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Classification techniques' performance evaluation for facial expression recognition

Mayyadah R. Mahmood[1], Maiwan B. Abdulrazzaq[2], Subhi R. M. Zeebaree[3], Abbas Kh. Ibrahim[4], Rizgar R. Zebari[5], Hivi Ismat Dino[6]
[1,2,4,6]Computer Science Department, Faculty of Science, University of Zakho, Duhok, Iraq
[3]Department Duhok Polytechnic University Presidency, Duhok Polytechnic University, Duhok, Iraq
[5]Information Technology Department, Duhok Polytechnic University, Duhok, Iraq

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ABSTRACT

Facial expression recognition as a recently developed method in computer vision is founded upon the idea of analazing the facial changes in which are witnessed due to emotional impacts on an individual. This paper provides a performance evaluation of a set of supervised classifiers used for facial expression recognition based on minimum features selected by chi-square. These features are the most iconic and influential ones that have tangible value for result dermination. The highest ranked six features are applied on six classifiers including multi-layer preceptron, support vector machine, decision tree, random forest, radial baised function, and K-Nearest neioughbor to figure out the most accurate one when the minum number of features are utilized. This is done via analyzing and appraising the classifiers' performance. CK+ is used as the research's dataset. random forest with the total accuracy ratio of 94.23 % is illustrated as the most accurate classifier amongst the rest.

Corresponding Author:

Rizgar R. Zebari
Information Technology Department
Duhok Polytechnic University
61 zakho Road, 1006 Mazi Qr Duhok, Kurdistan-Iraq
Email: rizgar.ramadhan@dpu.edu.krd

1. INTRODUCTION

As a form of pattern recognition and machine learning, Facial Expression Recognition is being eye-catchingly developed and has played an important role in the facilitation of forensic prosidures through face recognition and lie detection. Simultanously, the development of the field has had prominent positive impacts on various medical fields. With the emergence of the complicated visionary hardwares such as high definition cameras, the field started a new practical phase through out its flourishment since it was previously discussed merely in academic arena [1, 2]. Dealing with FER, different methods are being suggested from both sequencial and static images [3]. Dealing with FER in terms of applied fields and accademia, different projects are being implemented. These educational endeavors are being implemented in fields of face detection and tracing, expression classification, and feature extraction [4, 5].

Sudha et al. [6], offered an emotion detection program that evaluated a mobile phone user's facial expression. The framework was applied for operating region selection and face-registration for compact facial Action Unit representation. Action Unit classification and intelligent mapping of the predicted AUs to detect emotional traits. The system utilized databases such as Mind Reading, Multi Pie, JAFFE, FACS, ISL, and CK+. Kumbhar and Patil [7] illustrated that the application of the explicit facial parts provides more accuracy than the holistic approaches. The researchers applied HOG to obtain features from the facial platform points instead of considering the whole face for constructing a vigorous system. The authors elaborated Gabor filter for feature extraction combined with feed forward neural networks for to recognize 7 emmotional expressions from human captured images. The research illustrated 60% to 70% rate of facial recognition accuracy rate for the whole JAFEE database.

Singh and Nasoz [8] demonstrated an original method to enhance future accuracy concerning the process f face recognition via reprocessing. It embeds two major steps of face detection and correction of the illumination. In order to extract the most important facial expression features, feature extraction is applied. The reaserchers, in 2013, managed to achieve 61.7% of accuracy ratio for Face Expression Recognition in 7 classes via Convulational Neural Network classification comparing to 75.2 % of accuracy gained by State-of-Art classifier. Zhong et al. [9] suggested a novel Face Expression Recognition based on subspace learning on local structure. Both methods managed to achieve higher accuracy rate from the other traditional approaches when applied on CAS-PEARL-R1 and AR databades.

Bilkhu et al. [10] suggested a new method of Face Expression Recognition in order to recognize six emotional features. Using three classifiers, Cascade Regression Tree is used for the purpose of feature extraction in this method. The system applies Logistic Regression, Support Vector Machine, and Neural Network classifiers. Comparison of the applied classifiers, when utilized CK+, illustrates SVM as the most accurate classifier with total accuracy ratio of 89%. Neural Network comes to the second rank with 80% of accuracy, and 77.06 percent of accuracy is achieved for Logistic Regression.

The current research suggests an influential method of classification and feature selection 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. Three fundamental stages of classification, face extraction, and feature extraction are suggested through Face Expression Recognition [11, 12]. As a coral phase, feature selection is done to elecit the most important features that would have the most significance impact value [13] in which factors such as computational performance and the classification competence are manipulated by [14, 15]. Naturally, the information that is associated with the selected features are fair enough for an accurate determination of the input class. In other words, selecting the highest ranked features and elimination of the unnecessary features would make the whole process less time-consuming and easier through the training and testing stage. Feature selection methods that apply modest division of patterns, having a position with different classes, fail in classification tasks with repeated edges and complicated distribution techniques [16]. The suggested approach applies Chi-Square to select the lest number of features that have most significant values. After carrying out the process of try and test, the strategy choses the first 6 features that could be considered as the most important attributes of the pictures that are captured fro the individuals faces. The chosen attributes are utilized to classify the facial emotional states [17] via Random Forest, Multi-Layer Preceptron, Support Vector Machine [18], Dadial Base Function [19], K-Nearest Neighbor [20], and Decision Tree [21] classifiers.

2. DATASET

CK+ dataset is one of the most applied banks of information that is widely used universally that embraces 593 image clusters of 123 individuals who are mostly adult and mature [22]. Eight basic facial expression of angry, disgusted, happy, surprised, sad scared contemp and normal are recorded in the images [23]. From all the pictures that are included in the dataset, 31% are of male gender between 18 to 50 years old and 69% are females from the same age range [24]. As far as it is concerened with the ethnical diversity of the dataset, 81%, 13%, and 6% are respectively for Euro-American, Afro-American and and other racial backgrounds. In the respected dataset, 20 people project 2 expressions, 26 reflect 4 facial expressions, 22 have all the facial expressions, 8 individuals show 3 expressions, and finally 28 people demonstrate 5 emotional reflections. In CK+ dataset, different illumination is being applied and the pictures' resolution is 640 x 490. The current study has adopted 4090 instances from CK+. Some instances adopted by the research are being illustrated in Figure 1 [25]. Table 1 demonstrates a number of samples that illustrate each facial expression in CK+ dataset.

3. METHODOLOGY

The current experiment attempts to provide its readers with a facial expression recognition method in order to recognize the main 8 emotional projections. To meet the study goals, the research is carried out through four main phases that are Data Processing, Face detection, Feature Selection, and Classofication, as illustrated in Figure 2.

Figure 1. Sample of expressions from CK+ dataset [26]

Table 1. The number of random selected exprission 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
8	Surprised	602

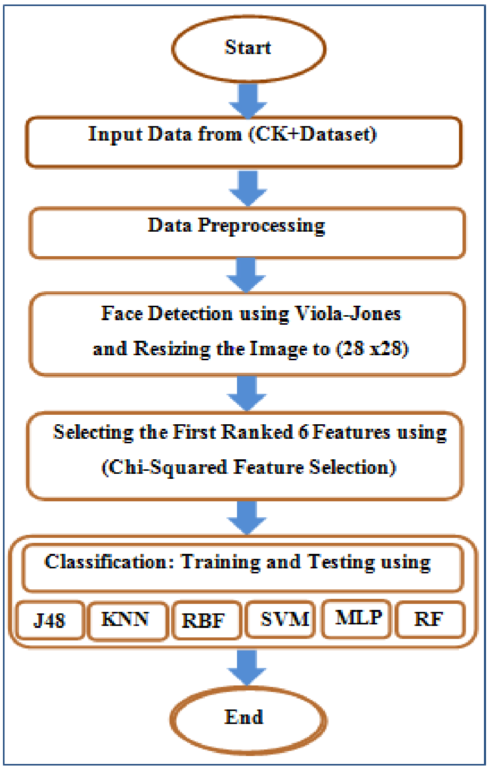

Figure 2. Block diagram for main steps that applied in classification system

3.1. Data processing

Facial Expression Recognition triggers with the standardizing of the images, meaning that the would-be processed pictures have to get cleaned of any unwanted noise that would reduce the work's accuracy. Generally, in data processing phase the images are cleared from the noises, resized into ideal sizes, and if nesasary onverted into easily processable data. The chosen images from the dataset are changed into black and white and fed into Viola-Jones to detect the 8 emotional traits.

3.2. Face detection

As a widely applied method, Viola-Jones [27] is considered as one of the most vigorous face-detection approaches because of its exceptional accuracy and robustness [28]. Add to that, it is especially applied for real time detection [29]. This method goes through four sequential steps of selection of Haar features which are extracted through complex computation to integral image creation, Adaboost are used to distinguish the face features from the rest, and cascading the sub windows that contain face image. When the face is recognized, the images are cropped resized to 28 x 28. Then, the 784 attributes are fed to Chi-square feature selection method to rank the features. Then, the most distinctively high ranked attributes will be elicited from the rest in order to be used in six classifiers to distinguish the most accurate one.

3.3. Feature selection

Chi-Square test is useful in machine learning. This method scoring the features, prioritize the features based on their diversity in the whole dataset. The Chi-Square test is illustrated in (1):

$$x^2(t,c) = \frac{N(AD-CB)^2}{(A+C)(B+D)(A+B)(C+D)} \tag{1}$$

When A represents a document frequency that includes the variavle t and belongs to the category c, the B could be the document frequency that consist the variable t and doen't belong to the category c. Then, C shows the repeatition of the document which does not include t and belongs to subset c. Therfore, D represents the number of the documents that do not belong to t and does not include class c. Meanwhile, N presents the quantity of the documents in the mass [30]. The method applies Chi-Square feature selection approach on CK+ and the first six outranked features are selected as shown in Table 2.

Table 2. Chi-Square feature selection

Feature Numbers	Anger	Contempt	Disgust	Fear	Happy	Normal	Sad	Surprise
1	95	378	150	595	499	545	37	605
2	96	431	151	596	510	550	38	627
3	101	436	160	609	511	551	39	628
4	102	546	177	610	512	570	433	633
5	103	565	178	623	526	571	437	634
6	130	592	179	637	527	572	601	655

3.4. Classification

The study applies and compares the six supervised learning machines via application of the six features achieved by Chi-Square approach. 10-fold-cross is iplimented through the process of training and testing. The applied six supervised machines are explained as:

3.4.1. Decision tree (J48)

J48 is a more developed and advanced pattern of C4.5 algorithm. Based on the growed tree from the trained dataset, a new sample will be classified from the tested dataset by Decision Tree. The time span in which is spent through training set determines the attribute that is accountable for classifying various samples in a shorter time. The concerned branch is a mark to ignore the possible feature significance with no ambiguity [31]. This classifier, due to its widely use and being constructed upon information entropy, is believed to be as the best classifiers among the six algorithms [32]. In this method each attribute of the data could be employed via dismanteling into smaller elements that include nodes of the tree root. Basically, each tree is formed from three nodes that construct the whole tree anatomy: leaves, internal node, and the root node. In this approach, a class label is determined by the leaf node since the root node has no incoming edges. J48 grantees satisfactory outcomes from all the edges of the constructed tree.

3.4.2. K-nearest neighbors (KNN)

K-Nearest Neighbour classifier is designed to function based on measuring the distance. It attempts to classify numeral data records after finding the K-Nearest neighbor via measuring the distance between the training samples and the test samples according to Euclidian [33]. In this approach, the output is class-labled and K is usually a positive and integer digit of its neighbors. A sample is classified according to the received votes received from the neighbors according to the nature and location of the attribute. In other words, if a tested sample shares particular attributes of a class, considering the distance of the sample to the class, then the sample will be classified to that category [34]. As shown in (2) demonstrates calculation of the Euclidian distance:

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

3.4.3. Radial base function (RBF)

Being an optimal network for input and output mapping operations in any feed forward network, Racial Base Function is highly accurate and fast convergant [35]. It is a type of artificial neural network that could be utilized for multi-classification cases that includes three-layer and non-linear classifiers. Radial Base Function consist a two-layered neural network which each part functions a circular activated operation. The output parts apply a weighted sum of hidden segment output. It is important to note that in Radial Base Function the output is linear and the input is non-linear [36].

3.4.4. Support vector machine (SVM)

This algorithm due to its strong compatibility to be utilized in machine learning cases of high quantity data such as computer vision and pattern recognition has taken a special attention from scholars [34]. Being highly utilized, this classifier attempts to build the optimal hyper plane-like margins. Support Vector Machine carries out the function of the maximization of the distance between the hyperplane and the closest training sata samples. Various researches have approved that in a linearly dividable instance, the optimal hyperplane would provide more accuracy with all sorts of datasets [37].

3.4.5. Multi layer perceptron (MLP)

In MLP approach neurons are arranged in one direction. In this classifier, transmission of data occurs through three layers. In input layer the number of the nodes have instant relation with the number of the features that are selected by the operator. The hiden layer that is responsible for making a balanced state in the accuracy of the output. In this method, node numbers and the number of the classes are even and the relationship between the layers are labelled by certain weights. Nodes in Multi-Layer Preceptron could carry out two major tasks that are summation and activation [38].

3.4.6. Random forest (RF)

Random Forest classifier is a supervised machine that functions through creation and merging various decision trees in the form of a forest. Utilization of this method enables the operators to get advantage of applying different learning models in order to advance accuracy to a new level. What makes this approach distictivly different from other learning machines is that in this method root nodes are linked in a redundant manner [39].

4. PERFORMANCE EVALUATION AND RESULTS

The average weight significance of TP ratio, Precision, Recall, FP ratio, and the processing time over second for each instance of each classifier in relation to the applied feature selection methods are illustrated in Tables 3 to 8, demonstrate the Chi-Square feature selection. This process's aims to carryout a comparative account of each classifier in order to point out the most accurate one. The research result points out that when adopting the six attributes from Chi-Square method, Random Forest achieves the highest rank among all the experimented classifiers with the total ratio of 94.23%. Meanwhile KNN achieves the total accuracy ratio of 94.18%. In the other hand, Random Forest gets the third rank in term of accuracy with the total ratio of 92.87 %. Furthermore, MLP, SVM, and RBF go to the next level with the respectively achieved ratios of 92.09%, 90.48%, and 90. 38% of accuracy ratio, as illustrated in Tables 4, 5, 6, 7, 8, and 9.

Table 3. Expressions accuracy for J48 classifier using Chi-Square

Expressions	TP Rate	FP Rate	Precision	Recall	F-Measure	Accuracy
Anger	0.97	0.42	0.94	0.99	0.95	91.93
Contempt	1.00	0.64	0.99	1.00	1.00	99.12
Disgust	0.99	0.51	0.95	0.99	0.97	93.94
Fear	0.99	0.62	0.93	0.99	0.96	92.47
Happy	0.99	0.17	0.97	0.99	0.98	96.26
Normal	0.95	0.58	0.85	0.95	0.90	83.01
Sad	0.98	0.62	0.91	0.98	0.95	90.02
Surprise	0.99	0.19	0.97	0.99	0.98	96.19
Avg. Rate	0.98	0.47	0.94	0.98	0.96	92.87

Table 4. Expressions accuracy for KNN classifier using Chi-Square

Expressions	TP Rate	FP Rate	Precision	Recall	F-Measure	Accuracy
Anger	0.99	0.35	0.95	0.99	0.97	94.48
Contempt	1.00	0.75	0.99	1.00	1.00	99.14
Disgust	1.00	0.37	0.96	1.00	0.98	96.14
Fear	1.00	0.66	0.92	1.00	0.96	92.54
Happy	0.99	0.26	0.96	0.99	0.97	95.58
Normal	0.96	0.41	0.88	0.96	0.93	87.95
Sad	0.99	0.66	0.91	0.99	0.95	90.69
Surprise	1.00	0.19	0.97	1.00	0.98	96.94
Avg. Rate	0.99	0.46	0.94	0.99	0.97	94.18

Table 5. Expressions accuracy for RBFclassifier using Chi-Square

Expressions	TP Rate	FP Rate	Precision	Recall	F-Measure	Accuracy
Anger	0.99	0.83	0.89	0.99	0.94	88.17
Contempt	1.00	0.77	0.99	1.00	1.00	99.12
Disgust	0.99	0.67	0.93	0.99	0.96	92.91
Fear	0.99	0.77	0.91	0.99	0.95	90.81
Happy	0.96	0.29	0.95	0.96	0.95	92.20
Normal	0.95	0.80	0.81	0.95	0.87	78.41
Sad	0.99	0.87	0.88	0.99	0.93	87.75
Surprise	1.00	0.41	0.93	1.00	0.96	93.67
Avg. Rate	0.98	0.68	0.91	0.98	0.95	90.38

Table 6. Expressions accuracy for SVM classifier using Chi-Square

Expressions	TP Rate	FP Rate	Precision	Recall	F-Measure	Accuracy
Anger	1.00	0.92	0.88	1.00	0.93	87.78
Contempt	1.00	0.75	0.99	1.00	1.00	99.10
Disgust	1.00	0.79	0.92	1.00	0.96	92.91
Fear	0.99	0.76	0.91	0.99	0.95	90.95
Happy	0.98	0.32	0.95	0.98	0.96	93.77
Normal	1.00	1.00	0.78	1.00	0.87	77.68
Sad	1.00	1.00	0.87	1.00	0.93	86.80
Surprise	0.99	0.25	0.96	0.99	0.97	95.43
Avg. Rate	1.00	0.72	0.91	1.00	0.95	90.48

Table 7. Expressions accuracy for MLP classifier using Chi-Square

Expressions	TP Rate	FP Rate	Precision	Recall	F-Measure	Accuracy
Anger	0.97	0.59	0.92	0.97	0.94	89.76
Contempt	1.00	0.75	0.99	1.00	1.00	99.14
Disgust	0.99	0.60	0.94	0.99	0.97	93.74
Fear	1.00	0.62	0.93	1.00	0.96	92.64
Happy	0.97	0.18	0.97	0.97	0.97	95.14
Normal	0.93	0.61	0.84	0.93	0.89	81.17
Sad	0.99	0.77	0.89	0.99	0.94	88.73
Surprise	0.99	0.20	0.97	0.99	0.96	96.41
Avg. Rate	0.98	0.54	0.93	0.98	0.96	92.09

Table 8. Expressions accuracy for RF classifier using Chi-Square

Expressions	TP Rate	FP Rate	Precision	Recall	F-Measure	Accuracy
Anger	0.97	0.27	0.92	0.97	0.97	94.11
Contempt	1.00	0.64	0.99	1.00	1.00	99.19
Disgust	0.99	0.43	0.96	0.99	0.98	95.43
Fear	0.99	0.58	0.93	0.99	0.96	92.79
Happy	0.99	0.14	0.98	0.99	0.98	97.07
Normal	0.96	0.43	0.89	0.96	0.92	87.24
Sad	0.97	0.52	0.93	0.97	0.95	90.91
Surprise	0.99	0.14	0.98	0.99	0.98	97.09
Avg. Rate	0.98	0.39	0.95	0.98	0.97	94.23

The ultimate result achieved for Chi-Square feature selection approach applied on eight types of emotional reflections on idividuals faces demonstrate that KNN is the most accurate classifier detecting anger with the total accuracy ratio of 94.48%, disgust gains the total ratio of 96.14%, and normal achieves 87.95% of accuracy in expression recognition. This is when contempt achieves 99.19% of accuracy ratio, fear gets 92.79%, happy gets 97.07%, sad achieves 90.91%, and surprised gains 97.09% of accuracy in expression detection utilizing Random Forest classifier. Hence, as far as it is concerned with facial expression recognition, Random Forest is the most accurate classifier for Chi-Square.

Based on the demonstrated outcomes, when utilizing the algorithms on the attributes demonstrated from the Chi-square feature selection approach, the expression outcome sequentially initiates with Anger with the highest accuracy rate 94.48% by KNN, and the lowest rate by SVM of 87.78%. Contempt with the highest accuracy rate 99.19% by RF, and the lowest rate by SVM 99.10%. Disgust with the highest accuracy rate 96.14% by KNN, and the lowest rate by SVM 92.35%. Fear with the highest accuracy rate 92.79% by RF, and the lowest rate by RBF 90.81%. Happy with the highest accuracy rate 97.07% by RF, and the lowest rate by RBF 92.20%. Normal with the highest accuracy rate 87.95% by KNN, and the lowest rate by SVM

77.68%. Sad with the highest accuracy rate 90.91% by RF and the lowest rate by SVM 86.80%. Surprise with the highest accuracy rate 97.09% by RF, and the lowest rate by RBF 93.67% as shown in Figure 3.

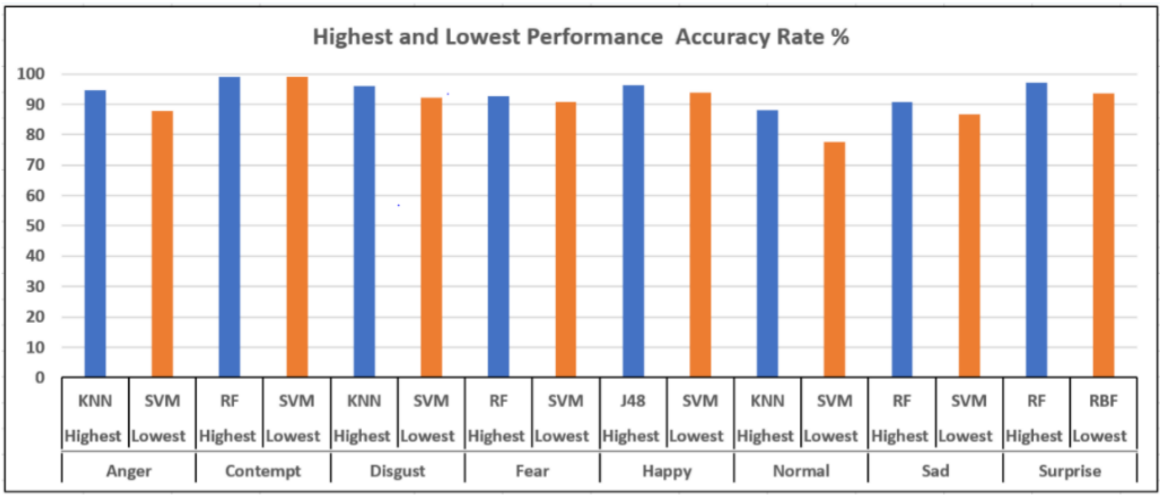

Figure 3. Expressions performance accuracy rate

5. COMPARISON WITH PREVIOUS WORKS

Table 9, shows the comparison summary between results obtain by our proposed system and those previous related works. From this table, it is clear that the scientists of previous closest-works depended many approaches of feature selection besides classification and various datasets with different directions of facial expressions. Compared to the related works, the provided approach obtains a good recognition rate with fewer features and more recognized facial expressions. However, researchers in [4-6] obtained a good recognition rate ranged (60%-70%) but using different number of features (17, 20, 8) respectively with different classifiers. Also, researchers in [7, 8] could gain a high accuracy using large number of features but with the ability to recognize fewer expressions from different dataset. This work uses fewest features with six classifiers to reach excellent accuracy.

Table 9. Comparison between this work with the others

Reference	Dataset	Emotion No.	Feature No.	Feature Selection	Classifier	Result
[4]	CK+, ISL FACS, JAFFE, Mind Reading	6	17	Spin Support LGBP, Geometric Features, Texture Features	Adaboost, SVM	Valstar 67.5 Moon 72.7 MER 87.6
[4]	JAFEE	6		HOG	FFNN	60% - 70%
[4]	FER2013	7			CNN State - of-Art	61.7% 75.2%
[4]	Ar and CAS PEAL-RI	4	Ar<120 CAS<65	LTP	NN	Ar 99.0% CAS 91.4%
[4]	CK+	5	68	FER	SVM, Logistic Regresion, NN	SVM 89% Logistic Regresion 80% NN 77.06%
This work	CK+	8	6	Chi-Square	J48, KNN, RBF, SVM, MLP, FM	J48 92.87% KNN 94.18% RBF 90.38% SVM 94.48% MLP 92.09% RF 94.23%

6. CONCLUSION

Eye-catching utilization of Chi-square by numurous researchers during the last decade has assured scholars' intense attraction towards the approach. The best high ranked six attributes from Chi-Square are being applied in six classifiers and the experimental outcomes demonstrate that RF with the 94.23 % of accuracy illustrates the most accurate and efficient classifier in facial expression according to CK+ dataset. In the other hand, KNN could be considered as a strong contestant against RF with the accuracy rate of 94.18%. J48 and MLP with the respective accuracy rates of 92.87% and 92.09% are average classifiers. The last two classifiers respectively are SVM with the accuracy ratio of 90.48% and RBF with the accuracy rate of 90.38% of accuracy.

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