Off-the-shelf Convolutional Neural Network (CNN) features for Automatic Face Quality Prediction

Nabila Saiyed, Shikha Nema, Akanksha Joshi

Abstract—Estimation of face image quality helps in correctly recognizing faces which in turn helps in many practical applications related to face. This paper presents a face quality prediction approach using Off-the-Shelf CNN features. Here we evaluated three image descriptors—binary patterns (LBP), Histogram of oriented gradients (HOG), Oriented Fast and Rotated Brief (ORB), and deep Convolution Neural Network (CNN) Networks pre-trained on ImageNet-VGG19, ResNet50, and VGG Small (4 layers) for feature extraction to detect face region image quality. Furthermore, to classify extracted features, we have evaluated three classifiers, that are different from each other in their own ways (SVM, DT and MLP). For experimental analysis, we created a face quality dataset by collecting images from web and publicly available face datasets and manually labeled images under seven categories—Good and six bad quality classes (e.g. Expression, Makeup, Pose, Occlusion, Illumination and Blur). The accuracy of face image classification using VGG19 along with MLP as a classifier was the highest (i.e.98.76%) followed by ResNet50 and MLP at 98.69% of accuracy. The lowest accuracy was obtained with LBP and SVM, this shows that deep features gives a better solution.

Keywords: About four key words or phrases in alphabetical order, separated by commas.

I. INTRODUCTION

The problem of determining the quality of images has been explored for a long time in the area of image processing. Image quality is pretty sensitive to the following factors such as lossy compression, brightness, sharpness, and resolution. In 1960’s, [1] face recognition was introduced and since then a lot of efforts have been made to make it as advanced as the human mind in terms of recognizing faces. These self operating systems are capable of classifying how good or bad the image which is used for biometrics, visa application, security and definitely a lot more where face images are used to process an application.

Identity of individuals can be performed accurately when face images of individual is of good quality. Therefore, if a system has the potential to classify the poor-quality face images, lot of system computations and time can be saved.

The poor quality images are generally obtained when image acquisition conditions are not constraint such as when the image is clicked where the lighting is not in control of the person being clicked, if the person is not looking in camera and many such factors where the choice of getting a good quality image is not in the control of the subject contribute to the quality of image being affected.

The basic aim of face recognition research is to create software that is powerful against factors of the dataset that is chosen by us. Our ambition is to solve the difficulty in recognizing faces from uncontrolled factors and making it a tad bit simpler. The latest research [9] on prediction of classes has devoted efforts towards recognition of the not so constrained factors where facial variations of any kind can be concurrently present (e.g., face images from surveillance cameras, CCTV footage).

Face acquired of individuals wearing a lot of makeup, makes them almost unrecognizable [3]. Expression, pose, occlusion contribute to recognizing faces a much more difficult task and that is the primary aim of face recognition to develop systems that are powerful to such factors. Quality thus gets affected during image acquisition in some cases making the image challenging. During transmission and storage the quality of images sometimes gets degraded. Face images can be collected from uncontrolled environment such as surveillance cameras or CCTV footage or mug shots of faces which are acquired under controlled and conditioned environments. Quality of face images thus affects the face recognition algorithm. Griffin [4] thus came up with the concept of ‘Face Quality Algorithm’. Researchers since then have been working and contributing to FQA algorithm.

In this work, our major focus is on predicting how good or bad the image is. These face images that are collected from a not so constrained environment; determine the image quality of face images. For evaluation, we collected images from publically available datasets (face image databases (e.g., LFW [12], FRGC [10], and Internet)).

A quality measure for face recognition was introduced in [2], where greedy pruned ordering (GPO) was approximated to an image quality oracle. Here, GBU, PaSC, ICE 2006 and a manually created dataset was trained using SVM. The Greedy Pruning Order analysis is used by the face recognition system by means of an image quality metric to dispose of images prior to recognition. For PaSC, FRR is 19 % after 20% images are cut off. For GBU, FRR is 27% after 6% images are pruned. By using gist and HOG as descriptors it was seen that it is possible to use holistic representation of images to detect quality of face images.
Off-the-shelf Convolutional Neural Network (CNN) features for Automatic Face Quality Prediction

We try to achieve the following contributions in the world of quality of face images. First, we created a face quality prediction framework based on the extraction of the detected features and determining their category. Second, we created a dataset under 7 face quality categories- Good, Illumination, Pose, Occlusion, Expression, Makeup, Low Resolution. Then we evaluated, three local and three Convolutional Neural Network (CNN) based features extraction methods. Furthermore, we evaluated three image classifiers- SVM, Decision Tree and Multilayer Perception (MLP). For local image descriptors we selected Local Binary Pattern (LBP), Histogram of Oriented Gradients (HOG) and Oriented FAST and Rotated BRIEF (ORB). Among deep learning based methods, we adopted VGGNet19 [6] ResNet50 [7] and smaller version of VGG; VGG8.

The remainder of this text is organized as follows. In Section II, we provide background with description of technologies utilized in this work. In Section III, we give a detailed description of experimental analysis and results. With Section 6, we end the paper by making some final conclusions.

II. BACKGROUND

A. Feature Extractors

Local Binary Pattern (LBP)

This 2D texture descriptor [8] is used for identifying faces and for pericocular recognition [5, 14, and 18]. LBP will take a window (R) which is normally considered to be an odd value, let us suppose R=1 which will be determined by a 3 × 3 window and R = 2 will indicate a 5 × 5 window.LBP then scans each centre pixel of our chosen image and its local neighborhood pixels (P) within our odd size window. Comparison of each pixel with its neighboring pixel is done to summarize the local structure of images. Each central pixel is compared with its eight neighbors (e.g., R = 1) and these pixels are normally followed along a circle. If the center pixel value is superior in value than the neighboring pixel value then it is safe to say that it can be replaced by the bit '0' and if not then it’s simply replaced by the bit value ‘1’. Once this binary pattern is generated, the next step is to generate the decimal code, basically for the sake of convenience. The product of the binary pattern and the weight results in the generation of the LBP code. Each and every pixels of the image is thus labeled with its LBP code (ranges from 0 to 255). This explanation is explained in Fig. 1.

Histogram of Oriented Gradients (HOG) [5]

This method is used for object recognition and it also detects edges and not only that but it also tracks the occurrences of orientation gradients in sections of an image.HOG is very much a twin of the very popular SIFT descriptors, and shape contexts, however it is computed on a matrix that is more on the dense side rather than usual sparse matrices. These dense matrices consist of cells that are spaced in a uniform manner and the local contrast normalization is used to improve its exactness in an overlapping manner. This descriptor was thus created as the local object appearance and the shape within an image can be described by the distribution of intensity and the direction of the edge. The histogram of oriented gradients thus uses [-1 0 -1] kernel for gradient magnitude and orientation calculation. Gradents are calculated in the range [0,180]. Histograms of 9 bins are calculated with magnitudes as weights. Each image is resized to 32x32 pixels and converted to grayscale. The images are normalized for gamma, and then, for normal contrast. Each 32x32 image pixel matrix, is organized into 8X8 cells and then, histograms are calculated for each cell. Then, a 4x4 matrix with 9 bins in each cell is obtained. This matrix is organized as 2x2 blocks (with 50% overlap) and normalized, by dividing with the magnitude of histogram bins' vector. A total of 4 blocks X 8 cells X 9 bins = 288 features. The HOG descriptor is explained in Figure 2. HOG has a very good speed and does a decent job. However, it definitely comes with one con that is it not as powerful as it should be. But then again it performs well because it uses a global feature to describe a particular face image instead of collection of local features.

ORB (Oriented FAST and Rotated BRIEF)

FAST: Features from Accelerated and Segment Test

This descriptor is widely used to detect corners/edges in images. Let us randomly assume a pixel ‘p’ in an array; once that is done the brightness of ‘p’ will be then compared with the other pixels that is 16 pixels. These pixels are arranged in such a manner forming a small circle around p. These pixels are divided in the following categories-1.)Pixels that is same as p, 2.) And pixels darker or 3.)Lighter than the center pixel p. Keypoint is selected when the intensity (darker or brighter) of 8 pixels or more is greater than that of pixel p; called ‘keypoint’.See Figure.3

![Figure 1: Computation of LBP Descriptor](image)

![Figure 2: Histogram of Oriented Gradients (HOG)](image)

![Figure 3: ORB Keypoint Detection](image)
BRIEF: Binary Robust Independent Elementary Feature

KeyPoints that are entirely found by the corner detector algorithm i.e. FAST are converted to a binary feature descriptor of 1’s and 0’s and is 128 to upto 512 bits string long representing an object. It is important to save the descriptor from noise and that is done by smoothing the image.

![Figure 2: Histogram of oriented gradients descriptor](image)

BRIEF makes use of a Gaussian kernel/filter to smooth the image out. Around our selected ‘keypoint’ (done by FAST) a pair of pixels (or patch of some width and height) is randomly defined in a neighborhood. From this patch our first pixel is selected without any order from a Gaussian distribution centered around the keypoint with a spread of sigma. Then similarly the next pixel is drawn in a random pair from a Gaussian distribution centered around the first pixel with a spread of sigma divided by two. If the intensity of the pixel that is selected first is more than the second pixel then a value of ‘1’ is assigned or else, it is assigned a bit that has no value i.e.0. For a 128-bit vector, this process is carried out 128 times for just a keypoint.

![Figure 3: An example of FAST](image)

This descriptor [23] was developed as an alternative to SIFT and SURF which are patented algorithms. The ORB descriptor is a fast binary descriptor based on BRIEF, also it is invariant to rotation and powerful against noise.

![Figure 4: BRIEF descriptor](image)

To create ORB, authors combined the keypoint found by the FAST descriptor and then using BRIEF descriptor which made a lot of changes to the former to obtain improved performance. In the approach, keypoints are detected using FAST and then top N points in them are selected using Harris corner measure. To generate multiscale-features it uses pyramid. This multiscale image pyramid consists of sequences of images all of which are basically versions of the same image at resolutions differing from each other. FAST first detects the intensity centroid of the patch. Then through this vector the direction is obtained from the corner point to the centroid. Further, moments are computed with x and y which should be in a circular region of radius R, to enhance the rotation invariance, where R is the size of the patch.

ORB has a high recognition rate compared to the other descriptors of this type. It also acts as an alternative to Speeded-up Robust Features and also to Scalar Invariant Feature Transform. Another reason of selecting ORB is because of the speed it provides.

![Figure 5: An example of keypoints matching using ORB](image)

Convolution Neural Networks (CNNs):

VGG19 (Pre-Trained on Imagenet) [6]

VGG 16 and 19 are deep convolutional networks (ConvNet) architecture first proposed by K. Simonyan and A. Zisserman from Visual Geometry Group of University of Oxford in 2014 [10]. Here [10] its seen that a very-deep networks for large-scale image classification was evaluated: the generic architecture of the network in [10] contained a convolution filter which was small and also with a small receptive field of 3 × 3 and the convolutional pace was fixed to only a single pixel, while five max-pooling layers carried out the spatial pooling( acting like a detector), over a pixel window of the size 2 × 2, with a convolution step of 2 [10]. There were three fully-connected layers of same configuration: the first and second layers had 4096 channels each, whereas, the third layer contained 1000 channels and performed ILSVRC-2012 dataset classification [10]. VGG 19 gives less error rate making it an apt choice of deep network used for extracting features.
then later on soft-margins was brought into the scene so that a minimal subset of error in the training data is permit table, allowing the other half of the training data to be separated by constructing an optimal separating hyperplane. The major pros of SVM that makes it a popular choice of classifier by almost all of the researchers is because of - its generalization of binary and regression forms and notation simplification [20]. With more and more researches multiple kernels in SVM have been introduced such as- polynomial kernel, linear kernel, and the gaussian Radial Basis Function (RBF) kernel.

Decision Trees (DT)

Decision Trees (DTs), introduced by J. R. Quinlan, is calculated using tree structure. Decision Trees are different than SVM and neural networks as they do not make any statistical assumptions about the inputs and they do not scale the data. These models are created as a tree structure with dataset divided into subsets at different branches. Finally, the model results in a tree with branches having decision nodes and leaf nodes. DTs have application in various areas of pattern recognition [18]. The major benefit of DTs are self-explanatory logic flow, richness in representing discrete-value classifier, and ability for handling data sets with errors and missing data, while the disadvantages are a shortage in classifier interaction and over-sensitivity to irrelevant data and noise [19].

Multilayer Perceptron (MLP) [23]

This simple algorithm that was brought into existence to solve the problem of classification dealing with the 1’s and 0’s; i.e. it predicts whether input belongs to a certain category of interest or not. A multilayer perceptron (MLP), is not only an artificial neural network, but it has many layers that make it deep. It is composed of more than one perceptron. Signals are received from the input layer; decisions are made at the output; about the input, and in between those two, an arbitrary number of hidden layers that are the true computational engine of the MLP.

III. AUTOMATIC FACE QUALITY PREDICTION

The proposed pipeline for automated face quality prediction is shown in Figure 8.

Face Detection

For face region quality estimation, the basic step is to identify the facial location in the image. For face identification, we utilized Multi-task Cascaded Convolution Networks (MTCNN) approach [11]. The MTCNN method is based on deep learning and provides very high accuracy. After alignment, the face region is cropped from the images with a margin of 60% (e.g. 30% in the left, top, right and bottom) around the detected face bounding box. The process of face detection and alignment is shown in Figure 9.

For feature extraction we have selected six methods as mentioned in Section II above-LBP, HOG, ORB, VGG16, VGG-small, ResNet-50 and for classification we have used three methods-Support Vector Machine (SVM), Decision Tree (DT), and Multilayer Perceptron (MLP).
Our dataset contains 1690 good quality images and 8310 bad quality images. The images are collected from Web and publicly available face datasets- LFW [12], FRGC [10]. All the images are labeled manually into seven classes- Good, Expression, Makeup, Pose, Occlusion, Illumination and Blur. The sample images in our dataset are shown in Figure 10 and Figure 11, we demonstrate the distribution of images in the dataset. Google image search was used to download images for a specific query. To collect all these data, we use 30 specific queries and separate into different folder that indicates its classes. The downloaded data was manually verified and corrected for any errors such as wrong label, no human present.

### A. Experimental Setup

The code for implementation is written in Python-3.5, and training of deep neural networks is conducted on a machine with Tesla K40m GPU with 12GB memory. The CNNs are implemented using Tensorflow-1.5 framework.

### B. Data Augmentation for Deep Networks

In order to make the training dataset enlarged artificially by using class preserving transformations of the original images, we also performed data augmentation. Firstly, we scale the smallest side to 227 leaving us with a 227 × N or N × 227 sized images. We used a total of four scales of each images. In addition, we performed transposition and horizontal flip. We also rotated images randomly in the range of ±5 degrees.
C. Multilayer Layer Perceptron (MLP)

To design MLP, we took 3 fully connected layers with 2048 neurons. The validation set is used to test what kind of face images may detect error. For MLP training, our models were trained using stochastic gradient descent with a batch size of 32 examples, momentum of 0.9, and weight decay of 0.0005. According to the experimental results on the test set, we stopped training after 100 epochs. In figure 12, we have illustrated the MLP training on image features extracted using pre-trained ResNet50 or VGG19 models.

![Figure 12: Illustration of MLP training with Pre-trained VGG19 or ResNet50 models](image)

### IV. RESULT AND DISCUSSION

Table 1 demonstrates the accuracies and computational times for testing process. Total 18, evaluations are done to compare the performance based on extractors and three deep learning features along with three classifiers, above in terms of recognition accuracy and speed. In our experiments, local descriptors have shown comparatively lesser accuracy than deep learning methods. The best accuracy is reported by VGG19 + MLP classifier (i.e. 98.76%). In all of our experiments, the training, validation and testing data is kept separately.

Table 1. Results for different Feature Extraction and Classification methods for Face quality

| Feature Extraction Approach | Classifier | Accuracy (%) | Time (ms) |
|-----------------------------|------------|--------------|-----------|
| LBP                         | SVM        | 33.95        | 57        |
| HOG                         | SVM        | 66.59        | 306       |
| ORB                         | SVM        | 50.41        | 903       |
| VGG.Small (trained from scratch) | SVM | 63.08 | 112 |
| VGG19 (pretrained ImageNet) | SVM        | 84.80        | 213       |
| ResNet50 (pretrained ImageNet) | SVM | 86.80 | 223 |
| LBP                         | DT         | 50.89        | 55        |
| HOG                         | DT         | 49.17        | 299       |
| ORB                         | DT         | 41.46        | 874       |
| VGG.Small (trained from scratch) | DT | 65.03 | 108 |

Results in Table I, are computed on test set. It can be seen that, among local descriptors, HOG features when trained with Multilayer Perceptron (i.e. 80.6%) are giving best results. It should also be noted that with VGG19, the improvement in accuracy compared to local descriptors is huge (i.e. ~40%). The time complexity as reported in Table 1, is found lowest for LBP descriptor. The Deep learning models are found little slower on CPU, however they were found faster than ORB and HOG descriptor computation.

### V. CONCLUSION

Here, we studied the performance of features extracted using pretrained convolutional neural networks for face quality estimation. We found that CNN architectures are capable of learning powerful features from small size labeled data. The accuracy of CNN features surpassed descriptor based approaches significantly. Based on the work that we have proceeded here we believe that the off-the-shelf CNN features are promising and has attractive features. We desire to improve the dataset size and then with it we plan to fine-tune all the layers in VGG19 and ResNet50 CNN networks. Also we plan learn big size deep models like ResNet50 from scratch so that we can add into the field of image processing.

**REFERENCES**

1. Systems (BTAS), Arlington, VA, 2012, pp. 391-398. doi:10.1109/BTAS.2012.6374605
2. P. Griffin, "Understanding The Face Image Format Standards", American National Standards Institute National Institute of Standards and Technology Workshop, 2005.
3. Akanksha Joshi, Abhishek Gangwar, Renu Sharma and Zia Saquib, “Periocular Feature Extraction Based on LBP and DLDMA”, International Conference on Computer Science, Engineering & Applications, Springer, Delhi, India, May 25-27, 2012. DOI: 10.1007/978-3-642-30157-5_101
4. V. Khryashchev, I. Nenakhov, A. Lebedev and A. Priorov, “Evaluation of face image quality metrics in person identification problem,” 2016 19th Conference of Open Innovations Association (FRUCT), Jyvaskyla, 2016, pp.80-87.doi:10.23919/FRUCT.2016.7892186
AUTHORS PROFILE

Nabila Saiyid, had completed her completed her Bachelors in Electronics and Telecommunication Engineering from the University of Mumbai following which she has pursued her Masters in the same from Usha Mittal Institute of University, SNDT University. She has interests in Networking and also believes that Deep Learning is the future of Machine Learning.

Dr. Shikha Nema, received her PhD degree in 2010 and M.Tech in Digital Communication from Maulana Azad Institute in 2002.She is working as a Professor and HOD in Electronics and Telecommunication Department, SNDT university.She has published over 70 papers in various journals and conferences. She had received a grant of over 3.5 Lac from Project Oscar in collaboration with IIT, Bombay in year 2013.Her research are in wireless communication and networking with emphasis on Cooperative Spectrum Sensing, Resource Allocation in Cooperative Cognitive Radio network,MIMO antennas and IoT.

Akanksha Joshi, is working with CDAC, India and is a researcher in Machine Vision and Deep Learning.She has almost 13+ years of industry experience in the field of Biometrics, Image Processing and Natural Language Processing and has actively been involved in her field of interest.