Facial Expression Recognition: Machine Learning Algorithms and Feature Extraction Techniques

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Abstract

Facial expression recognition (FER) systems accurately identify facial expressions by extracting facial features. The extraction of robust facial features comes after automatic face detection in this procedure. On the FAR2013 dataset, a five-step system developed to assess the performance of machine learning algorithms. Components of the system include preprocessing, feature extraction, model training and testing, classification, and evaluation. Three machine-learning algorithms utilized in this study: logistic regression (LR), random forest (RF), and AdaBoost (ADA). The RF algorithm achieved the highest degree of precision with a 61% success rate. The purpose of the study was to evaluate the performance of machine learning algorithms on the FAR2013 dataset. The study highlights the importance of facial feature extraction in FER systems and the precision of machine learning algorithms in facial expression recognition.

Keywords- Face expression; Machine learning, Feature extraction, Random Fore, logistic regression. PCA, GLCM.

I. INTRODUCTION

To recognize facial expressions, an advanced program-using machine learning and geometric classification developed using feature extraction, PCA, and GLCM techniques to accurate classify emotions [1]. Facial expression recognition usually involves two types of features: geometric and appearance features. Geometric features are concerned with the shape and positioning of facial features, while appearance features focus on details like wrinkles and furrows. For identifying facial expressions. However, the use of appearance features can be limited when it comes to recognizing expressions across different individuals. Geometric features, on the other hand, can provide sufficient information to recognize facial expressions accurately, even if they are sensitive to noise and can be challenging to track [2]. Recognizing facial expressions using still images requires identifying and classifying particular features. In contrast, dynamic sequential images of facial expressions capture the continuous changes of expressions and provide insight into the evolving process of the facial expressions [3]. GLCM is a statistical algorithm used in image processing and computer vision for texture analysis. The GLCM method is based on the calculation of the co-occurrence matrix, which defines the frequency with which pairings of pixel values occur at a given distance and orientation. GLCM texture features extensively used in image classification problems, and the method defined by the extraction of seventeen GLCM texture features. The efficient GLCM-based method used to extract texture features for classification tasks in a number of applications [4]. Preprocessing steps to develop emotion recognition systems, such as standardizing images, detecting faces and facial components, extracting emotions, and matching or classifying emotions. Data augmentation used to apply transformations to the dataset, allowing for the discovery of invariant features learned by the network [5]. RF is a well-known algorithm for supervised machine learning commonly applied to classification and regression problems. It is an algorithm consisting of multiple decision trees for classifying multiple data sets. A random forest classifier consists of a collection of decision trees N (such as decision trees T1, T2, TN), each of which is a classifier with one vote, and the ultimate result of random forest classification is the weighted average of all of the voting results of the decision trees. [6]. RF method employed in facial expression recognition research. Several studies [7]. Have proposed classification frameworks for facial expressions that employ random forest as the classifier. AdaBoost is an algorithm for machine learning that generates weak learners by storing weights over training data and modifying them after each cycle of weak learning. It increases the weights of training samples that the current feeble learner incorrectly classified while decreasing the weights of training samples that is correctly classified. It quickly converges, is simple to implement, and is applicable to real-world application [8].

II. RELATED WORK

Jia, Ju., et al. The proposed framework for facial expression classification extracts facial expression features using random forest (RF) as the classifier and 2DPCA, an enhanced version of PCA. Using the JAFFE database, the RF algorithm achieved a higher recognition rate than the SVM algorithm. The experimental results demonstrated, with an accuracy of 87.6%, that the proposed novel approach outperformed other conventional methods in terms of recognition performance. The conclusion of the study was that the random forest facial expression recognition system with enhanced PCA feature extraction is effective [6]. Gu, Wenfei. et al. proposed a hybrid facial expression recognition system that utilized Gabor wavelet and Harris corner features for feature extraction and random forest for classification. Gabor wavelets are mathematical functions that can extract features from images, while Harris corner features used to detect and describe the corners of an image. Tested the system on the JAFFE database. The results showed that the proposed method achieved an accuracy rate of 87.32% [9] Wang, Yubo. et al. Propose a system capable of recognizing seven facial expressions automatically and in real-time, AdaBoost was used for feature selection and classification. The system consisted of three modules: face detection, extraction of facial feature landmarks, and recognition of facial expressions. The expression classifier learned by augmenting weak classifiers of the Haar feature-based Look-Up-Table type. Comparing the proposed method with SVMs using the JAFFE database, the study found that the boosting method obtained superior performance, particularly in terms of speed. The average rate of accuracy was 92.4%, and the average image processing time was 0.11 milliseconds [10]. Vijayarani, S. et al. The objective of this study was to utilize the Face Part Detection (FPD) algorithm and the GLCM algorithm to extract features from human facial images. GLCM employs the affine moment invariants method, whereas FPD uses the bounding box method. In this research, the accuracy of feature extraction and execution time assessed as performance factors. Using the JAFFE database, the study determined that the proposed GLCM algorithm extracted features more precisely and, in less time, than the FPD algorithm. The GLCM execution time was 13 seconds, while the FPD execution time was 28 seconds. The GLCM was 90% accurate, while the FPD was 78% accurate [11] The proposed methodology consists of two components: a training dataset for emotion detection utilizing the PCA algorithm and GLCM for feature extraction and a novel face identification scheme based on phase and GMMs. The study inputted various emotion images, extracted image features using PCA and GLCM texture features, trained the dataset using SVM, and evaluated the accuracy of emotion detection. Before classification, the performance of SVM, kNN, and dimensionality reduction on feature vectors evaluated. The experimental results demonstrated that the overall performance of SVM was superior to that of kNN in all cases and that applying dimensionality reduction to the feature vectors prior to the classification stage enhanced the performance in the majority of experiments [12]. The article discusses the most effective facial recognition techniques and evaluates the performance of PCA and LDA using the Jaffe database. PCA has a 70% recognition rate, while LDA has a 30% rate of recognition. The study concludes that performance can be enhanced by combining neural networks and fuzzy logic into a hybrid approach. As a classifier, the Euclidean distance used to calculate the distance between the image to evaluate and the available images used for training. In testing, the Euclidean distance between the new (testing) image Eigenvector and the Eigen subspace for each expression computed, and classification is performed based on the minimum Euclidean distance to recognize the input image's expression [13]

III. RESEARCH ELABORATIONS

The proposed system includes five phases: pre-processing, feature extraction, model training and testing, classification, and evaluation. Figure 1 depicts the phases of the proposed system in detail:

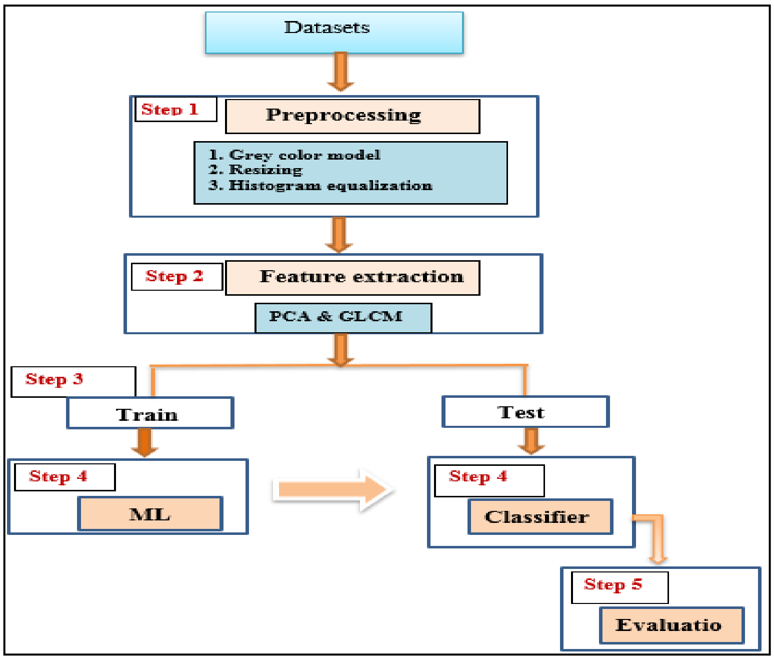

Fig 1. Diagram outlining the steps of the system used to recognize facial expressions

3.1 Pre-processing

The initial stage is pre-processing, which entails converting the image to grayscale using equation (1) [14], using histogram equalization to improve image quality as demonstrated by equations (2) and (3) [15], and then resizing the image with bilinear interpolation. 20 by 20 pixels is the size of the resulting image to generate a smoother image [16].

$$\mathbf{GRAY_{LEVEL} = 0.59\,G + 0.30\,R + 0.11\,B \ldots\ldots\ldots (1)}$$

$$\mathbf{CDF\ (X) = \sum_{i=1}^{X} H(i) \ldots\ldots\ldots (2)}$$

Where X represents the grayscale value and H represents the image's histogram.

$$\mathbf{P[pixel] = round\left(\left(\frac{CDF\ (X) - CDF(X)_{min}}{N*M - CDF(X)_{min}}\right) * (l-1)\right) \ldots\ldots\ldots (3)}$$

$CDF(X)_{min}$: Minimum value of cumulative distribution function, N * M: the dimensions of the image in terms of its columns and row, l: Gray levels.

3.2 Feature Extraction

In the second stage, the system extracts features using PCA/GLCM. The purpose of this stage is to extract facial features that will enhance the classifier's ability to recognize faces [17].

PCA is a statistical technique that derives unique facial characteristics by representing a face as a linear combination of Eigenfaces obtained through an iterative procedure [18][19].

To perform PCA, several stages are undertaken:

First, subtract the mean from the data for each variable.

Calculate and construct a covariance matrix in the second stage.

Calculate eigenvectors and eigenvalues from the covariance matrix in the third stage.

Step 4 is to choose a feature vector step.

Multiply the transposed feature vector in the fifth stage [12].

Additionally, in **GLCM** a texture analysis method calculates features using a square matrix derived from an area of interest in facial expression images. GLCM yields six distinct features, namely contrast, angular second-moment feature (ASM), energy, dissimilarity, homogeneity, and correlation [20].

3.3 Train and test

After extracting the features, three machine-learning algorithms (RF, LR and ADA) trained and evaluated using a labelled dataset. During the training phase, the parameters of the model optimized to reduce the difference between predicted and observed outputs. During the trial phase, the efficacy of the model evaluated using a distinct data set.

3.4 Classification

After training and testing, the trained (RF, LR, and ADA) models used for classification. It allocates input data to one or more predefined classes or categories based on the taught characteristics. This requires associating each test image with one of seven emotions, including surprise, fear, derision, revulsion, anger, happiness, and sorrow.

3.5 Evaluation Metrics

In the fifth phase**,** the metrics assessed. Precision, recall, accuracy, and the F-score are the four measurements computed. These metrics provide a quantitative measure of the system's facial expression recognition performance

$$\textbf{Precision} = \frac{\textbf{TP}}{\textbf{TP+FP}} \quad \dots\dots\dots.(4)$$

$$\textbf{Recall} = \frac{\textbf{TP}}{\textbf{TP} + \textbf{FN}} \quad \dots\dots\dots\dots..(\textbf{5})$$

$$\textbf{F1} = \textbf{2} * \frac{\textbf{Precision} * \textbf{Recall}}{\textbf{Precision} + \textbf{Recall}} \quad \dots\dots.(\textbf{6})$$

$$\textbf{Accuracy} = \frac{\textbf{TP} + \textbf{TN}}{(\textbf{TP} + \textbf{TN} + \textbf{FP} + \textbf{FN})} \dots\dots..(7)$$

True Negatives (TN): Samples in the findings graded as true negatives if they do not adequately match the required class. True positives (TP) are samples correctly classified in binary classification as belonging to the target class.
False Negatives (FN): Data with samples incorrectly designated as not belonging to the required class. False positives (FP): data samples wrongly designated as belonging to the target class [21], [22].

IV. EXPERIMENTAL RESULTS

Data set; there are 35,887 images in the FER2013 dataset used to illustrate seven unique emotions [23]. Deep learning and machine learning are better equipped to handle nonlinear datasets [24]. The 70% of the data used for training, while 30% used for assessment. Various evaluation metrics, including accuracy, recall, precision, and F1 score used to assess the effectiveness of the proposed system. Figures (2), (3), and (4) depict the outcomes of the pre-processing stage:

Fig 2. Facial image after applying gray scale.

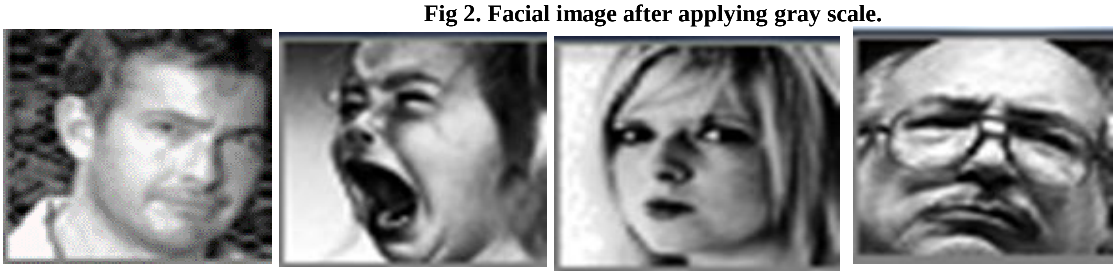

Fig 3. Facial image after applying histogram equalization.

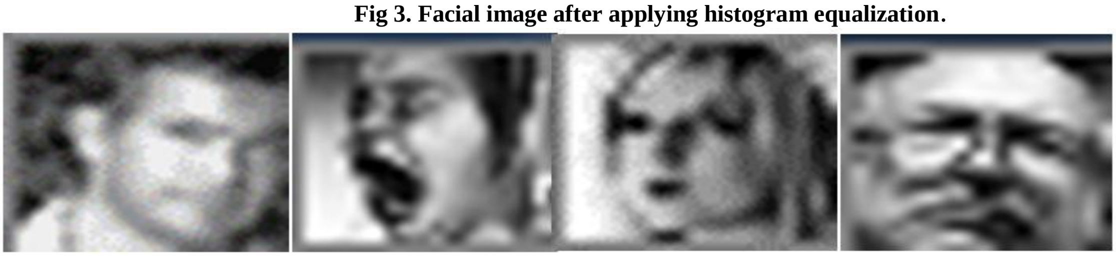

Fig 4. Facial image after applying Resize.

In order to simplify the processing, feature extraction is one of the steps that reduces a large dataset to a smaller one [25]. This operation extracts the most significant features. For the processing of these variables, a substantial computational system is required. Figure (5) depicts a sample of the feature table produced by the feature extraction stage using PCA and GLCM methods, yielding 400 PCA feature vectors and 6 fixed GLCM feature vectors.

a400	a401	a402	a403	a404	a405	a406
-3.97946	0.005925	1094.21	0.714771	0.024336	2.37135	106.111
14.10136	0.006627	386.252	0.723819	0.013644	2.3354	90.8553
-8.90146	0.006236	455.616	0.729012	0.033849	2.3496	164.195
10.67291	0.007819	534.079	0.725816	0.027562	2.32111	165.742
20.27233	0.006756	633.037	0.719947	0.017179	2.33242	81.9763
-15.2624	0.005897	942.713	0.71079	0.015975	2.3728	110.793
-4.47018	0.006229	415.319	0.724795	0.017481	2.36779	118.104
4.180977	0.006766	748.074	0.716083	0.019326	2.34456	126.155
6.768603	0.006676	601.14	0.712524	0.016246	2.35096	85.8697
1.669698	0.016375	969.835	0.726992	0.020739	2.20663	190.707
10.59955	0.006427	1342.42	0.712315	0.010825	2.35096	118.039

Fig 5. Examples of extracted features using PCA and GLCM

Following the completion of feature extraction, a 1D-table of feature vectors obtained and input into machine learning algorithms. The results of the study's three machine-learning algorithms tabulated and illustrated in table (1) and figure (6). Includes the Precision measure, the Recall measure, the F-measure, and the Accuracy measure.

Table (1) the outcomes produced by machine learning algorithms

Algorithm	Precision	Recall	f-measure	Accuracy
ADA	0.44	0.29	0.33	0.29
LR	0.46	0.35	0.37	0.3488
RF	0.61	0.45	0.49	0.45

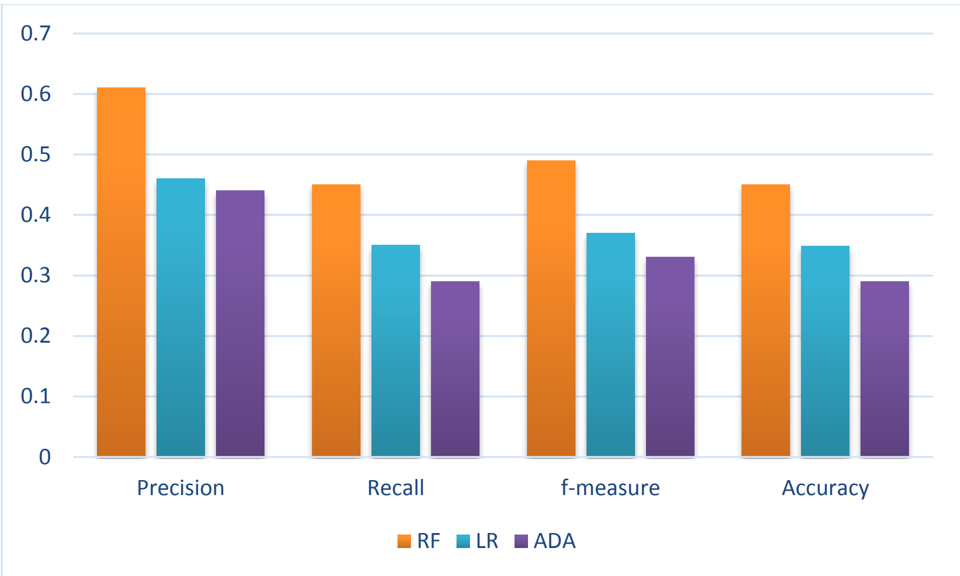

Fig 6. Performance Measures
The provided graph contrasts the precision, recall, f-measure, and accuracy of three algorithms (ADA, LR, and RF). RF has the highest precision, recall, and f-measure, whereas ADA has the lowest values for these metrics.

V. CONCLUSION

This study concludes that the combination of preprocessing techniques, feature extraction, and machine learning algorithms improves facial emotion recognition. Particularly, the use of logistic regression, random forest, and AdaBoost algorithms was effective in attaining high levels of accuracy and precision in emotion recognition. In addition, by converting images to a 1D matrix, the proposed method reduces the recognition process's computational complexity and processing time.

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