

IMPROVED ANALYSIS MODEL FOR FACIAL EXPRESSION DETECTION FROM LOW-RESOLUTION IMAGES

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Abstract

Facial Expression Detection and the classification of images according to the recognized human emotion has its own significance in the development of the latest artificial intelligence-based systems and the latest research trends. The new technologies and facial expression detection systems are playing a vital role in improving the accuracy of results. However, existing systems perform better when working on high resolution image. The results of Facial expression detection for human emotion recognition from low-resolution images are still uncertain. In this research, an artificial intelligence evaluation model is developed to classify and evaluate the performance of facial expression detection systems for low-resolution images. The performance of three facial expression detection systems, including Azure Face API, Face++ and Face Reader, is analysed in two facets: (1) human emotion recognition from low resolution image, and (ii) the classification of these images according to the class of human emotion through the trained model. The training is performed on the dataset to evaluate the performance in terms of precision, recall, mAP and f-score. These three systems also perform accurately with high-resolution images. The Azure Face API provide more accurate results than the other two systems (i.e., 80% of the images are manipulated and classified accurately). However, there are some limitations for some specific human facial expressions. So, there is a need for experimental evaluation of these systems for the guidance of future system developments and research in the discipline of facial expression detection.

Keywords: *Facial Expression Detection, Emotion Recognition, Low Resolution Images, Face API, Computer Vision, Artificial Intelligence, Image Classification.*

Introduction

Various research disciplines like Information Retrieval or Processing, Psychology, Neuroscience, Emotions Influence Information Processing, Decision Making, Attitude Formation, Sentiment Analysis, and Political Science require facial expression detection (FED) significantly [1, 2]. Facial expression detection is an ever-best technique to recognize the emotional reactions of humans. Some typical facial expression detection techniques are FACS (Facial Action Coding System), based on expert observations, and EMG (Electromyography), a direct computation of facial muscle movement using electromyography [3, 4]. Both techniques have many drawbacks, such as being more time-consuming and harder to implement at the application level.

Computerized facial expression detection (CFED) or recognition through images is an alternative technique to facilitate, regulate, and scale the application of facial expression and related research. These are the recent trends that emerged from the technologies of digital image processing, artificial intelligence, and computer vision [5]. The facial expressions are detected or classified by using machine learning algorithms that compute the scores of extracted emotions from observed data. Various algorithms have been developed by various researchers for this purpose. These algorithms are significantly more time-saving and cost-effective than classical techniques [6]. The CFED is easily available anytime and anywhere to researchers and organizations of all fields who need it, and is progressively used in scientific applications by the community. Various examples found for the application of CFED, such as FED algorithms, are used in Psychology to envisage the psychological or mental health of humans from still images, the validation of autism interventions, and the screening of Parkinson's disease [7]. The analysis of collective contentment in a society from the images collected from different media is another example of computerized facial expression detection implementation or application in the field of sociology [8, 9]. The study about the representations of politicians in their constituencies and media using computerized facial expression detection is also an example or application in political science [10]. Furthermore, this technology is also used in marketing and customer research feedback through facial expressions to predict the effectiveness of advertisements [11].

Normally, the training and testing phase of FED systems is performed on datasets consisting of images of high resolution [12]. These datasets are created under detailed professional directions to the performers in professional shooting environments, including good lighting and camera angles. In this regard, the accuracy rate is high for such images with high resolution [13]. These results overestimated results as compared to the results of FED systems from low-resolution images.

This study of facial expression detection provides the assessment of the strength of specific expressive facial expressions through a couple of successive phases: (1) face detection, including the detection of facial features or structures, and (2) the classification of a face into an expressive category or class. In the face detection phase, a variety of still images is used, and different images of males and females of different ages are used in training. In this phase, it also took care of the facial characteristics, such as glasses on the face. A beard on the face may increase the rate of failure of facial expression detection and result in higher rates of dropout. It is tried to standardize the expressions that cause less dropout due to the failure in the detection of faces, and no other substances that obstruct the faces. It is expected in this research that the total performance on non-standard datasets will be lower. This experimentation also focuses on the generalization of facial expression detection to more natural expressions, and the performance analysis of a specific facial expression detection system, Microsoft Azure Custom Vision, in terms of effective results.

Literature Review

In previous research works related to facial expression detection, there are various flaws in the classification of human facial expressions. In these studies, researchers continuously find lower accuracy rates as compared to other human emotion classes [14]. Some FED systems [15] report significant lower accuracy rate for the anger class, whereas [14] improved the result of FED in their research work. The study presented in [14, 16] observed less accuracy for sad and disgust classes. The research work [16] also reports high accuracy in the classification of images falling in joy and disgust classes. The research works evaluating various FED systems continuously report large dissimilarities in the performance results of systems [15, 17]. Therefore, there is a great need for the development of models for comparative evaluations.

The practical evaluation of FED systems is needed instead of the direct comparison of these systems using datasets. Moreover, these direct comparisons are limited to the planned modelled picturizations (i.e. controlled environment datasets). In comparison to such datasets, naturalistic images of facial expressions report strong dissimilarities and are found less penetrating in comparison to posed facial expressions [18]. In [19], the authors report good correlation between the parameters of the FED system and the human face image responding to happy emotion expressions, but they fail to provide strong and valid facial expression detection of the sad expression of human emotion. The study in [20] reports that there is a big reduction in FED emotion recognition for the image with the lowest resolution and captured in natural environments.

The work presented in the research article [21] is the automatic facial expression recognition from the standardized and non-standardized face images. Authors still receive less accurate results with non-standardized image of facial expressions. The authors of [22] present the research work on the development of a face recognition system and face mask detection using deep learning. The system provides better results with high-quality images. The early detection and diagnosis of Alzheimer's disease by using a Microsoft Azure Custom Vision model is presented in [23], but there is no discussion about the image quality used for training and testing purposes. Recently presented research work [24] provides a comparative evaluation of three FED systems, but they did not include the effectiveness of the results due to image quality. However, in all the related studies, the datasets used for experimentation still consisting images of high resolution or captured in controlled environments, which significantly affects the performance of FED systems.

Methodology

In this article, a study of an artificial intelligence approach for the detection of facial expressions and the classification of images through trained models is presented. Three different FED systems (including Microsoft Azure Custom Vision Cognitive Service, Face++, Face Reader systems) and human emotion recognition data are used to analyze emotional facial expressions with more or less standardized facial expressions (as an approximation, low-resolution or low contrast images of human facial expressions) in the proposed approach. The approach consists of four basic phases, as shown in Figure 1: (1) The first phase retrieves the low-resolution image stored in a repository. (2) A new project is created on the FED system selected for evaluation. After the new project, the images are uploaded to the project under different tags or classes for training purposes. Then the model is trained on the uploaded data so that it can predict new images. (3) The third phase provides the computed values of performance metrics against each of the tags or categories. Based on these values f-score and other metrics are computed. The performance of the proposed approach is computed based on pre-calculated primary performance measures: precision, recall,

f-score and mAP (Mean Average Precision). (4) The classification phase is performed to classify new images. The system then predicts the image into a specific class according to the probability score computed by the system.

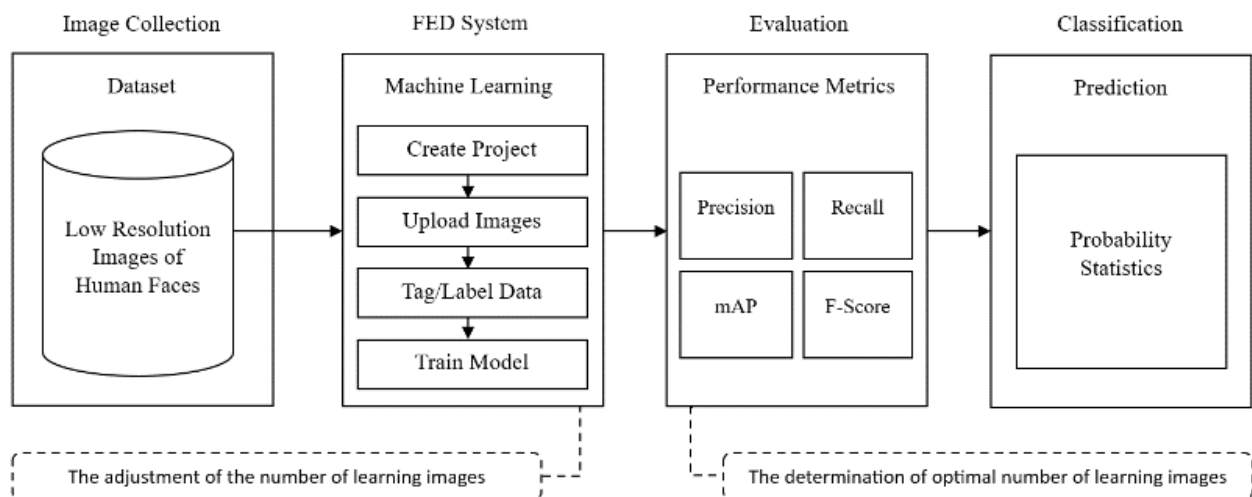


Fig. 1. Evaluation Model of Facial Expression Detection Systems

Dataset

The dataset selected in this study is available on Kaggle and is named 'Face Expression Recognition Dataset' [25]. The dataset contains approximately 36k black and white (greyscale) human face images of size 48x48, including images of males and females of different age clusters. In addition, the dataset includes still image inventories of people who were not instructed to display prototypical emotional expressions and have more naturalistic emotional facial expressions in still images. The human faces are aligned in the centre of the image, and each human face almost covers the same area of the image. There is a total of seven categories of facial expressions into which these images are divided, and each image must belong to one of these categories. Figure 2 shows some low-resolution sample images in the dataset uploaded to the system for training under the neutral tag.



Fig. 2. Sample low-resolution images uploaded to the systems for training with a neutral tag.

The data was originally contained in arrays with greyscale colour combinations. The data is in the converted form of raw images, and these images are divided into seven categories and saved in their relevant folder. These folders are entitled Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral. In this dataset, 80% of the data images are stored in the training folder for training purposes, and 20% of the data images are stored in the validation folder for testing purposes. In this study, only 5k images are used for training due to the storage space limitation on Microsoft Azure Custom Vision and other FEDs.

Facial Expression Detection Systems

Three different most popular FED systems, including Microsoft Azure Face API, Face++ and Face Reader, are used for the evaluation using the model with low resolution image dataset. The Microsoft Azure Custom Vision is a transfer learning-based model, and exact discrimination is conceivable even with a minor volume of image data. However, in this study, a large number of images are selected for training to attain optimal performance. The other two FED systems, Face API and Face++, are freely available online to the user. The Face Reader is available to the user as software to be downloaded and installed locally on the machine. These FED systems are well known in the research communities. These FED systems enable the user to analyse the face in a still image with some common functions like face detection, verification, and human emotion recognition. These systems are also able to classify the still images according to seven facial expressions or human emotions, including happy, sad, anger, fear, surprised, disgust and neutral. Further, these FEDs also compute probability scores for each classified image against these expressions. The scores provided by the systems are rescaled in a uniform way from 1 to 100 instead of 0 to 1, because some systems provide scores between 0 and 1.

These FED systems are Cognitive Services for the development of the artificial intelligence approach, and are normally used in visual data analysis-related tasks. These systems classify the stored image data and assign tags to those images in the dataset. These are transfer learning-based models that detect major differences between data images and optimize the image data for the rapid identification of tagged images. The neural network structure is introduced by transfer learning, which is trained in an explicit discipline without alteration, tunes a fragment of the lower layer, and the upper layer remains frozen. It means that in this process, the scores are retrieved from the upper layer without any alteration or modification. These scores are adapted to fit and applied to the novel input of facial expression image data from the lower layer. In this way, the proposed approach provides more accurate and faster results from training by inputting a small volume of facial expression image data during the detection and classification of images.

Results and Discussion

The proposed approach experimentation is performed on three FED systems, and a complete report of results in terms of precision, recall, mAP and F-score for each system is presented in this section. The human face images for training and testing purposes are collected from the dataset available on Kaggle (see details in the dataset section), and 5k human face images with different expressions are uploaded for training to each FED system. Furthermore, the hyperparameters are determined by the trained model through K-fold cross-validation for overfitting avoidance, and the basic performance analysis is performed.

The results from FED systems are presented in the form of a table and a graph. The numerical values computed during the experimentation are presented in Table 1, where detailed statistical evaluation can be found. It can be noticed that FED systems do not perform much better on low-resolution images, except for the MS Azure Face API. The highest rates of performance metrics are computed on Face API, almost 80% of the images are manipulated correctly and classified with the highest probability scores.

TABLE I. OVERALL PERFORMANCE RESULTS

Facial Expression	Azure Face API				Facial Expression	Face++			
	Precision	Recall	mAP	F-Score		Precision	Recall	mAP	F-Score
Happy	82.50	70.60	80.60	76.09	Happy	76.30	48.10	70.40	59.00
Neutral	64.70	49.70	58.30	56.22	Neutral	34.70	40.40	31.30	37.33
Surprized	72.00	68.30	77.20	70.10	Surprized	20.30	66.40	14.70	31.09
Anger	61.60	28.30	48.40	38.78	Anger	36.10	15.20	33.20	21.39
Disgust	55.00	57.90	58.40	56.41	Disgust	17.40	16.00	13.50	16.67
Sad	49.20	20.80	40.00	29.24	Sad	40.18	19.10	34.60	25.89
Fear	41.00	11.00	33.40	17.35	Fear	18.20	18.60	15.80	18.40

Facial Expression	Face Reader			
	Precision	Recall	mAP	F-Score
Happy	52.40	42.20	47.80	46.75
Neutral	20.90	68.40	17.30	32.02
Surprized	33.20	34.60	28.10	33.89
Anger	42.30	14.50	35.90	21.60
Disgust	17.20	15.60	12.20	16.36
Sad	32.10	15.30	26.70	20.72
Fear	0.00	0.00	0.00	0.00

The two systems, Face API and Face++, both classify 60% of the images correctly on average, while Face Reader show lower performance as compared to these FED systems. If we examine a specific expression class, the happy class is best classified by the systems. Overall, the MS Azure performance is best compared to other systems on the same dataset of low-resolution images of human faces for face expression detection. The performance of Azure is best, although the training image count value is decreased in comparison to high-resolution images. The numerical results are also presented in the form of a graph as a visual, see Fig. 3.

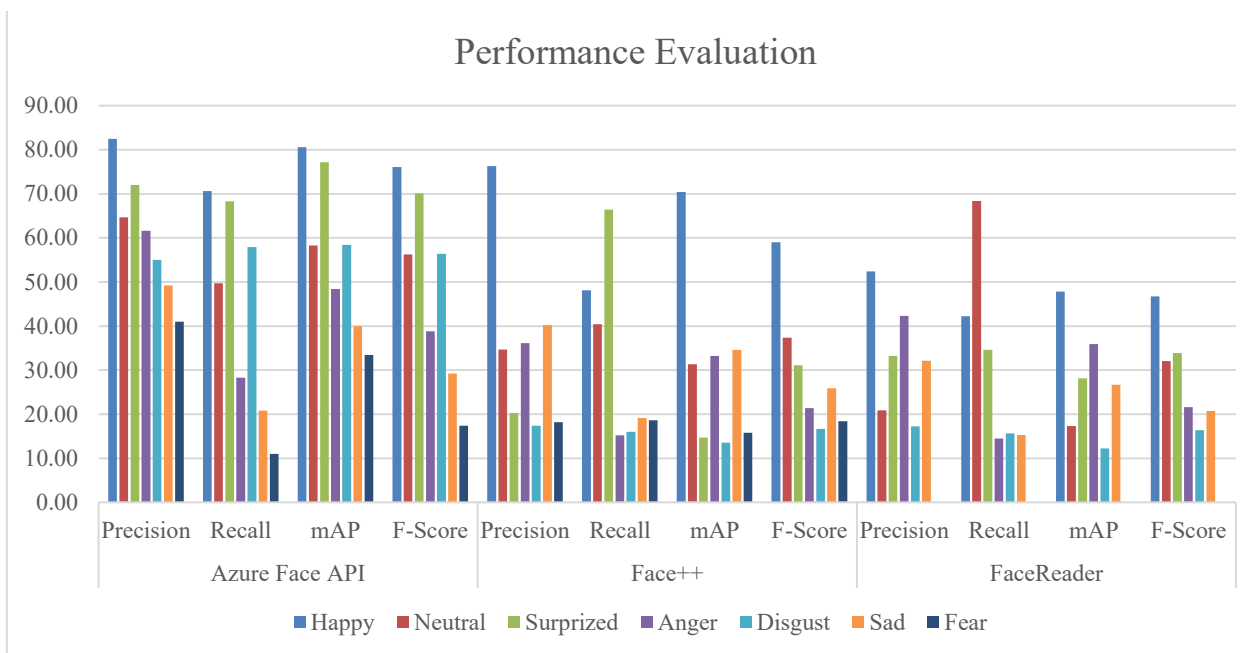


Fig. 3. Overall Performance Evaluation Graph

Microsoft Azure Custom Vision is the best service of Artificial Intelligence and Computer Vision provided by Microsoft Azure for the classification of low-resolution images. It enables users to develop a customized model for the detection and classification of images. This also provide user interface that makes the procedure of creating a computer vision model without coding. A facial expression detection and image classification system can be developed from the beginning without coding by using a user-friendly user interface. The average precision, recall and mAP values computed on this system for all emotion classes on the given dataset are also presented in Fig. 4.



Fig. 4. Average Performance Measures of all Human Facial Expressions on the Given Low-Resolution Dataset

In this article, three widely used FED systems are evaluated. A low-resolution image dataset is selected for experimentation to perform the comparative evaluation. A state-of-the-art evaluation model is implemented to complete the task. The results are presented in different formats. However, the performance of FED systems varies strongly between training data size, data classes, quality of images and the systems. MS Azure Face API shows the best results on low-resolution image data as compared to other FED systems.

Conclusion

In this study, a state-of-the-art evaluation model is developed to compare the effectiveness in results of different FED systems by classifying the low-resolution image after model training on the relevant dataset. The study shows that the selected FED systems for experimentation perform better on high-resolution images, but the performance varies on the low-quality image dataset. Three well-known FED systems, including MS Azure Face API, Face++, and Face Reader, are selected to implement the approach for the

performance evaluation of these systems. A common low resolution images standard dataset is selected for experimentation on all systems. Relatively, the Azure system provides higher rates of performance metrics, which provide more accurate results as compared to other systems. In future, more research is needed in different case studies, like the classification and disease identification from low contrast medical images using FED systems to improve the performance of the FED system, and to make healthcare systems more improved and efficient.

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