ciri-ciri tempatan dan global disatukan dengan lancar ke dalam rangkaian dan saling mempengaruhi antara satu sama lain semasa latihan. Lebih-lebih lagi, untuk memasukkan usia manusia dalam imej keputusan akhir, Gender Aware Age Estimation Net atau ringkasnya GeAeNet. GeAeNet menganggarkan usia di bawah keadaan sifat jantina wajah yang dikenal pasti bagi menjadikan anggaran lebih tepat. Lebih-lebih lagi, fungsi kerugian dicadangkan untuk mengawasi GeAeNet. Dengan menggunakan fungsi kerugian ini, rangkaian cenderung menghasilkan taburan kebarangkalian kelas usia yang lebih munasabah, di mana kebarangkalian yang diramalkan bagi setiap kelas umur berkadar songsang dengan penyimpangan dari kelas usia kebenaran dasar secara umum. Gabungan HoLoNet dan GeAeNet membentuk AgeHoLoNet yang dicadangkan tidak termasuk kes Positif Palsu (FP) di mana imej yang tidak dapat dikesan hanya manusia yang berada di bawah usia dewasa. GeAeNet mengungguli teknik canggih di kedua-dua persekitaran terkawal dan terbiar dengan mencapai Mean Absolute Error (MAE) 2.43 dalam dataset anggaran usia wajah (MORPHII) dan 2.64 dalam dataset penuaan wajah (FG-NET) dan 5.12 dalam Pangkalan Data Umur (Set data AgeDB). Akhirnya, membandingkan model yang tidak menyenangkan dengan teknik canggih membuktikan bahawa HoLoNet sahaja mengatasi karya yang berkaitan dengan ketepatan 0.956 dan AgeHoLoNet dengan ketepatan 0.964 berbanding set data Pornografi Dataset (NPDI).

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LIST OF ABBREVIATIONS

HoLoNet	-	Holistic Local Aware Deep Network
GeAeNet	-	Gender Aware Age Estimation Network
AgeHoLoNet	-	Age Aware Holistic Local Aware Deep Network
MTS	-	Mahalanobis Taguchi System
MD	-	Mahalanobis Distance
TM	-	Taguchi Method
UTM	-	Universiti Teknologi Malaysia
XML	-	Extensible Markup Language
ANN	-	Artificial Neural Network
GA	-	Genetic Algorithm
PSO	-	Particle Swarm Optimization

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CHAPTER 1

INTRODUCTION

1.1 Introduction

In last decade with overwhelming pace of growth in penetration rate of internet in world, people witnessed lots of benefits which before internet era was not accessible globally. Not only access to internet became available globally but the speed of internet access and convenience for all users led to some advantages such as facilitating knowledge management and sharing globally, producing helpful content in massive scale for all users around the world which can be used for improving skills or enhancing careers and connecting people which are far from each other geographically but able to communicate using voice or video calls and conference. However, this technology advancement was not harmless and likewise some other technology features, some challenges were raised while internet access was growing. For instance, development of harmful content and sharing it through internet became easier and faster. Therefore, the demand for development and implementing filtering techniques which blocks unwanted contents which objectionable image is one of content types which is known most offensive for users to maintain safe internet surfing raised significantly. While rapid growth of internet brought advantages to human being such as more convenience, but some drawbacks also emerged like getting exposed to objectionable content mostly pornographic (Jin, Wang and Tan, 2019).

Statistics presented in Maris, Libert and Henrichsen (2019) shows traffic of websites which are delivering content are higher than Amazon, Netflix and other well-known websites. Surprisingly in 2017, 30 percent of all data transfer in internet was pornographic related content. Although there is no accurate method which calculates number of visitors and maintains total number of internet sites which are producing objectionable content and sharing them globally but there are some estimates available such as the estimates mentioned in Ahmed, Shafiq and Liu (2016) which suggests there are at least 4 million adult websites on the internet. Considering that number, number of adult websites makes at least 12% of all websites on the internet for the time of report. The result which is shown in Table 1.1 presents overwhelming numbers which reported from a research which was done in 2006 (Islam, Watters, Yearwood, Hussain and Swarna, 2013) . This shocking information reveals the huge amount of offensive media content which is generated every single second in the world. While since 2006, technology was enhanced and therefore this information shall be higher. Although this information is surprising for everybody but most of all parents are resented due to its social impact on youngsters.

Table 1.1 Pornography Statistics

Every Second	
Expenditure on porn	$3,075.64
Number of viewers	28,258
Number of people searching for porn	372

It is important to mention that many users are innocent users of internet and leveraging it for their daily usages from communication to streaming TV and movies and work from home while they are not aware of risks that they can encounter in internet. However, danger of being exposed to objectionable images are studied in different research and their impacts have been investigated and direct correlation was reported between watching objectionable content and increasing social concerns such as raise in number of divorces, reducing morale and productivity and increasing aggressive behaviour (Sun, Bridges, Johnson and Ezzell, 2016; Rasmussen and Bierman, 2016; Stanley, Barter, Wood, Aghtaie, Larkins, Lanau and Överlien, 2018; Malamuth and Hald, 2016; Wright and Tokunaga, 2016; Malamuth, 2018; Mellor and Duff, 2019).

These mentioned dangers raised the concern and urged demand to governments for controlling the risk especially for those who are in high risk which are minors by regulating objectionable image access (Qamar Bhatti, Umer, Adil, Ebrahim, Nawaz and Ahmed, 2018; Roy, Paul, Pirsiavash and Pan, 2017; Gangwar, Fidalgo, Alegre and González-Castro, 2017). Considering the statistics and mentioned concerns by society, industry and government, the need for filtering the objectionable images is serious issue. Developing an effective objectionable image classifier and filtering technique is a valid concern.

As mentioned, rapid growth of internet made content creation and sharing through internet easier and as a result, sharing unwanted content became a threat to internet users. Among Not Suitable/Safe For Work (NSFW) images which are shared in internet, objectionable images which also known as pornographic images are most unwanted (Shen, Zou, Song, Yan and Zhou, 2018a).

Initially, the main approach to solve this challenge was manual or with utilization of simple techniques such as blacklisting IP addresses or dictionary of keywords. But pace of development was fast and volume of new content which was spread in internet was vast and manual solution were not capable of handling the size of objectionable images shared. Therefore, researchers were investigating new techniques to overcome this challenge.

Meanwhile, recent development in field of computer vision opened new opportunities and proved promising results in different problem areas such as skin segmentation, face detection, biometrics, pose tracking and motion tracking and object detection. The compelling result of advanced computer vision techniques initiated some research in leveraging sophisticated computer vision techniques to overcome challenge of objectionable image detection.

1.2 Background of the Problem

As mentioned, in order to make internet a safer place for exchanging information among users, researchers were studying different techniques to filter objectionable images. Available methods for objectionable image filtering cans be divided to three categories as keyword-based methods, methods relying on blacklisting of IP addresses and finally techniques which are relying on visual content (Nian, Li, Wang, Xu and Wu, 2016; Zhou, Zhuo, Geng, Zhang and Li, 2016).

While keyword-based methods as well as methods relying on blacklisting of IP addresses are efficient in terms of implementation complexity and computational power but reliable filtering of objectionable images using these approaches is not feasible due to their shortcomings. These methods are relying on comprehensive dataset of keywords or internet site addresses which contain objectionable images and hence these lists are dynamic and pace of adding and updating new sites are faster than possible speed of updating the dataset, these methods are not effective (Hettiarachchi and Peters, 2016).

Visual content-based techniques are addressing the mentioned limitations by analysing image contents (Yaghoubyan, Maarof, Zainal and OGHAZ, 2016; Osman, Maarof and Rohani, 2016). These methods rely on skin detection and image processing. One step that among all these methods is common is detection on nudity. The fact that these methods are not accurate enough to be applied reliably is acknowledged regardless of their complexity and being expensive in terms of computation power (Rahmat, Chairunnisa, Gunawan and Sitompul, 2016; Brancati, De Pietro, Frucci and Gallo, 2017; Nugroho, Hardiyanto and Adji, 2016; Mao, Li, Liu and Zou, 2018; Wang, Cheng, Wang, Sun, Liu and Zhou, 2018).

Forsyth et al (1996), (1996), (1997) are well known for their research conducted in this field as pioneers. Their approach was a two-stage approach by utilizing human skin detection and in second stage using grouper for identifying human shape to detect images which contain human subject which is naked presented in image. In this technique, colour information as well as texture data was used for skin detection in first stage to identify region of containing human skin exposed. In second stage, for identifying shape of human using identified skin regions, geometry analysis is employed.

One important challenge in this field is lack of well accepted definition which is shared among academia working in this field. Some researchers focused on intentions, some focused-on exposures of sensitive parts and so on (Shayan, Abdullah and Karamizadeh, 2015; Osman et al., 2016) . They have shown that a vase range of objectionable postures exists. While some images exhibit several naked people or very light dressed. Some other images present small body parts of one person. In this research, the definition mentioned in (Zaidan, Karim, Ahmad, Zaidan and Kiah, 2015b) is used which defines any image that depicts body exposed between neck and knee area as objectionable image.

Machine Learning approaches are used in classification problems in order to reduce human interventions in solving these issues and increasing accuracy. This approach can be applied in classification of objectionable images to overcome this problem with higher accuracy and simpler (Zaidan et al., 2015b; Hettiarachchi and Peters, 2016).

Classification of objectionable images needs to follow a few steps, starting with skin detection (Yas, Zadain, Zaidan, Lakulu and Rahmatullah, 2017). Detection of skin is popular in image processing field. Outcome of skin detection phase which is generated feature vectors extracted from image will be used in training phase and classification of objectionable images (Zaidan et al., 2015b; Jang and Lee, 2018). However, existing skin detection methods are not perfectly effective due to lack of high accuracy skin colour models (Yas, Zaidan, Zaidan, Rahmatullah and Abdul Karim, 2018; Naji, Jalab and Kareem, 2019). The need to develop a robust skin detection is highly justifiable as it is foundation of objectionable image classifier. The reliable skin detector should prove high accuracy by improving number of true positives and meanwhile reducing false negatives. Also, it is important to address classification of objectionable images which contain people with skin colours rather than white which was missed in existing methods (Zaidan, Karim, Ahmad, Zaidan and Kiah, 2015a; Tariq, Razi, Badillo-Urquiola and Wisniewski, 2019a).

1.3 Problem Statement

Since the first phase of all content based objectionable image classifiers is skin detection, some of challenges lie in this stage such as variant colour of human skin presented in given image, which mainly is related to the illumination and available conditions of lighting and colour when given image is initially captured. Maintaining colour consistency and its invariance especially against illumination is important challenge. Choosing the appropriate colour space will help to increase robustness of skin detector against illumination invariant. Another challenging concern in selecting robust skin detector against water and glass reflections (Naji et al., 2019). In order to make an algorithm widely accepted in automatic objectionable image classification field, the accuracy of algorithm is crucial to make it reliable. Models introduced in Ou et al. (2017) and Wang et al. (2018) shows higher accuracy and suggests that techniques which are utilizing local features with global features are achieving better performance. However, combining local feature and global feature extraction in closely integration and mutually affecting is missing and age estimation is not included in existing algorithms and false positive errors due to this is not inevitable.

Therefore, this research proposes to ensemble facial age estimation with objectionable image classifier which is deep neural based and has holistic view as well as local view to images in order to decrease false positive and increase accuracy of objectionable image detection.

1.4 Research Questions

Research questions which led this study are as follow:

(a) What are the available state-of-the-art techniques of age estimation and classifying pornographic images?

(b) How will the ensemble deep neural technique improve the accuracy of pornographic image classification?

(c) How the accuracy of proposed algorithm with existing state-of-the-art techniques will be compared?

1.5 Research Objectives

The main objective of this research is to improve accuracy of objectionable image classifier techniques. Therefore, research objectives of this research which are providing response to mentioned research questions are stated as following:

(a) To investigate existing age estimation techniques based on face images and objectionable image classification techniques.

(b) To design and enhancement of ensemble of age estimation deep neural based algorithm of objectionable image classifier.

(c) To evaluate accuracy of proposed technique with other objectionable image classifier algorithms.

1.6 Research Scope

The scope of this research is as follow:

(a) Ensemble algorithm which combines objectionable image classifier and age estimation is introduced,

(b) Image size greater than 50 × 50.

(c) The NPDI Dataset introduced in (Avila, Thome, Cord, Valle and de A. Araújo, 2013) is used to be able to benchmark objectionable image classifier with state-of-the-art techniques for different skin colours.

(d) Objectionable Image Classification or OIC dataset is used for ablation study on objectionable image classifier.

(e) MORPHII, AgeDB and FG-NET datasets are used for benchmarking GeAeNet with state-of-the-art age estimation techniques.

(f) C# and Python is used for programming of algorithm.

1.7 Significant of the Study

The outcome of this research would greatly contribute to objectionable image classification and age estimation based on facial attributes with the following contributions:

(a) Developing and demonstrating a deep neural network-based algorithm which employs global and local features together and learns them in multi-task learning which enables seamless integration and correlated mutually. This algorithm which benefits of highly representative feature extraction and make the algorithm both globally and locally context aware.

(b) Developing and introducing a novel age estimation algorithm which is deep neural network-based and utilizes facial attributes which contributes to facial aging process. The algorithm outputs the age and gender as age related attribute, and it is extendable to include more age-related facial attributes. Design of algorithm is based on conditional problem decided by facial attributes involved in facial aging process.

(c) New Loss function used in supervision of GeAeNet which results in more accurate probability distribution by making estimated age class distribution deviation a standard deviation. This function not only reduces the deviation from ground truth and more accurate age estimation but improved the performance of AgeHoLoNet by reducing the error for age estimation of adult border age subjects.

(d) Ensemble algorithm which integrates HoLoNet and GeAeNet to make AgeHoLoNet, improves the accuracy of objectionable image classification by reducing False Positive cases which a naked underage person is only seen in image. Moreover, this approach can be used in tagging child sexual abuse detection by considering the estimated age of human subject presented in objectionable image.

(e) Developing Objectionable Image Classification or OIC and its subset which is used for training objectionable image classifier and human sensitive body parts region of interest detector.

1.8 Thesis Outline

The outline of this thesis is formed from 6 chapters which its organization is as following:

(a) Chapter 1 starts with introduction and background of problem and followed by research objectives to be achieved. Background of research is explained in this chapter and after elaboration over problem statement and highlighting the research questions, research objectives and scope of research is described.

(b) Chapter 2 starts with different objectionable image filtering techniques and age estimation techniques are explained and reviewed. Explanation of basics of deep learning and evaluation metrics leads to elaboration of related works and critical analysis of them.

Chapter 3 describes research methodology, design, and procedures. Moreover, implementation of proposed technique, HoLoNet Implementation details and GeAeNet and AgeHoloNet with details and formulas are explained and elaborated with diagrams and pseudocode.

(c) Chapter 4 presents analysing and discussing on the results. First of all, hypermeter selection for both HoLoNet and GeAenet is explained. Ablation study is then conducted for both HoLoNet and GeAenet and analysed the result. Comparison with state-of-the-art algorithms is done for both objectionable image detection and age estimation and finally some sample image are showcased to illustrated performance of age estimation and objectionable image detection using HoLoNet and GeAenet and AgeHoLoNet over sample images from datasets.

(d) Chapter 5 reveals conclusion of this research, elaborates novelty of proposed scheme, contribution, and suggested future work.

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Appendix A Python Coding for AgeHoLoNet

Developing Age Aware Holistic Local Aware Deep Network for Objectionable Image Classification

Introduction	This research aims to develop an objectionable image classifier which is integrating local and global features of image and is aware of age and gender of human subjects in given image. The machine is installed with a python software that enables to run the code of machine learning algorithms and visualization analysis.

Training Process of GeAeNet for Age Estimation

```
import argparse
from pathlib import Path
import numpy as np
from keras.callbacks import LearningRateScheduler, ModelCheckpoint
from keras.optimizers import SGD, Adam
import better_exceptions
import random
import math
from PIL import Image
import pandas as pd
import cv2
from keras.utils import Sequence, to_categorical
import Augmentor
from keras.applications import ResNet50
from keras.layers import Dense
from keras.models import Model
from keras import backend as K




def get_args():
    parser = argparse.ArgumentParser(description="This script trains
GeAeNet for Age Estimation.",

formatter_class=argparse.ArgumentDefaultsHelpFormatter)
    parser.add_argument("--appa_dir", type=str, required=True,
                        help="path to the APPA-REAL dataset")
    parser.add_argument("--utk_dir", type=str, default=None,
                        help="path to the UTK face dataset")
    parser.add_argument("--output_dir", type=str,
default="checkpoints",
                        help="checkpoint dir")
    parser.add_argument("--batch_size", type=int, default=32,
                        help="batch size")
    parser.add_argument("--nb_epochs", type=int, default=30,
                        help="number of epochs")
```

```
    parser.add_argument("--lr", type=float, default=0.1,
                        help="learning rate")
    parser.add_argument("--opt", type=str, default="sgd",
                        help="optimizer name; 'sgd' or 'adam'")
    parser.add_argument("--model_name", type=str,
default="ResNet50",
                        help="model name: 'ResNet50'")
    args = parser.parse_args()
    return args


class Schedule:
    def __init__(self, nb_epochs, initial_lr):
        self.epochs = nb_epochs
        self.initial_lr = initial_lr

    def __call__(self, epoch_idx):
        if epoch_idx < self.epochs * 0.25:
            return self.initial_lr
        elif epoch_idx < self.epochs * 0.50:
            return self.initial_lr * 0.2
        elif epoch_idx < self.epochs * 0.75:
            return self.initial_lr * 0.04
        return self.initial_lr * 0.008


def get_optimizer(opt_name, lr):
    if opt_name == "sgd":
        return SGD(lr=lr, momentum=0.9, nesterov=True)
    elif opt_name == "adam":
        return Adam(lr=lr)
    else:
        raise ValueError("optimizer name should be 'sgd' or 'adam'")


def main():
    args = get_args()
    appa_dir = args.appa_dir
    utk_dir = args.utk_dir
    model_name = args.model_name
    batch_size = args.batch_size
    nb_epochs = args.nb_epochs
    lr = args.lr
    opt_name = args.opt

    if model_name == "ResNet50":
        image_size = 224


    train_gen = FaceGenerator(appa_dir, utk_dir=utk_dir,
batch_size=batch_size, image_size=image_size)
    val_gen = ValGenerator(appa_dir, batch_size=batch_size,
image_size=image_size)
    model = get_model(model_name=model_name)
    opt = get_optimizer(opt_name, lr)
    model.compile(optimizer=opt, loss="categorical_crossentropy",
metrics=[age_mae])
    model.summary()
    output_dir =
Path(__file__).resolve().parent.joinpath(args.output_dir)
    output_dir.mkdir(parents=True, exist_ok=True)
```

```
    callbacks = [LearningRateScheduler(schedule=Schedule(nb_epochs,
initial_lr=lr)),
                 ModelCheckpoint(str(output_dir) +
"/weights.{epoch:03d}-{val_loss:.3f}-{val_age_mae:.3f}.hdf5",
                                 monitor="val_age_mae",
                                 verbose=1,
                                 save_best_only=True,
                                 mode="min")
                 ]

    hist = model.fit_generator(generator=train_gen,
                               epochs=nb_epochs,
                               validation_data=val_gen,
                               verbose=1,
                               callbacks=callbacks)

    np.savez(str(output_dir.joinpath("history.npz")),
history=hist.history)




def get_transform_func():
    p = Augmentor.Pipeline()
    p.flip_left_right(probability=0.5)
    p.rotate(probability=1, max_left_rotation=5,
max_right_rotation=5)
    p.zoom_random(probability=0.5, percentage_area=0.95)
    p.random_distortion(probability=0.5, grid_width=2,
grid_height=2, magnitude=8)
    p.random_color(probability=1, min_factor=0.8, max_factor=1.2)
    p.random_contrast(probability=1, min_factor=0.8, max_factor=1.2)
    p.random_brightness(probability=1, min_factor=0.8,
max_factor=1.2)
    p.random_erasing(probability=0.5, rectangle_area=0.2)

    def transform_image(image):
        image = [Image.fromarray(image)]
        for operation in p.operations:
            r = round(random.uniform(0, 1), 1)
            if r <= operation.probability:
                image = operation.perform_operation(image)
        return image[0]
    return transform_image


class FaceGenerator(Sequence):
    def __init__(self, appa_dir, utk_dir=None, batch_size=32,
image_size=224):
        self.image_path_and_age = []
        self._load_appa(appa_dir)

        if utk_dir:
            self._load_utk(utk_dir)

        self.image_num = len(self.image_path_and_age)
        self.batch_size = batch_size
        self.image_size = image_size
        self.indices = np.random.permutation(self.image_num)
        self.transform_image = get_transform_func()
```

```
    def __len__(self):
        return self.image_num // self.batch_size

    def __getitem__(self, idx):
        batch_size = self.batch_size
        image_size = self.image_size
        x = np.zeros((batch_size, image_size, image_size, 3),
dtype=np.uint8)
        y = np.zeros((batch_size, 1), dtype=np.int32)

        sample_indices = self.indices[idx * batch_size:(idx + 1) *
batch_size]

        for i, sample_id in enumerate(sample_indices):
            image_path, age = self.image_path_and_age[sample_id]
            image = cv2.imread(str(image_path))
            x[i] = self.transform_image(cv2.resize(image,
(image_size, image_size)))
            age += math.floor(np.random.randn() * 2 + 0.5)
            y[i] = np.clip(age, 0, 100)

        return x, to_categorical(y, 101)

    def on_epoch_end(self):
        self.indices = np.random.permutation(self.image_num)

    def _load_appa(self, appa_dir):
        appa_root = Path(appa_dir)
        train_image_dir = appa_root.joinpath("train")
        gt_train_path = appa_root.joinpath("gt_avg_train.csv")
        df = pd.read_csv(str(gt_train_path))

        for i, row in df.iterrows():
            age = min(100, int(row.apparent_age_avg))
            # age = int(row.real_age)
            image_path = train_image_dir.joinpath(row.file_name +
"_face.jpg")

            if image_path.is_file():
                self.image_path_and_age.append([str(image_path),
age])

    def _load_utk(self, utk_dir):
        image_dir = Path(utk_dir)

        for image_path in image_dir.glob("*.jpg"):
            image_name = image_path.name  #
[age]_[gender]_[race]_[date&time].jpg
            age = min(100, int(image_name.split("_")[0]))

            if image_path.is_file():
                self.image_path_and_age.append([str(image_path),
age])


class ValGenerator(Sequence):
    def __init__(self, appa_dir, batch_size=32, image_size=224):
        self.image_path_and_age = []
        self._load_appa(appa_dir)
        self.image_num = len(self.image_path_and_age)
        self.batch_size = batch_size
```

```
        self.image_size = image_size

    def __len__(self):
        return self.image_num // self.batch_size

    def __getitem__(self, idx):
        batch_size = self.batch_size
        image_size = self.image_size
        x = np.zeros((batch_size, image_size, image_size, 3),
dtype=np.uint8)
        y = np.zeros((batch_size, 1), dtype=np.int32)

        for i in range(batch_size):
            image_path, age = self.image_path_and_age[idx *
batch_size + i]
            image = cv2.imread(str(image_path))
            x[i] = cv2.resize(image, (image_size, image_size))
            y[i] = age

        return x, to_categorical(y, 101)

    def _load_appa(self, appa_dir):
        appa_root = Path(appa_dir)
        val_image_dir = appa_root.joinpath("valid")
        gt_val_path = appa_root.joinpath("gt_avg_valid.csv")
        df = pd.read_csv(str(gt_val_path))

        for i, row in df.iterrows():
            age = min(100, int(row.apparent_age_avg))
            # age = int(row.real_age)
            image_path = val_image_dir.joinpath(row.file_name +
"_face.jpg")

            if image_path.is_file():
                self.image_path_and_age.append([str(image_path),
age])



def age_mae(y_true, y_pred):
    true_age = K.sum(y_true * K.arange(0, 101, dtype="float32"),
axis=-1)
    pred_age = K.sum(y_pred * K.arange(0, 101, dtype="float32"),
axis=-1)
    mae = K.mean(K.abs(true_age - pred_age))
    return mae


def get_model(model_name="ResNet50"):
    base_model = None

    if model_name == "ResNet50":
        base_model = ResNet50(include_top=False, weights='imagenet',
input_shape=(224, 224, 3), pooling="avg")
    elif model_name == "InceptionResNetV2":
        base_model = InceptionResNetV2(include_top=False,
weights='imagenet', input_shape=(299, 299, 3), pooling="avg")

    prediction = Dense(units=101, kernel_initializer="he_normal",
use_bias=False, activation="softmax",
                       name="pred_age")(base_model.output)
```

```
    model = Model(inputs=base_model.input, outputs=prediction)

    return model
```

Performing Age Estimation Using GeAeNet

```
from pathlib import Path
import cv2
import dlib
import numpy as np
import argparse
from contextlib import contextmanager
from keras.utils.data_utils import get_file


pretrained_model = "GEAENET.hdf5"


def get_args():
    parser = argparse.ArgumentParser(description="This script
estimates age for the detected faces.",

formatter_class=argparse.ArgumentDefaultsHelpFormatter)
    parser.add_argument("--model_name", type=str,
default="ResNet50",
                        help="model name: 'ResNet50'")
    parser.add_argument("--weight_file", type=str, default=None,
                        help="path to weight file GEAENET.hdf5")
    parser.add_argument("--margin", type=float, default=0.4,
                        help="margin around detected face for age-
gender estimation")
    parser.add_argument("--image_dir", type=str, default=None,
                        help="target image directory; if set, images
in image_dir are used")
    args = parser.parse_args()
    return args


def draw_label(image, point, label, font=cv2.FONT_HERSHEY_SIMPLEX,
               font_scale=1, thickness=2):
    size = cv2.getTextSize(label, font, font_scale, thickness)[0]
    x, y = point
    cv2.rectangle(image, (x, y - size[1]), (x + size[0], y), (255,
0, 0), cv2.FILLED)
    cv2.putText(image, label, point, font, font_scale, (255, 255,
255), thickness)




def yield_images_from_dir(image_dir):
    image_dir = Path(image_dir)

    for image_path in image_dir.glob("*.*"):
```

```
        img = cv2.imread(str(image_path), 1)

        if img is not None:
            h, w, _ = img.shape
            r = 640 / max(w, h)
            yield cv2.resize(img, (int(w * r), int(h * r)))


def draw_label(image, point, label, font=cv2.FONT_HERSHEY_SIMPLEX,
               font_scale=0.8, thickness=1):
    size = cv2.getTextSize(label, font, font_scale, thickness)[0]
    x, y = point
    cv2.rectangle(image, (x, y - size[1]), (x + size[0], y), (255,
0, 0), cv2.FILLED)
    cv2.putText(image, label, point, font, font_scale, (255, 255,
255), thickness, lineType=cv2.LINE_AA)



depth = 16
k = 8
weight_file = get_file("weights.hdf5", pretrained_model,
cache_subdir="pretrained_models", file_hash=modhash, cache_dir=None)
margin = 0.4
image_dir = 'images'


# for face detection
detector = CenterFace_detector()

# load model and weights
img_size = 64
model = WideResNet(img_size, depth=depth, k=k)()
model.load_weights(weight_file)

image_generator = yield_images_from_dir(image_dir)



for img in image_generator:
        input_img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
        img_h, img_w, _ = np.shape(input_img)

        # detect faces using dlib detector
        detected = detector(input_img, 1)
        faces = np.empty((len(detected), img_size, img_size, 3))

        if len(detected) > 0:
            for i, d in enumerate(detected):
                x1, y1, x2, y2, w, h = d.left(), d.top(), d.right()
+ 1, d.bottom() + 1, d.width(), d.height()
                xw1 = max(int(x1 - margin * w), 0)
                yw1 = max(int(y1 - margin * h), 0)
                xw2 = min(int(x2 + margin * w), img_w - 1)
                yw2 = min(int(y2 + margin * h), img_h - 1)
                cv2.rectangle(img, (x1, y1), (x2, y2), (255, 0, 0),
2)
                # cv2.rectangle(img, (xw1, yw1), (xw2, yw2), (255,
0, 0), 2)
                faces[i, :, :, :] = cv2.resize(img[yw1:yw2 + 1,
xw1:xw2 + 1, :], (img_size, img_size))
```

```
            # predict ages and genders of the detected faces
            results = model.predict(faces)
            predicted_genders = results[0]
            ages = np.arange(0, 101).reshape(101, 1)
            predicted_ages = results[1].dot(ages).flatten()

            # draw results
            for i, d in enumerate(detected):
                label = str(int(predicted_ages[i]))
                draw_label(img, (d.left(), d.top()), label)

        plt.figure(num=None, figsize=(20, 20), dpi=80,
facecolor='w', edgecolor='k')
        plt.imshow(img)
        plt.show()
```

Performing Objectionable Image Classification Using HoLoNet

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from keras.models import load_model
from datetime import datetime
import warnings
warnings.filterwarnings("ignore")
import matplotlib.image as mpimg
import cv2
from PIL import Image
import numpy as np
from skimage import transform

model = load_model("weights.h5")

def load(filename):
    np_image = Image.open(filename)
    np_image = np.array(np_image).astype('float32')/255
    np_image = transform.resize(np_image, (224, 224, 3))
    np_image = np.expand_dims(np_image, axis=0)
    img=mpimg.imread(filename)
    plt.imshow(img)
    return np_image

image = load("image.jpg")

ans = model.predict(image)

maping = {0 : "Normal", 1 : "Objectinable", 2 : "Racy"}

new_ans = np.argmax(ans[0])

print(maping[new_ans], np.round(ans,2))
```

```
print("With {} probability".format(ans[0][new_ans]))
```

Performing Objectionable Image Classification Using AgeHoLoNet

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from keras.models import load_model
from datetime import datetime
import warnings
warnings.filterwarnings("ignore")
import matplotlib.image as mpimg
import cv2
from PIL import Image
import numpy as np
from skimage import transform

model = load_model("weights.h5")

def load(filename):
    np_image = Image.open(filename)
    np_image = np.array(np_image).astype('float32')/255
    np_image = transform.resize(np_image, (224, 224, 3))
    np_image = np.expand_dims(np_image, axis=0)
    img=mpimg.imread(filename)
    plt.imshow(img)
    return np_image

image = load("image.jpg")

ans = model.predict(image)

maping = {0 : "Normal", 1 : "Objectinable", 2 : "Racy"}

new_ans = np.argmax(ans[0])

print(maping[new_ans], np.round(ans,2))
print("With {} probability".format(ans[0][new_ans]))
```

LIST OF PUBLICATIONS

Journal with Impact Factor

1. Karamizadeh, S., Abdullah, S. M., **Shayan, J**., Nooralishahi, P., & Bagherian, B. (2017). Threshold Based Skin Color Classification. *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)*, *9*(2-3), 131-134. **(Indexed by SCOPUS)**

2. Karamizadeh, S., Abdullah, S. M., **Shayan, J**., Zamani, M., & Nooralishahi, P. (2017). Taxonomy of Filtering Based Illumination Normalization for Face Recognition. Journal of Telecommunication, Electronic and Computer Engineering (JTEC), 9(1-5), 135-139. **(Q4, IF:0.15)**

Indexed Book Chapter

1. Karamizadeh, S., Abdullah, S. M., Zamani, M., **Shayan, J**., & Nooralishahi, P. (2017). Face recognition via taxonomy of illumination normalization. In Multimedia Forensics and Security (pp. 139-160). Springer, Cham. **(Indexed by SCOPUS)**

Indexed Conference Proceedings

1. **Shayan, J**., Abdullah, S. M., & Karamizadeh, S. (2015, August). An overview of objectionable image detection. In 2015 International Symposium on Technology Management and Emerging Technologies (ISTMET) (pp. 396-400). IEEE. **(Indexed by SCOPUS)**