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

Nabila Saiyed, Shikha Nema
SNDT Women's University, Mumbai, India
nabilasaiyedmk@gmail.com,shikha.nema@umit.sndt.ac.in

Akanksha Joshi
CDAC Mumbai, India
akanksha@cdac.in

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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 pretrained 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- *LBP, ORB, HOG, SVM, CNN, face quality*

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

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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 publicly 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.

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 periocular 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

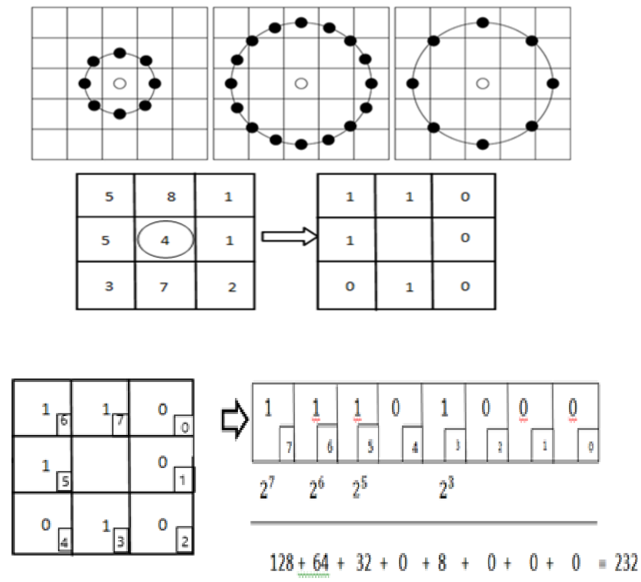

Figure 1: Computation of LBP Descriptor

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 matrixes. These dense matrixes 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. Gradients are calculated in the range [0,180]. Histograms of 9 bins are calculated with magnitudes as weights. Each image is

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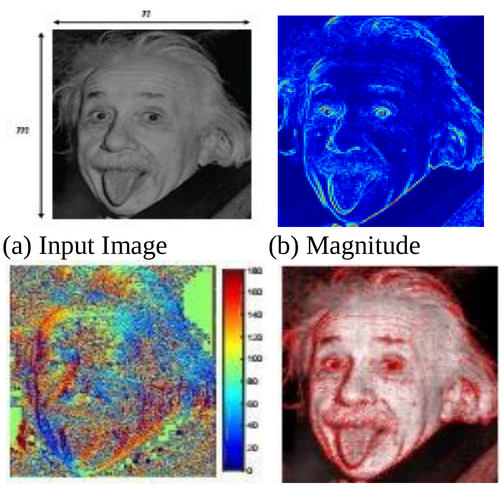
resized to 32x32 pixels and converted to grayscale. The images are normalized for gamma, and then, for normal contrast. Each 32x32 image pixel matrix, is organized into 8X8 cells and then, histograms are calculated for each cell. Then, a 4x4 matrix with 9 bins in each cell is obtained. This matrix is 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.



(a) Input Image (b) Magnitude

(c) Angle (d) Gradient

Figure 2: Histogram of oriented gradients descriptor

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’.SeeFigure.3

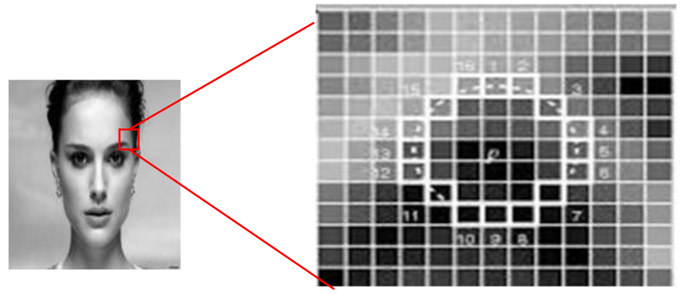


Figure 3: An example of FAST

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. 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.

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.

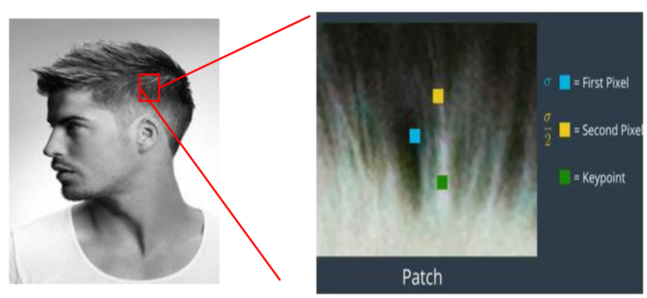


Figure 4: BRIEF descriptor

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

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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.

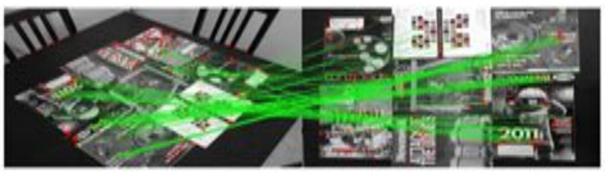

Figure 5: An example of keypoints matching using ORB

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.

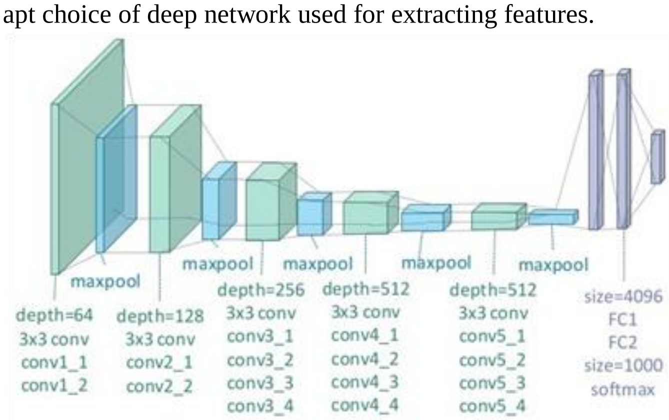

Figure 6: VGG19 Network Architecture

VGG_Small (VGG8, Trained from scratch)

The network structure of VGG8 is shown in Figure 7. An image of size 224×224 is the input. Convolution layers and fully connected layer of 5 and 3 layers make our network. Once convolution is performed; it is then followed by ReLU, pooling and Normalization. Inner product and ReLU together contribute to create the fully connected layers. Performance is made powerful by making use of the dropout strategy.

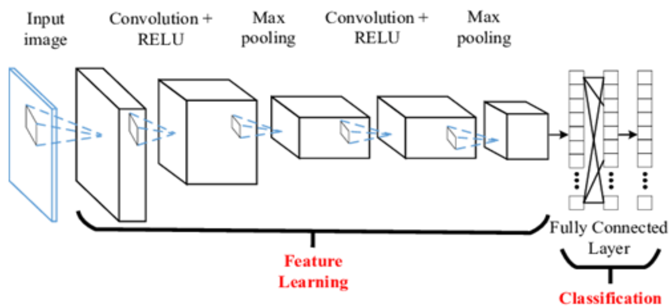

Figure 7: Small_VGG (VGG8) Network Architecture

ResNet50(Pre-Trainet on Imagenet) [7]

ResNet is a short name for Residual Network. As the name of the network indicates, the new terminology that this network introduces is residual learning.

In general, in networks with too many layers, are arranged in the form of a stack and is trained one task at a time and most of the features are learned at the end of the layers. Here instead of learning each and every level of features we will just focus on learning the residuals of networks. ResNet subtracts features from the source using shortcut connections (directly connecting input of nth layer to some (n+x) th layer. ResNets solves the problem of vanishing gradients where we see that the former layers disappear in deep networks and along with that it also solves the issue of degradation; where huge parameter space is optimized, which adds layers leading to an escalation in error.

B. Image Classifiers

Support Vector Machines (SVM): SVM introduced by Cortes and Vapnik in 1995, is a classifier which was mainly designed for binary problems however later on it has also been extended for multi-class problems [20]. Basically SVM maps data to a dimensional feature space that is a lot high, this was done to improve models generalization capabilities. Initially, in SVM [20], authors divided the data by a separating hyperplane that had no faults or error in it and 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

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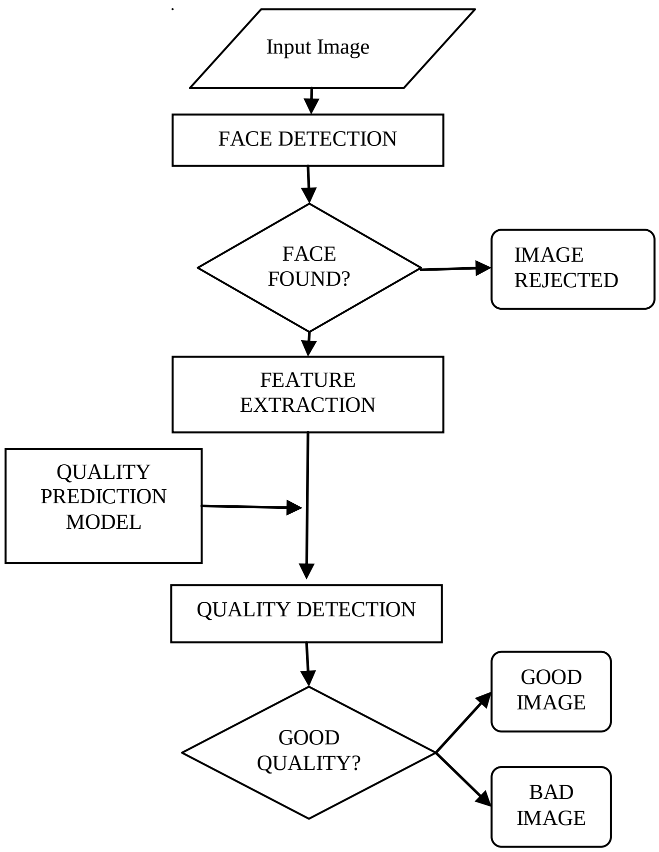

Figure 8: Flowchart of proposed approach

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.

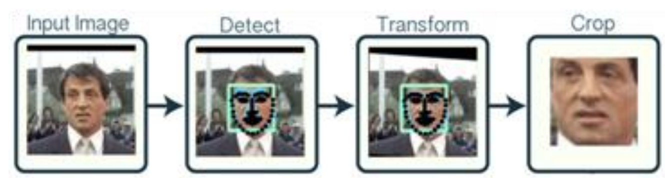

Figure 9: Face detection and Alignment

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 MTCN 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).

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IV. EXPERIMENTAL ANALYSIS AND RESULTS

A. Dataset

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.

B. 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.

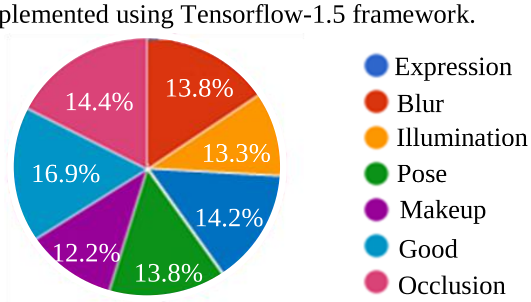

Figure 11: Data distribution of the Face Quality dataset across the seven quality categories.

We first divided the dataset into training, validation and test sets by randomly selected 75% images for training, 10% for validation and 15% for testing purposes. Then features for LBP, HOG, ORB, VGG19 and ResNet50 approaches are extracted for training, validation and testing set. In case of VGG19 and ResNet50, features are extracted from last layer after removing softmax layer. The pretrained model for VGG19 and ResNet50 are obtained from Internet trained on ImageNet classification task. For VGGSmall (VGG8) we trained it from scratch on training dataset and then features for images in training, validation and testing set are extracted. The classifiers-SVM, Decision Tree (DT) and Multilayer Layer Perceptron (MLP) are trained using image features extracted from training set images.

The accuracy of our approaches is computed as follows:

$$Accuracy = 100 \times \frac{Number\ of\ Correctly\ Predicted\ Instances}{Total\ Number\ of\ Instances} \quad (1)$$

Figure 10: examples of 7 category dataset (a) good quality image (b) low quality image (c) pose (d) expression (e) occlusion (f) makeup; (g) Illumination

C. 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.

D. 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.

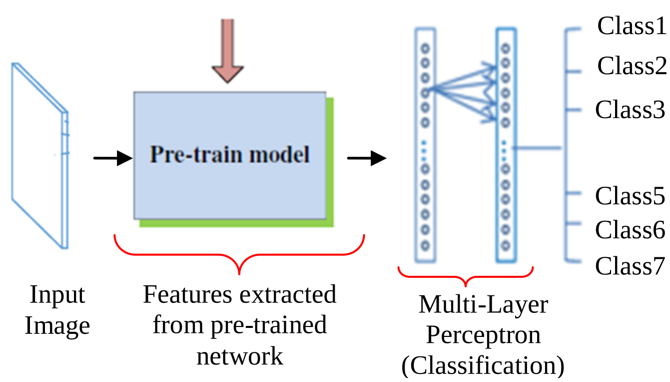

Figure 12: Illustration of MLP training with Pre-trained VGG19 or ResNet50 models

E. Results

Table 1 demonstrates the accuracies and computational times

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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 separate.

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
VGGSmall (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
VGGSmall (trained from scratch)	DT	65.03	108
VGG19 (pretrained ImageNet)	DT	60.81	213
ResNet50 (pretrained ImageNet)	DT	62.32	204
LBP	MLP	62.90	49
HOG	MLP	80.6	298
ORB	MLP	72.30	896
VGGSmall (trained from scratch)	MLP	66.03	99
VGG19 (pretrained ImageNet)	MLP	98.76	199
ResNet50 (pretrained ImageNet)	MLP	98.69	209

Results in Table 1, 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 AND FUTURE SCOPE

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.

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