An Analytical Appraisal for Supervised Classifiers’ Performance on Facial Expression Recognition Based on Relief-F Feature Selection

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Abstract. Face expression recognition technology is one of the most recently developed fields in machine learning and has profoundly helped its users through forensic, security, and biometric applications. Many researchers and program developers have allocated their time and energy to figure out various techniques which would add to the technology’s functionality and accuracy. Face expression recognition is a complicated computational process in which is implemented via analyzing changes in facial traits that follow different emotional reactions. This paper endeavors to inspect accuracy ratio of six classifiers based on Relief-F feature selection method, relying on the utilization of the minimum quantity of attributes. The classifiers in which the paper attempts to inspect are Multi-Layer Perceptron, Random Forest, Decision Tree, Support Vector Machine, K-Nearest Neighbor, and Radial Basis Function. The experiment illustrates that K-Nearest Neighbor is the most accurate classifier with the total accuracy ratio of 94.93% amongst the rest when applied on CK+ Dataset.

1. Introduction
As a promising field in data science and computer vision, Facial Expression Recognition has achieved special attention universally during the last decade [1]. It has instantly being applied in many professional arenas such as education, social marketing, and health-care systems [2]. Several methods are being suggested to carry out face expression recognition tasks from both cluster and single images [3]. As far as it is concerned with EFR in applied and educational systems, during the last decade, various researches are implemented. These educational travails are being implemented in the fields of facial expression classification, feature extraction, and face tracing and detection [4].

Peng and Yin [5] suggested a facial expression recognition approach via the combination of the photorealistic expression manifolds in order to expand the exhibition set. More inside subject could be acquired through blending neutral faces. Eigen transformation has been used for producing the details of expression and form for new subjects. Face Recognition and the classification of the extracted instances functioned on the expanded training dataset. The approach applied MMI, MUG, JAFFE,
Sporous, AR, and CK+. The approach managed to achieve the total accuracy rate of 90% of face expression recognition. Munir et al. [6] suggests a new methodology in which combines Contrast Limited Adaptive Histogram Equalization with Fast Fourier Transform to make up the weak illumination factor. After that for each pixel a merged code for binary pattern is issued. For each neighborhood two bits are generated in order to make a sixteen-bit code for each pixel. This operation would capture the changes along the edges and iconic facial traits in front head, cheeks, lips, chin, and face wrinkles. The outcomes of the suggested approach are compared with various LGC and LBP methods for both zoned and holistic images. The experiment, applying SFEW dataset, illustrates that the MBPC outshines other methods in term of accuracy with the total percentage of 67.2% and 96.5% respectively for division-based and holistic approaches.

Applying Cascade Regression Tree for feature extraction, Bilkhu et al. [7] introduced a novel Facial Expression Recognition approach to detect the 6 major facial emotions. The method applies three classifiers including Logistic Regression (LR), Support Vector Machine (SVM), and Neural Network (NN). The study continued with a detailed comparison of the applied classifiers in terms of accuracy ratio via implementing the CK+ dataset. The research's study concludes with 89 percent of accuracy for SVM as the most accurate classifier in this regard. Respectively, 80 percent of accuracy rate for Neural Network, and the total ratio of 77.06 percent of accuracy rate for Logistic Regression are achieved. Li, D., et al. [8] suggested a new ensemble pruning method depending on clustering and ordering (RTCRelief-F) based on three datasets, including CK+, FER2013, and JAFFE. The system applies a new pairwise scale in the process of feature selection. The experiment on the three datasets illustrates that the proposed method enhances the quality and performance of facial expression recognition. Pk, A.M.N., X. Ding, and T. Page [9] proposed an approach for feature extraction called Histogram Oriented Gradients. The method applies Multi-Layer Support Vector Machine for facial recognition. The system is designed a one-to-one process to achieve multi-classification. YALE ORL, and a self-created dataset are utilized to carry out the experiment. The study demonstrates that the face recognition accuracy rates for these datasets are above 96%.

This paper provides an effective method to feature selection and classification for Facial Expression Recognition from sequence facial images. To achieve this goal, six classifiers are being applied and their performances are compared to distinguish the most accurate one.

Facial Expression Recognition fundamentally goes through 3 basic steps that are face-detection, feature-extraction, and classification, consequently [10]. Feature selection could be summarized as the procedure of selecting the most relevant attributes in order to illustrate the training data instances [11] that the computational recitals and the classification aptitude are manipulated by [12]. It is important to note that through the training and testing operation, what makes the process kind of time-consuming is processing of the unwanted features big amount. Depended approach of feature assortment which fair enough towards different configurations partition consuming residence through different classes fail. Hence progressively composite distribution methods [13]. This research attempts to offer a method in which feature selection is implemented as a Relief F approach that scores the attributes based on their values that make them significant within the process. The first 6 attributes are elicited after the process of try and test to produce the most accurate characteristic features of facial images. The elicited attributes are applied for training and testing the classifiers: KNN [14], J48 [15], RBF [16], SVM [17], MLP, and RF classifiers.

2. Dataset

Approving the suggested approach, it implements CK+ dataset that consist of 593 image sequences of 123 adults [18]. The images include the 8 basic emotional traits that are normal, surprised, sad, scared, happy, disgusted, angry, contempt, and scared [19]. From the ultimate participants whose facial expressions are being archived in the dataset, 31% are males and 69% are females and of 18-50 years old [20]. When 13% of the participated models are Americans of African race, 81% are of European-American ethnicity, and the rest 6% are from other racial ethnicities. In the appointed dataset, 20 models express two facial emotional indicators, 28 share five facial expression indicators, 8 people share three
indicators, 26 share four facial emotional features, and the remaining 22 individuals share all the indicators in projecting their emotional stance. The captured images are implemented in various light instances with 640x490 or 640x480 of resolution. This study has implemented 4090 models from the dataset arbitrarily to experiment and validate the suggested approach. Samples from the dataset are demonstrated in Figure 1[21]. Table 1 illustrates the randomly selected number of the samples adopted for each expression from the CK+ dataset.

![Sample expressions from CK+ dataset](image)

Table 1. The number of random selected expression on instances from CK+ dataset.

| No. | Expressions | No. of Instances |
|-----|-------------|------------------|
| 1   | Angry       | 527              |
| 2   | Contempt    | 47               |
| 3   | Disgust     | 389              |
| 4   | Fear        | 458              |
| 5   | Happy       | 614              |
| 6   | Normal      | 913              |
| 7   | Sad         | 540              |

3. Methodology
The paper suggests a method to recognize the expression of human faces with the face’s eight emotional expressions. The procedure of this approach goes through four fundamental stages, which are (Data Processing, Face Detection, Feature Selection and Classification), as demonstrated in Figure 2.

![Block diagram for main steps](image)
3.1. Data processing
FER process triggers with the calibration of the images which are noisy. It exceeds with the elimination of the noisy sections, resizing, besides input images modification. Images-set that are espoused from CK+ dataset been modified to black and white then nourished to Viola-Jones classifier for facial expression detection.

3.2. Face detection
Viola-Jones approach [23] considered as one of greatest fruitful face detection approaches and is widely used for face detection purposes due to its robustness in face detection rate and being outstandingly accurate among other techniques [24]. Add to this, it is a real time detection tool [25]. This method consists of the following steps: Haar feature selection, integral image creation, and Adaboost training and cascading classifiers. The detected faces from Viola-Jones picked then resized to 28x28. Seven hundreds eighty four attributes nourished in Relief-F feature selection method for features ranking based on their positional importance. Then, the most distinctively high ranked features will be elicited from the rest in order to be used in six classifiers to distinguish the most accurate one.

3.3. Feature selection
Relief-F is considered as a supervised feature selection method [26]. Each feature’s weight is calculated based on its relevance to other features. The weight of a learning feature is estimated depending on the probability that is assumed as the nearest hits and misses [27]. Since this algorithm relies on the feedback received from the nearest neighbor classifier, it is considered as one of the most accurate feature selection methods [28]. Applying convex optimization puts the algorithm in an efficient position in weighting features to solve problems. Despite of all the advantages this algorithm possesses, acquisition of the samples in a random manner and high frequency of sampling places this algorithm in a vulnerable position. Such defects can reduce accuracy to some extent [29].

\[ W_i = W_i - (x_i - \text{nearHit}_i)^2 + (x_i - \text{nearMiss}_i)^2 \]

The nearest x sample chosen by the Euclidian distance in each class depends on the weight vector \( (W_i) \). The nearMiss is the difference in class instance and the nearHit resembles the closest sample [14]. Relief-F feature selection method is implemented on CK+ dataset and the highest ranks six features for each facial expression are being selected as illustrated in Table 2.

**Table 2.** The highest ranked six feature from Relief-F feature selection for each expression

| Feature Numbers | Anger | Contempt | Disgust | Fear | Happy | Normal | Sad | Surprise |
|-----------------|-------|----------|---------|------|-------|--------|-----|----------|
| 1               | 93    | 64       | 121     | 120  | 526   | 543    | 93  | 571      |
| 2               | 94    | 65       | 149     | 568  | 539   | 570    | 104 | 572      |
| 3               | 103   | 431      | 150     | 569  | 540   | 571    | 121 | 577      |
| 4               | 104   | 436      | 151     | 580  | 541   | 572    | 132 | 579      |
| 5               | 121   | 564      | 159     | 581  | 553   | 573    | 133 | 599      |
| 6               | 131   | 784      | 160     | 757  | 554   | 574    | 404 | 600      |

3.4. Classification
In order carry out facial expression recognition from the face images, six classification methods are utilized to compare the classifiers performance. To achieve higher performance, the minimum number of the features are used. The highest six ranked features from Relief-F are selected. Ten-fold-cross authentication approach is utilized for the purpose of training and testing. The supervised methods are briefly explained.

3.4.1. Decision Tree (J48)
J48 is a more developed offshoot of C4.5 to deal with continuous data [30]. The method utilizing the training data, initially builds a tree via a training stage. An instance from the testing data is tested on the built tree in order to identify its class [31]. Due to the shape and form of the technique as a tree, it tends to be one of the most accurate and time-efficient classifiers. The anxious subdivision considered as emblem for closure conceivable feature standards through without uncertainty [32]. Actuality broadly applied through several scholars, Decision Tree is believed to be as one of the simplest classifiers to get benefit from. It is designed and created with data entropy foundation [33]. This one works with manner individually data could feature applied via separating them into minor elements including wanted nodes. Individually tree contains 3 nodes-kinds consisting of the root node, internal node, and the leaves. The classifier ensures satisfactory conditions through all the edges of the tree.

3.4.2. K-Nearest Neighbor (KNN)

KNN is one of the most applied classifiers which its performance is based on the concept of distance measure [34]. Euclidian distance is used to determine the nearest K neighbor instance from the training samples [35]. K is usually a positive integer number of neighbors [36]. The production is class-labeled. Instantly the classification done via major election to a neighboring one via feature presence located toward class neighboring of K adjacent neighbors. As an example, doubt a tested sample closer to a specific class, based on its distance, then the feature will be classified to that class [37]. The following equation is used to calculate the Euclidian distance.

\[ d(x, y) = \sqrt{\sum_{i=1}^{m} (x_i - y_i)^2} \]

3.4.3. Radial Basis Function (RBF)

RBF system considered as best linkage on behalf of I/O planning purpose as feed-forward organization [38], as quick meeting rapidity besides great precision [39]. RBF tends to be kind of artificial neural network [40]. This approach is utilized for multi-classification issues consist of three-layer classifiers [41]. RBF’s consist of a two-layer neural network, while individual buried part functions rounded motivated task. Output elements adopt biased amount hidden element outputs. However, production in RBF grid scheme considered undeviating, and input nonlinear [42].

3.4.4. Support Vector Machine (SVM)

It is clear that SVM simplest and supreme functional classifiers that is used to carry out machine learning problems [43] like: pattern recognition plus computer visualization [44] typically anxious through handling gigantic amounts of information [30]. Extensively accepted procedure via various investigators. SVM objects to build the optimal hyper planes named boundary to maximize distance commencing adjacent keeping fit set information sample for hyper plane [45].

3.4.5. Multi-Layer Perceptron (MLP)

Agreeing MLP, neurons should agree to one-track-guiding style. Data broadcasting via this process participating in three layers. Data process initiates from the first layer (input layer) which depends on the number of the selected features. The classified output balance depends on the second layer (hidden layer) [46]. The number of the classes are equal to the number of the output nodes [47]. Classification stands for the duty of assigning an attribute vector or a set of attributes in the dataset applied for facial expression recognition. Connection amongst layers should labelled thru several heaviness. In MLP, nodes be able to function 2 jobs: instigation and aggregation. Prejudice result, heaviness, besides inputs accumulated implementing accumulation job in Equation (3).

\[ S_j = \sum_{i=1}^{n} w_{ij} l_i + \beta_j \]

Where: n is I/P quantity, li I/P variable i, βj bias span, wij considers linking heaviness. Instigation job should observed exploiting Eq. (3) O/P. Different types of initiation roles might be useful with MLP procedure, as illustrated in Equation (4) [48].
\[ f_j(x) = \frac{1}{1+e^{-x_j}} \]

3.4.6. Random Forest (RF)
This method creates a forest via merging multiple decision trees to achieve high classification rate [49]. The ultimate purpose behind utilization of this supervised classifier machine is to prevent mere dependence upon only one learning model [50]. The important distinction between this inventive technique and the normal decision tree classifier is that the root nodes feature divided nodes connected superfluously [51].

4. Performance evaluation and results
In order appraise the accuracy of each classifier, which are utilized confusion matrix. The experimental outcome illustrates that when the applying 6 attributes from Relief-F method, KNN archives the optimum recognition ratio with 94.93%, while RF’s accuracy ratio is 93.95%. Meanwhile, J48 gets 92.27% of recognition ratio, MLP gets 89.89% of recognition ratio, RBF gets 89.65% of recognition ratio, and SVM provides us with the lowest recognition ratio as 89.43%, as shown in Table 3, 4, 5, 6, 7, and 8.

**Table 3.** System Assessment using J48 Classifier and Relief-F Feature Selection

| Expressions | TP Rate | FP Rate | Precision | Recall | F-Measure | Accuracy |
|-------------|---------|---------|-----------|--------|-----------|----------|
| Anger       | 0.97    | 0.33    | 1.00      | 0.97   | 0.96      | 93.35    |
| Contempt    | 1.00    | 0.75    | 1.00      | 1.00   | 1.00      | 99.14    |
| Disgust     | 0.98    | 0.47    | 1.00      | 0.98   | 0.97      | 93.72    |
| Fear        | 0.98    | 0.53    | 1.00      | 0.98   | 0.96      | 92.18    |
| Happy       | 0.97    | 0.19    | 1.00      | 0.97   | 0.97      | 94.67    |
| Normal      | 0.94    | 0.68    | 1.00      | 0.94   | 0.88      | 80.42    |
| Sad         | 0.96    | 0.55    | 1.00      | 0.96   | 0.94      | 89.61    |
| Surprise    | 0.98    | 0.23    | 1.00      | 0.98   | 0.97      | 95.06    |
| **Avg. Rate** | **0.97** | **0.47** | **1.00** | **0.97** | **0.96** | **92.27** |

**Table 4.** System Assessment using KNN and Relief-F

| Expressions | TP Rate | FP Rate | Precision | Recall | F-Measure | Accuracy |
|-------------|---------|---------|-----------|--------|-----------|----------|
| Anger       | 0.99    | 0.12    | 0.98      | 0.99   | 0.99      | 97.58    |
| Contempt    | 1.00    | 0.75    | 0.99      | 1.00   | 1.00      | 99.14    |
| Disgust     | 1.00    | 0.31    | 0.97      | 1.00   | 0.98      | 96.77    |
| Fear        | 0.99    | 0.46    | 0.95      | 0.99   | 0.97      | 94.25    |
| Happy       | 0.77    | 0.01    | 0.96      | 0.77   | 0.85      | 96.04    |
| Normal      | 0.96    | 0.47    | 0.88      | 0.96   | 0.91      | 85.92    |
| Sad         | 0.98    | 0.26    | 0.96      | 0.98   | 0.97      | 94.96    |
| Surprise    | 1.00    | 0.33    | 0.95      | 1.00   | 0.97      | 94.74    |
| **Avg. Rate** | **0.96** | **0.34** | **0.95** | **0.96** | **0.96** | **94.93** |

**Table 5.** System Assessment using RBF and Relief-F
### Table 6. System Assessment using SVM and Relief-F

| Expressions | TP Rate | FP Rate | Precision | Recall | F-Measure | Accuracy |
|-------------|---------|---------|-----------|--------|-----------|----------|
| Anger       | 0.98    | 0.83    | 0.89      | 0.98   | 0.93      | 87.75    |
| Contempt    | 1.00    | 0.75    | 0.99      | 1.00   | 1.00      | 99.14    |
| Disgust     | 0.98    | 0.77    | 0.92      | 0.98   | 0.95      | 91.10    |
| Fear        | 1.00    | 1.00    | 0.89      | 1.00   | 0.94      | 88.80    |
| Happy       | 0.96    | 0.38    | 0.93      | 0.96   | 0.95      | 91.20    |
| Normal      | 0.95    | 0.74    | 0.82      | 0.95   | 0.88      | 79.24    |
| Sad         | 1.00    | 0.97    | 0.87      | 1.00   | 0.93      | 87.04    |
| Surprise    | 0.99    | 0.40    | 0.94      | 0.99   | 0.96      | 92.91    |
| **Avg. Rate** | **0.98** | **0.73** | **0.91** | **0.98** | **0.94** | **89.65** |

### Table 7. System Assessment using MLP and Relief-F

| Expressions | TP Rate | FP Rate | Precision | Recall | F-Measure | Accuracy |
|-------------|---------|---------|-----------|--------|-----------|----------|
| Anger       | 1.00    | 1.00    | 0.871     | 1.00   | 0.93      | 87.12    |
| Contempt    | 1.00    | 0.79    | 0.991     | 1.00   | 1.00      | 99.71    |
| Disgust     | 1.00    | 1.00    | 0.905     | 1.00   | 0.95      | 90.49    |
| Fear        | 1.00    | 1.00    | 0.888     | 1.00   | 0.94      | 88.80    |
| Happy       | 0.97    | 0.38    | 0.935     | 0.98   | 0.95      | 91.96    |
| Normal      | 1.00    | 1.00    | 0.777     | 1.00   | 0.87      | 77.68    |
| Sad         | 1.00    | 1.00    | 0.868     | 1.00   | 0.93      | 86.80    |
| Surprise    | 0.99    | 0.40    | 0.935     | 0.99   | 0.96      | 92.91    |
| **Avg. Rate** | **0.99** | **0.82** | **0.90** | **1.00** | **0.94** | **89.43** |

### Table 8. System Assessment using RF and Relief-F

| Expressions | TP Rate | FP Rate | Precision | Recall | F-Measure | Accuracy |
|-------------|---------|---------|-----------|--------|-----------|----------|
| Anger       | 0.96    | 0.59    | 0.92      | 0.96   | 0.94      | 89.10    |
| Contempt    | 1.00    | 0.75    | 0.99      | 1.00   | 1.00      | 99.14    |
| Disgust     | 0.98    | 0.60    | 0.94      | 0.98   | 0.96      | 92.81    |
| Fear        | 0.99    | 0.69    | 0.92      | 0.99   | 0.95      | 90.98    |
| Happy       | 0.97    | 0.25    | 0.96      | 0.97   | 0.96      | 93.40    |
| Normal      | 0.86    | 0.66    | 0.82      | 0.86   | 0.84      | 74.40    |
| Sad         | 0.98    | 0.92    | 0.88      | 0.98   | 0.93      | 86.36    |
| Surprise    | 0.99    | 0.40    | 0.94      | 0.99   | 0.96      | 92.91    |
| **Avg. Rate** | **0.97** | **0.61** | **0.92** | **0.97** | **0.94** | **89.89** |
Table 1. Highest and Lowest Performance Accuracy ratio for each Expression.

| Expressions | TP Rate | FP Rate | Precision | Recall | F-Measure | Accuracy |
|-------------|---------|---------|-----------|--------|-----------|----------|
| Anger       | 0.98    | 0.18    | 1.00      | 0.98   | 0.98      | 96.19    |
| Contempt    | 1.00    | 0.51    | 1.00      | 1.00   | 1.00      | 99.22    |
| Disgust     | 0.99    | 0.40    | 1.00      | 0.99   | 0.98      | 95.57    |
| Fear        | 0.99    | 0.47    | 1.00      | 0.99   | 0.97      | 93.91    |
| Happy       | 0.99    | 0.16    | 1.00      | 0.99   | 0.98      | 96.43    |
| Normal      | 0.95    | 0.49    | 1.00      | 0.95   | 0.91      | 84.89    |
| Sad         | 0.99    | 0.50    | 1.00      | 0.99   | 0.96      | 92.47    |
| Surprise    | 0.99    | 0.40    | 1.00      | 0.99   | 0.96      | 92.91    |
| Avg. Rate   | 0.98    | 0.39    | 1.00      | 0.98   | 0.97      | 93.95    |

Figure 3. Highest and Lowest Performance Accuracy ratio for each Expression.

Based on previous demonstrations, when utilizing the classifiers on the attributes selected from the Relief-F feature selection approach, the expression result sequentially starts with Anger as the highest accuracy ratio 97.58% by KNN, and the lowest accuracy ratio by RBF of 87.75%. Contempt with the highest accuracy ratio 99.71% by SVM, and the lowest accuracy ratio by J48, KNN, RBF and MLP 99.14%. Disgust with the highest accuracy ratio 96.77% by KNN, and the lowest accuracy ratio by SVM 90.49%. Fear with the highest accuracy ratio 94.25% by KNN, and the lowest accuracy ratio by RBF and SVM 88.8%. Happy with the highest accuracy ratio 96.43% by RF, and the lowest accuracy ratio by RBF 91.20%. Normal with the highest accuracy ratio 85.92% by KNN, and the lowest accuracy ratio by MLP 74.40%. Sad with the highest accuracy ratio 94.96% by KNN, and the lowest accuracy ratio by...
MLP 86.36%. Surprise with the highest accuracy ratio 95.06% by J48, and the lowest accuracy ratio by RBF, SVM, MLP and RF 92.91% as shown in Figure 3.

**Table 9. Comparison of Related Works**

| Reference | Dataset | Emotion No. | Feature No. | Feature Selection | Classifier | Result |
|-----------|---------|-------------|-------------|-------------------|------------|--------|
| [5]       | CK+, AR, Bosphons, JAFFE, MUG, MMI | 7 | AU 29 | Correlation Coefficient and Normalized Distance | EMS | MMD & MDA, PCA 90% |
| [6]       | SFEW | 7 | 40, 60, 80, 100, 120 | MSBC | Holistic division | SVM, Logistic Regression, NN | SVM 89% Logistic Regression 80% NN 77.06% |
| [7]       | CK+ | 5 | 68 | FER | | |
| [8]       | Fer2013 JAFFE CK+ | 7 | 28,9, Pyleam2 (16,32,48,6, 4,80,96) 510 -Keras (32,64,128, 256) | CNN | RTCRelief-F | Fer2013 73.36% JAFFE 50.23% CK+ 78.13% |
| [9]       | ORL YALE Self-created database | 6 | - | HOG | Multi-Class SVM | ORL 96.5% YALE 96.67% Self 96.92% |
| This work | CK+ | 8 | 6 | Relief-F | J48, KNN, RBF, SVM, MLP, RF | 48 92.27% KNN 94.93% RBF 89.65% SVM 89.43% MLP 89.88% RF 93.95% |

Table 9 shows the comparison summary of the related works. From this table, it is clear that the researchers in the related papers used various methods of feature selection and classification and different datasets with different numbers of facial expressions. Compared to the related works, the provided method acquires a good recognition rate with fewer attributes and more recognized facial expressions. However, researcher in [5] obtained (90%) by using different datasets, feature selection methods and classifiers. Researcher in [6] obtained a good recognition rate ranged (96.5%-67.2%) but using various number of attributes (40, 60, 80, 100, 120) respectively with several classifiers. Also, researcher in [7] could gain a high accuracy (89%) from SVM, (80%) from regression, and (77.06%) from NN classifiers using large number of features (68) but with the ability to recognize fewer expressions from CK+ dataset. Researcher [8] uses several datasets with different feature selection methods to reach (73.36%) for Fer2013 dataset, (50.23%) for JAFFE and (78.13%) for CK+. Researcher in [9] has managed to gain high accuracy (96.5%) for ORL dataset, (96.67%) for YALE and (96.92%) for self-created dataset, using HOG feature selection. This work uses fewest features with several classifiers to reach (94.93%) of accuracy via KNN.
5. Conclusion

During the last decade, Relief-F feature selection has been used by many researchers. This method ranks the features in sequential order depending on their variance values. The highest ranked detected was six features of Relief-F presence used with the 6 classifiers. Investigational results show that greatest precise classifier is KNN with 94.93% of accuracy ratio in facial expression recognition according to CK+ dataset. Meanwhile, RF could be considered as the nearest classifier to KNN with the accuracy ratio of 93.95%. J48 with the accuracy ratio of 92.27% is in the middle among the other classifiers. The last three classifiers respectively are MLP, RBF, and SVM with the accuracy ratios of 89.89%, 89.65%, and 89.43%.

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