

REAL TIME EMOTION RECOGNITION AND GENDER CLASSIFICATION

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Abstract: The proposed prototype aims to classify the gender and the emotions of a person in real time or using the image of the person in live cam or hard copy of the photograph. The gender classification would be implemented by simple yet robust real time convolutional neural network. Whereas for the emotion recognition, instead of fully connected layers, this model boasts and consists of depth wise separable convolution. It not only reduces the number of parameters and computation utilized in convolution but further increasing the efficiency. It has proved to achieve success in image classification models in terms of both, i) in obtaining better models than previously possible for a given parameter count required to perform at a given level and ii) acquire state-of-the-art results. The output is provided in the form of classes and these are seven classes of emotion recognition (angry, fear, sad, happy, surprise, neutral, disgust) and two classes of gender classification (Male and Female). The present accuracy for gender classification is 95%, whereas the accuracy for facial emotion recognition is around 67%. Also, a large reduction of hyper parameters is the main goal to reduce the model size.

I. INTRODUCTION

GENERAL Face is among the foremost important biometric traits. Also, it is utilized to assess and evaluate the performance of a computer which is providing several services to the user, whether the user is satisfied or not. The human-computer connections add and sum up across the globe the access to tutoring, upgradation of information and knowledge and the transfer of useful and valued learning and instructions. Likewise, additionally, the dynamic model or prototype of machines making aware of and recognizing human emotions productively and dramatically is a professional evolution for the learning community. The autonomous identification and recalling of human sentiments reflected from facial gestures for making the system to acknowledge and realize human emotions and non-verbal emRWiRn iV cRined aV ³EmRWiRn RecRgniWiRn' [1]. But there are many challenges which are evident in the field of Facial Features recognition and emotion recognition. The first and the foremost problem is that, due to low lighting conditions, then the person who is using the system may be recognized as another person or in the worst case could be identified as unknown and wrong emotions are identified. Moreover, the pose of a person also brings in uncertainty whether a person will be correctly recognized or not as the face recognition systems are highly sensitive and error prone to variations occurred in the poses made by the person. Movements of head continuously can cause changes in face appearances and may result in a wrong outcome. Also, nowadays the existing systems on face recognition and emotional recognition are built from state-of-the-art methods involving the convolutional neural networks, which are resource heavy and are difficult to train in a system which lacks computing power much. A gender classification system uses the face of an individual from a given image to inform the gender (male/female) of the given person. Gender Classification is combined with emotion recognition to do the decision making and evaluation of the machine much better.

Real Time Emotion Recognition and Gender Classification By identifying gender certain traits can be observed depending if it is male or female, for some systems and achieve better machine performance. A successful and robust gender classification approach can uplift the performance and confidence level of implementation of many other applications including face recognition and smart devices. Hence, it is proposed to amalgamate the extracted features of facial expressions and gender classification. The cardinal and necessary matter in question that has to be thought in mind while acting with facial emotion recognition and gender classification are, face detection as well as befitting and relevant detection of facial features in low lighting situations as well as non-perfect situations. Machine Learning systems are the contemporary and continuously and tirelessly updated systems which are some of the buzzwords that are evolving rapidly nowadays, that are able to autonomously be able to carry out tasks at a human level of accuracy. This accuracy of the system can be empowered with the use of Convolutional Neural Network (CNN) whichever is a subfield of Deep Learning. Our prototype for emotion detection and gender classification are mainly based on the branch of applications of Machine Learning and Deep Learning.

Moreover, the contemporary, and relatively latest, new methods in image processing and other related tasks like image classification and real-time object detection are all constructed using the Convolutional Neural Networks (CNNs). These onuses involve using the CNN architecture with billions of parameters; therefore, their placement in robotic scaffolds and real-time systems becomes infeasible due to their memory constraints.

II. LITERATURE SURVEY

Title: Constants across cultures in the face and emotion Author: P. Ekman and W. V. Friesen. Year: 2019.

Description: Investigated the question of whether any facial expressions of emotion are universal. Recent studies showing that members of literate cultures associated the same emotion concepts with the same facial behaviors could not demonstrate that at least some facial expressions of emotion are universal; the cultures compared had all been exposed to some of the same mass media presentations of facial expression, and these may have taught the people in each culture to recognize the unique facial expressions of other cultures. To show that members of a preliterate culture who had minimal exposure to literate cultures would associate the same emotion concepts with the same facial behaviors as do members of Western and Eastern literate cultures, data were gathered in New Guinea by telling 342 Ss a story, showing them a set of 3 faces, and asking them to select the face which showed the emotion appropriate to the story. Ss were members of the Fore linguistic-cultural group, which up until 12 yr. ago was an isolated, Neolithic, material culture. Results provide evidence in support of the hypothesis. (30 ref.) (PsycINFO Database Record (c) 2016 APA, all rights reserved). 18

Title: Facial expression recognition based on local binary patterns: A comprehensive study. Author: C. Shan, S. Gong, and P. W. McOwan. Year: 2009. Description:

Automatic facial expression analysis is an interesting and challenging problem, and impacts important applications in many areas such as human-computer interaction and data-driven animation. Deriving an effective facial representation from original face images is a vital step for successful facial expression recognition. In this paper, we empirically evaluate facial representation based on statistical local features, Local Binary Patterns, for person-independent facial expression recognition. Different machine learning methods are systematically examined on several databases. Extensive experiments illustrate that LBP features are effective and efficient for facial expression recognition. We further formulate Boosted-LBP to extract the most discriminant LBP features, and the best recognition performance is obtained by using Support Vector Machine classifiers with Boosted-LBP features. Moreover, we investigate LBP features for low-resolution facial expression recognition, which is a critical problem but seldom addressed in the existing work. We observe in our experiments that LBP features perform stably and robustly over a useful range of low resolutions of face images, and yield promising performance in compressed low-resolution video sequences captured in real-world environments.

Title: Effects of cultural characteristics on building an emotion classifier through facial expression analysis. Author: Paras, Sanjay Mathur, Avinash Kumar, and Mahesh Chandra Year: 2009. Description:

Facial expressions are an important demonstration of humanity's humors and emotions. Algorithms capable of recognizing facial expressions and associating them with emotions were developed and employed to compare the expressions that different cultural groups use to show their emotions. Static pictures of predominantly occidental and oriental subjects from public datasets were used to train machine learning algorithms, whereas local binary patterns, histogram of oriented gradients (HOGs), and Gabor filters were employed to describe the facial expressions for six different basic emotions. The most consistent combination, formed by the association of HOG filter and support vector machines, was then used to classify the other cultural group: there was a strong drop in accuracy, meaning that the subtle differences of facial expressions of each culture affected the classifier performance. Finally, a classifier was trained with images from both occidental and oriental subjects and its accuracy was higher on multicultural data, evidencing the need of a multicultural training set to build an efficient classifier.

Title: Facial expression recognition with convolutional neural networks: Coping with few data and the training sample order. Author: A. T. Lopes, E. de Aguiar, A. F. D. Souza, and T. Oliveira-Santos. Year: 2016. Description:

Facial expression recognition has been an active research area in the past 10 years, with growing application areas including avatar animation, neuromarketing and sociable robots. The recognition of facial expressions is not an easy problem for machine learning methods, since people can vary significantly in the way they show their expressions. Even images of the same person in the same facial expression can vary in brightness, background and pose, and these variations are emphasized if considering different subjects (because of variations in shape, ethnicity among others). Although facial expression recognition is much studied in the literature, few works perform fair evaluation avoiding mixing subjects while training and testing the proposed algorithms. Hence, facial expression recognition is still a challenging problem in computer vision. In this work, we propose a simple solution for facial expression recognition that uses a combination of Convolutional Neural Network and specific image pre-processing steps.

Convolutional Neural Networks achieve better accuracy with big data. However, there are no publicly available datasets with sufficient data for facial expression recognition with deep architectures. Therefore, to tackle the problem, we apply some pre-processing techniques to extract only expression specific features from a face image and explore the presentation order of the samples during training. The experiments employed to evaluate our technique were carried out using three largely used public databases (CK+, JAFFE and BU-3DFE). A study of the impact of each image pre-processing operation in the accuracy rate is presented. The proposed method: achieves competitive results when compared with other facial expression recognition methods – 96.76% of accuracy in the CK+ database – it is fast to train, and it allows for real time facial expression recognition with standard computers.

Title: Image based static facial expression recognition with multiple deep network learning, Author: Z. Yu and C. Zhang Year: 2015. Description: We report our image based static facial expression recognition method for the Emotion Recognition in the Wild Challenge (EmotiW) 2015. We focus on the sub-challenge of the SFEW 2.0 dataset, where one seeks to automatically classify a set of static images into 7 basic emotions. The proposed method contains a face detection module based on the ensemble of three state-of-the-art face detectors, followed by a classification module with the ensemble of multiple deep convolutional neural networks (CNN). Each CNN model is initialized randomly and pre-trained on a larger dataset provided by the Facial Expression Recognition (FER) Challenge 2013. The pre-trained models are then fine-tuned on the training set of SFEW 2.0. To combine multiple CNN models, we present two schemes for learning the ensemble weights of the network responses: by minimizing the log likelihood loss, and by minimizing the hinge loss. Our proposed method generates state-of-the-art result on the FER dataset. It also achieves 55.96% and 61.29% respectively on the validation and test set of SFEW 2.0, surpassing the challenge baseline of 35.96% and 39.13% with significant gains.

III. RELATED WORK

In the following research papers and journals, it has been noted that the existing prototype was not as accurate and resource heavy. Also, the extraction of facial features is a very vital phase of properly and accurately recognizing emotions and gender.

The VGG16 has been used for emotion recognition, but failed miserably because of the large size and large numbers of parameters. The vital goal of our prototype is to efficiently and accurately detect and recognize emotions and genders in a single module with low processing power usage and concurrently fuse the modules of emotion and gender classification.

Disadvantages:

The structure is not total interpretable

- The accuracy of these systems is compromised as the system mostly works on inaccurate
- data and inputs. Due to inaccuracy in results, they are not always widely accepted.

IV. PROPOSED WORK

Face is among the foremost important biometric traits. Also, it is utilized to assess and evaluate the performance of a computer which is providing several services to the user, whether the user is satisfied or not. The human-computer connections add and sum up across the globe the access to tutoring, upgradation of information and knowledge and the transfer of useful and valued learning and instructions. Likewise, additionally, the dynamic model or prototype of machines making aware of and recognizing human emotions productively and dramatically is a professional evolution for the learning community.

The gender classification would be implemented by simple yet robust real time convolutional neural network. Whereas for the emotion recognition, instead of fully connected layers, this model boasts and consists of depth wise separable convolution ADVANTAGES It will require only less multiplications to reach the same output. . Type of convolution where we apply a single convolutional filter for each input channel.

4.4 System Architecture

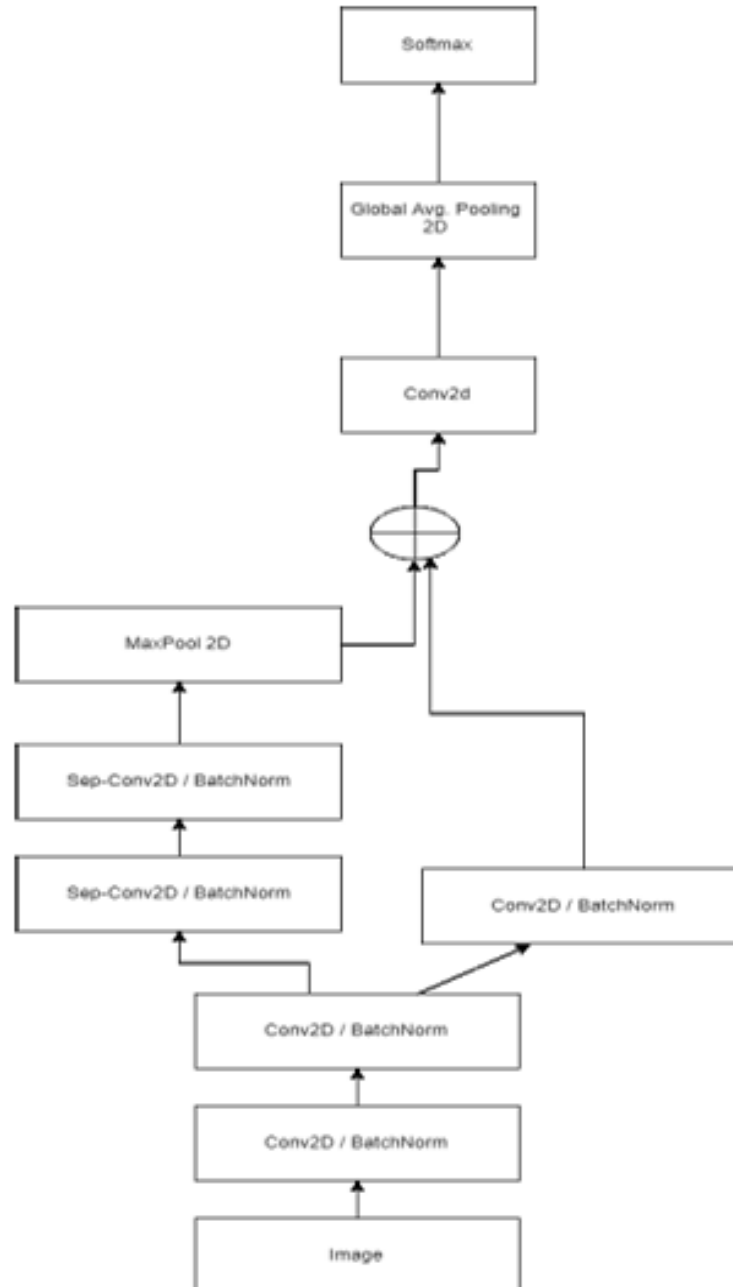
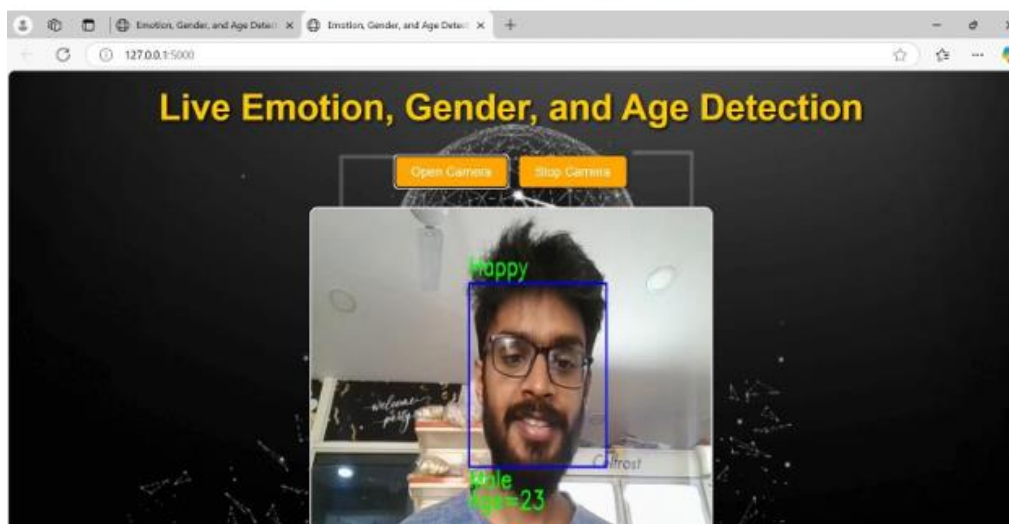
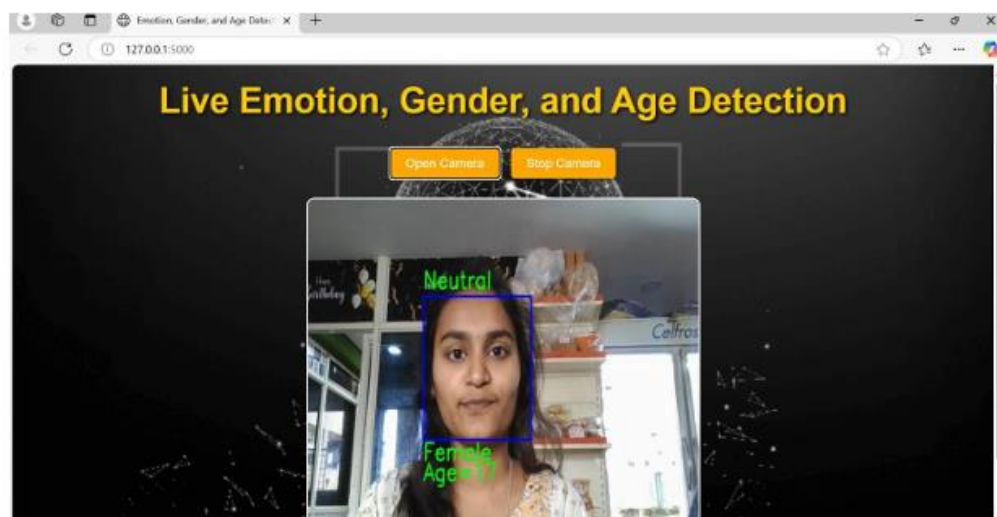
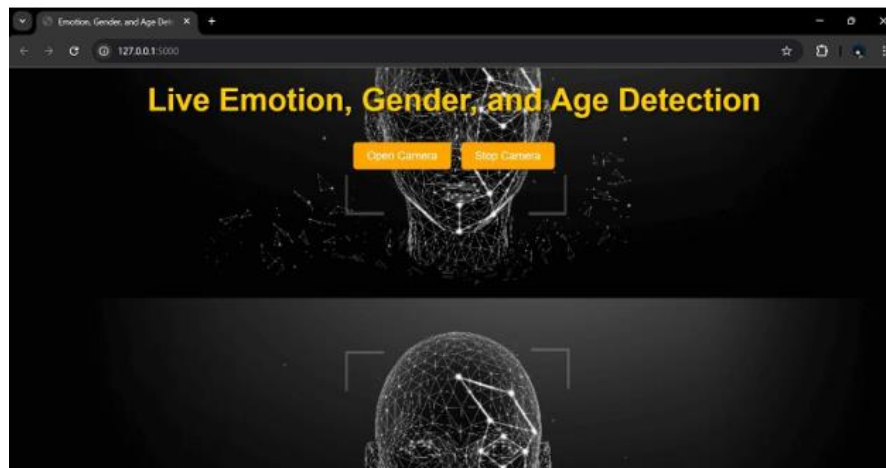
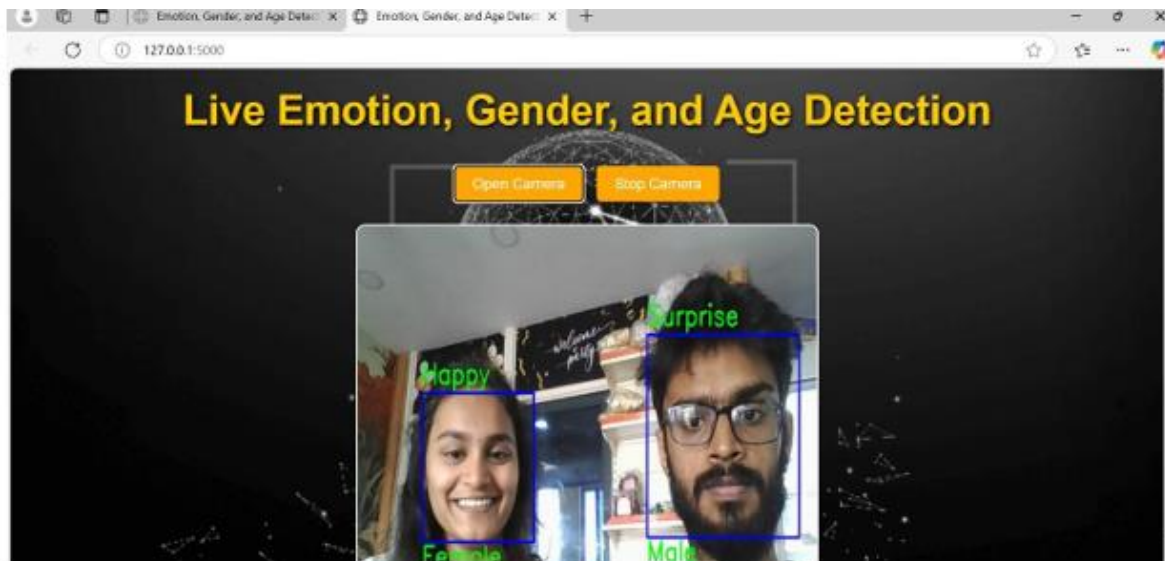


Fig : System Architecture

V. RESULTS

Real Time Emotion Recognition and Gender Classification





VI. CONCLUSION

Our proposed architecture is consistently and regularly built that one may to lessen and lower the numbers of parameters, and it is achieved by stamping out the fully connected layers. The original number of parameters were more than 6,00,000 in the original architecture, which we reduced it to 60,000 almost summing up to 10 times reduction in parameters in emotion recognition, thus reducing large computational overheads. The current accuracy of the emotion recognition comes around 67 % whereas the accuracy obtained for the gender classification is 95 %. The percentage of parameters that are trainable in our prototype sums up to 99.72% of total parameters and their numbers are around 6, 41,463. We are trying to achieve and realize human-level attainment and achievement in our apportionment process utilizing a single CNN that clouts contemporary architecture and model constructs. The prototype is having an edge over Whe RWheUV¶ SURWRW\Se b\ RbWaining faYRXUable UeVXIWV aW Whe same time. Lastly, we have posed a visualization of the learned features within CNN using the guided back propagation visualization.

Our proposed prototype is another plane on a big bias line instituted with Exception and Mobile Nets, that indicates that in any convolutional model, whether it is for 1D or for 2D data, it's expedient and acceptable to swap and transfer convolutions with depth wise separable convolutions and acquire a model that's synchronously low-priced as well as nominal to extract, small as well as minor, and transacts as well as percolates a twain of percentage points superior as well as sophisticated.

REFERENCES

- [1]. A. Mehrabian, "Communication without words," *Communication Theory*, pp. 193–200, 2008.
- [2]. P. Ekman and W. V. Friesen, "Constants across cultures in the face and emotion." *Journal of personality and social psychology*, vol. 17, no. 2, p. 124, 1971.
- [3]. C. Shan, S. Gong, and P. W. McOwan, "Facial expression recognition based on local binary patterns: A comprehensive study," *Image and Vision Computing*, vol. 27, no. 6, pp. 803–816, 2009.
- [4]. X. Zhang, M. H. Mahoor, and S. M. Mavadati, "Facial expression recognition using lp-norm mkl multiclass-svm," *Machine Vision and Applications*, vol. 26, no. 4, pp. 467–483, 2015.
- [5]. F. A. M. da Silva and H. Pedrini, "Effects of cultural characteristics on building an emotion classifier through facial expression analysis," *Journal of Electronic Imaging*, vol. 24, no. 2, pp. 023 015–023 015, 2015.
- [6]. A. T. Lopes, E. de Aguiar, A. F. D. Souza, and T. Oliveira-Santos, "Facial expression recognition with convolutional neural networks: Coping with few data and the training sample order," *Pattern Recognition*, 2016.
- [7]. A. Mollahosseini, D. Chan, and M. H. Mahoor, "Going deeper in facial expression recognition using deep neural networks," in *Applications of Computer Vision (WACV)*, IEEE Winter Conference on, 2016, pp. 1–10.
- [8]. P. Liu, S. Han, Z. Meng, and Y. Tong, "Facial expression recognition via a boosted deep belief network," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2014, pp. 1805–1812.
- [9]. P. Burkert, F. Trier, M. Z. Afzal, A. Dengel, and M. Liwicki, "Dexpression: Deep convolutional neural network for expression recognition," *arXiv preprint arXiv:1509.05371*, 2015.
- [10]. Z. Yu and C. Zhang, "Image based static facial expression recognition with multiple deep network learning," in *Proceedings of the 2015 ACM on International Conference on Multimodal Interaction*. ACM, 2015, pp. 435–442.