IIITM Face: A Database for Facial Attribute Detection in Constrained and Simulated Unconstrained Environments

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This paper addresses the challenges of face attribute detection specifically in the Indian context. While there are numerous face datasets in unconstrained environments, none of them captures emotions in different face orientations. Moreover, there is an under-representation of people of Indian ethnicity in these datasets since they have been scraped from popular search engines. As a result, the performance of state-of-the-art techniques can’t be evaluated on Indian faces. In this work, we introduce a new dataset IIITM Face for the scientific community to address these challenges. Our dataset includes 107 participants who exhibit 6 emotions in 3 different face orientations. Each of these images is further labelled on attributes like gender, presence of moustache, beard or eyeglasses, clothes worn by the subjects and the density of their hair. Moreover, the images are captured in high resolution with specific background colors which can be easily replaced by cluttered backgrounds to simulate ‘in the Wild’ behavior. We demonstrate the same by constructing IIITM Face-SUE. Both IIITM Face and IIITM Face-SUE have been benchmarked across key multi-label metrics for the research community to compare their results.

Additional Key Words and Phrases: multi-task learning, facial attribute classification, emotion recognition, multi-label classification

1 INTRODUCTION

Face-attribute detection, which is aimed at identifying all the facial attributes from a given image, is a classical problem in the domain of multi-label classification. These attributes provide essential information about mid-level representations of faces that are abstracted between very low pixel level features and high level identity labels. The attributes can be very diverse and can include, for instance, gender, presence or absence of facial hair like beard or moustache, color and density of hair etc. Reliable identification of these attributes is crucial so as to have an intuitive and human interpretable face description. Moreover, accurately recognizing these attributes can play an important role in designing Human Computer Interaction (HCI) systems which need to be aware of gender and emotion of the user to respond appropriately.

While there are several datasets available for face-attribute detection on faces in the Wild, they lack simultaneous variability in poses and emotions as they are obtained by scraping from popular search engines [Huang et al. 2008; Liu et al. 2015a]. There is also a question of variability of backgrounds in these images as they are often close-up shots of faces. Additionally, the research community also feels an insufficiency of data of Indian faces.

To address these challenges we have collected a dataset - IIITM Face which is being released with this work. IIITM Face has been constructed by the participation of 107 students and staff at ABV-IIITM Gwalior. The images in this dataset have captured subjects in all possible combinations of 6 emotions and 3 different orientations (Fig. 2). Along with this, constant facial attributes of the subjects are also marked (Fig. 1). The detailed description of the dataset across all the attributes has been provided in Table 2. The classification of these facial attributes has been achieved by using three classifiers - Logistic Regression (LR), Support Vector Machine (SVM) [Hearst 1998] and ResNet [He et al. 2016]. The implementation details and hyperparameters used are outlined in section 4. All the images in this dataset are captured in high resolution with specific background colors which can easily be replaced by cluttered backgrounds to simulate ‘in the Wild’ behavior. We use complex scenes from [Shi et al. 2015] and use them as backgrounds in order to construct a new dataset, IIITM Face Simulated Unconstrained.

Fig. 1. Attribute diversity in IIITM Face Dataset

Fig. 2. Pose and Emotion variation in IIITM Face Dataset

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Environment (hereafter referred to as IITM Face-SUE, see Fig. 3). All the faces in IITM Face-SUE are subjected to translation to ensure that learning is position invariant. Our experiments on IITM Face-SUE show that there is a significant performance degradation across all metrics, thereby presenting an opportunity for exploring approaches which are invariant to the background noise.

The contributions of this work are summarized as follows - (i) We release an extensively labelled face-attribute dataset, i.e., IITM Face Dataset with Indian Faces. (ii) We perform rigorous benchmarking of this dataset across key metrics of multi-attribute classification. (iii) We compare the classification performance on the IITM Face and IITM Face-SUE datasets.

2 RELATED WORK

In the early days of research in face-attribute detection, the dataset sizes were small (about 500-1000 images from 20-120 participants) and had relatively fewer attributes as is evident in [Georgiades et al. 2001; Jesorsky et al. 2001; Speech and Robotics Group 1992; Wechsler et al. 2012]. Recently, larger datasets have been constructed given the widespread availability of data. One of the first such datasets was Labelled Faces in the Wild (LFW) dataset [Huang et al. 2008] which contained 13233 images scraped from the internet identifying 5749 people. In recent research, CelebA [Liu et al. 2015a] dataset has been used dominantly due to its sheer size of 200K celebrity images, each with 40 attribute annotations. Another dataset, VGGFace [Parkhi et al. 2015], containing 2.6M images across 2.622 people is one of the largest publicly available datasets. The size of this dataset was further increased and released as VGGFace2 Dataset [Cao et al. 2018] containing 3.3M images of 9,131 people. VGGFace2, along with UMDFaces [Bansal et al. 2017] are among very few publicly available large scale datasets containing pose information corresponding to each face image instance.

However, in the Indian context, there has been a relative dearth of data. Racial diversity is an element that is crucial for making facial recognition systems more reliable. For instance, VGGFace2 [Cao et al. 2018] and FairFace[Kärkkäinen and Joo 2019] focused on increasing the proportion of ethnically diverse faces and faces from different professions. The earliest dataset on Indian faces is the Indian Face Dataset [Jain and Mukherjee 2002]. It contains 11 images of 40 different people containing pose and emotion attributes. There are also other datasets such as Indian Face Age Database (IFAD) [Sharma and Patterh 2015] which contains attribute information of Indian celebrities but has limited number of subjects and low resolution images. Another dataset, Indian Spontaneous expression [Happy et al. 2015], presented video frames of subjects while watching emotional video clips thus giving rich information on emotion transitions. One large scale dataset available for Indian personalities is Indian Movie Face Database [Shankar Setty and Jawahar 2013] which contains 34512 images of 100 Indian celebrities with attribute labels consisting of age, pose, gender, expression and amount of occlusion. But all these datasets on Indian faces are limited in either the resolution of images, diversity in attributes or size of the dataset.

One major class of problems that is often studied on these datasets is facial attribute classification[Liu et al. 2015b; Sun and Yu 2018; Taherkhani et al. 2018]. This can be posed as a multi task joint learning problem or can be learnt through an ensemble of models for every attribute. Joint learning has the advantage that it can discover relationships across attributes and this is especially useful since facial attributes are highly correlated. On the other hand, separate models fail when large facial variations are present. In our work, we will be exploring both ensemble of models approach and multi task joint learning on our presented dataset.

3 METHODOLOGY

3.1 Overview of IITM Face Dataset

The IITM Face Dataset contains 1928 images of 107 people spanning across a wide range of facial attributes such as pose, gender, emotion, facial hair (beard and moustache), glasses, hair and clothing. The subjects of the dataset are students and staff members of IITM institute and there are at least 18 images for each subject. While the facial attributes and apparel labels are constant across one subject, the pose and emotion attributes cover all possible combinations.

| Dataset     | # Subjects | # Images | Resolution | Emotion | Pose | Facial Attributes |
|-------------|------------|----------|------------|---------|------|-----------------|
| IITK Face   | 100        | 440      | 640X480    | Yes     | Yes  | No              |
| IIFBD       | 100        | 34512    | Yes        | Yes     | Yes  | No              |
| IFAD        | 55         | 3296     | Varying2   | Yes     | Yes  | No              |
| ISED        | 50         | 4283     | 1920X1080  | Yes     | No   | No              |
| IITM Face   | 107        | 1928     | 2992X2000  | Yes     | Yes  | Yes             |

Table 1. Comparison of Indian Face Databases

Table 1 compares IIITM dataset with other publicly available facial image datasets in Indian context. Note that this dataset isn’t meant to serve as a ‘in the Wild’ (unconstrained environment) dataset. However, in section 4.2 we describe how we can post-process this dataset to treat it as a ‘in the Wild’ dataset.

3.2 Attribute Descriptions

For each face we, manually label it for the following eight attributes:

- Pose: Front, Up and Down
- Gender: Female, Male
- Emotion: Neutral, Sad, Smiling, Surprised, Surprised with Open Mouth (S.O), Bored
- Beard: Heavy, Light, None
- Moustache: Yes, No
- Glasses: Yes, no
- Hair: Light, Dense
- Cloth: Female T-Shirt(F. Tee), Female Top (F. Top), Male Shirt (M. Shirt), Male T-Shirt (M. Tee)

Out of these eight attributes described, beard, hair and moustache are subjective and the final label was selected by majority vote across the image. The range of emotions were chosen so as to have maximum diversity in terms of how different regions of face are animated for expressing a particular emotion.

1All images are in grayscale

2Small images in the range of 100-350 pixels in width and height

3Videos of the participants at 50 frames per second
3.3 Problem Formulation

Consider $m$ instances of facial images constituting our training samples where each instance $x_i$ ($i \in \{1, \ldots, m\}$), is a colored image of dimension $h \times w$.

$k$ is the total number of attributes and $a_j$ ($j \in \{1, \ldots, k\}$) is the set of valid and mutually exclusive labels for attribute $j$. The task is to learn a classifier

$$H : [0, 255]^{h \times w \times 3} \rightarrow \{0, 1\}^{\left|a_j\right|}, j \in \{1, \ldots, k\}$$

(1)

Now, this problem can be solved in several ways. In our work, we convert it into a multi-label prediction problem. For doing so, we define $A$ as the union set of all labels occurring in the training samples across all attributes. This is formulated as

$$A = \bigcup_{j=1}^{k} a_j$$

(2)

The training labels $y_i$ can be defined as binarized label vectors of length $|A|$. We further define the label matrix as $Y \in \{0, 1\}^{m \times |A|}$. Therefore, the element $y_{ij} = 1$ or 0 represents whether $j$th label of $ith$ instance is relevant or not. Finally, the multi-label predictor $H$ becomes

$$H : [0, 255]^{h \times w \times 3} \rightarrow \{0, 1\}^{|A|}$$

(3)

Another method is to train $k$ different multi-class classification models for each attribute. Hence, $H = \{h_1, \ldots, h_k\}$ and the vector $h_j(x_i)$ will give probability distribution over labels $l \in a_j$.

3.4 Evaluation Metrics

Evaluating performance in multi-label classification is more complex as compared to single-label classification since multiple labels can occur simultaneously in an instance. As a result, we use 9 key metrics that have been proposed in past works focusing on measuring different aspects of multi-label classification tasks.

Hamming loss, zero-one loss and coverage loss have been considered in a multitude of works such as [Huang et al. 2012; Chaparle and Singer 1999; Zhang and Wu 2014], while F1 score and AUC score in multi label scenario can be extended to instance level (averaging on each instance), micro level (averaging on prediction matrix) and macro level (averaging across each label) metrics. For a unified view on these metrics for multi label classification and their significance, we refer the reader to the work in [Wu and Zhou 2017].

4 EXPERIMENTAL SETUP

We perform the following experiments on our dataset. Firstly, we train LR, SVM and ResNet-50 referred to as LR-MT, SVM-MT and RN-MT respectively by binarizing the attributes and perform multi-label classification (multi task learning) as described in section 3.3. Thereafter, we pick the best-performing model in multi-task learning (ResNet in our case, as can be seen in Table 3), and train 8 such models separately, each for a single attribute. To get a classifier for all attributes, we create an ensemble of these 8 models and refer to it as RN-Ens. Finally, we perform experiments on the IIITM Face-SUE dataset by employing RN-MT classifier which we refer to as RN-MT-SUE. For all the experiments, we keep all images of 85 subjects in the train set and that of 22 subjects in the test set.

4.1 Implementation Details

For training the multi-label classification model, we first use Logistic Regression (LR) and Support Vector Machine (SVM) Models. Both of them are trained as One Vs rest Classifiers across the union set of all the labels. The images are resized to 100X100X3 dimension and then flattened to give a feature vector which is passed to the model. For both LR and SVM models, we have used L2 regularization and C=1, keeping the other hyperparameters with default values as implemented in [Pedregosa et al. 2011]. The ResNet-50 (hereafter referred to as ResNet only) architecture, wherever used in our experiments, has been constructed as described in [He et al. 2016] with some changes as described below. All the images fed to the ResNet classifier are of dimensions 224X224X3 and the model has been initialized with pretrained weights on ImageNet [Deng et al. 2009] following [Yosinski et al. 2014]. The network is trained using Adam optimization algorithm [Kingma and Ba 2014] with a batch size of 64. Following [Smith 2015], we use the LR find mechanism to find initial learning rate and cyclical learning rates for updating the learning rate in subsequent epochs. Note that for all MT experiments, the background is removed to prevent learning pose from color.

For RN-MT we calculate the hinge loss as we want to predict multiple labels simultaneously using the Equation 4.

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + \Delta)$$

(4)

where $s_j$ is the score corresponding to the correct class, $s_{y_i}$ is the score corresponding to the incorrect class and $\Delta$ is the margin.

For RN-Ens, the loss for each sample $L_i$ is calculated depending on the number of classes $C$ in each label as shown in Equation 5.

$$L_i = \begin{cases} 
-\sum_{c=1}^{C} y_{o,c} \log(p_{o,c}) & \text{if } C = 2 \\
-(y \log(p) + (1-y) \log(1-p)) & \text{if } C > 2
\end{cases}$$

(5)

where $y$ (or $y_{o,c}$) indicates binary indicator (0 or 1) if class label $c$ is the correct classification for observation $o$.

4.2 Construction of IIITM Face-SUE

The original images were captured with a colored background for their easy removal. We use images from [Shi et al. 2015] to replace colored backgrounds with complex scenes (Fig. 3). 20% of these backgrounds were reserved and used for the test set while the remaining were used to distort the images in the train set with the objective that our classifier does not learn to ignore these backgrounds with the same ease as in case of the white background. The subjects were...
5 RESULTS

We make several key observations based on the results shown in Table 3. Firstly, our experiments show that ResNet is far more superior to LR and SVM when it comes to multi-attribute classification on image datasets. Moreover, it can be seen that RN-MT outperforms RN-Ens across all metrics of evaluation. We attribute this to the ability of RN-MT to learn correlation among various attributes whereas the ensemble model is not presented with this opportunity since all the individual classifiers are trained in isolation. Our claims are bolstered by the fact that the zero-one loss is substantially high in case of RN-Ens. Zero-one loss being a measure of absolute correctness across all the attributes signifies that the our single model is able to capture this correlation surprisingly well. The heatmap in Fig. 4 represents how close is the correlation between the true labels as compared to the predicted labels of both RN-Ens and RN-MT. A smaller value (light yellow cell) indicates that the model has learnt the underlined relationship between the labels. Further, the RN-Ens model, being an ensemble, was seen to be computationally expensive at evaluation time. Our experiment to simulate ‘in the Wild’ behavior using IIITM Face-SUE shows that there is a drastic degradation in performance of RN-MT-SUE classifier across all metrics. We attribute this to ResNet’s ability to easily filter out white backgrounds as compared to the complex scenes.

6 FUTURE WORKS

The release of IIITM Face presents several opportunities to the research community for future exploration. Being a high resolution image dataset, it can be used to evaluate the performance of models trained on low resolution images, on a high resolution dataset such as this one and vice-versa. Moreover, it can serve as a test-bed for evaluation of state-of-the-art techniques in emotion recognition, specifically in the Indian context. Additionally, the subsequent conversion to an ‘in the Wild’ dataset opens the doors for evaluation of state-of-the art techniques in face-attribute detection as well. In future works, we also intend to study activation maps of model to reveal where it is looking to get information about specific attributes.
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