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Performance evaluation of chi-square and relief-F feature selection for facial expression recognition

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ABSTRACT

Pattern recognition is a crucial part of machine learning that has recently piqued scientists' interest. The feature selection method utilized has an impact on the dataset's correctness and learning and training duration. Learning speed, comprehension and execution ease, and properly chosen features influence all high-quality outcomes. The two feature selection methods, relief-F and chi-square, are compared in this research. Each technique assesses and ranks attributes based on distinct criteria. Six of the most important features with the highest ranking have been chosen. The six features are utilized to compare the performance accuracy ratios of the four classifiers: k-nearest neighbor (KNN), naive Bayes (NB), multilayer perceptron (MLP), and random forests (RF) in terms of expression recognition. The final goal of the proposed strategy is to employ the least number of features from both feature selection methods to distinguish the four classifiers' accuracy performance. The proposed approach was trained and tested using the CK+ facial expression recognition dataset. According to the findings of the experiment, RF is the best accurate classifier on chi-square feature selection, with an accuracy of 94.23%. According to a dataset utilized in this study, the relief-F feature selection approach had the best classifier, KNN, with an accuracy of 94.93%.

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1. INTRODUCTION

Face expression recognition (FER) is a biometric authentication technique that is commonly used to identify people [1]. Recognition algorithms rely on individual variances in physical or behavioral traits [2]. A biometric recognition technology that is used to detect, recognize, identify, or authenticate a person in a digital image or video frame [3], computer vision [4], machine learning [5], real-web services [6], computer games [7], and time video [8]. Face recognition, authentication, tracking, expression categorization approaches, and feature expression mechanics are all under investigation [9].

Dino and Abdulrazzaq [9] presented a FER system that can distinguish all eight fundamental facial emotions in the CK+ dataset. The HOG is used as a descriptor to extract features from images of different faces, and then PCA is used to decrease the dimensionality of the features and show the most important ones. Lastly, they implemented three classifiers, which are multi layer perceptron (MLP), support vector machines (SVM), and k-nearest neighbor (KNN), to classify facial emotional expressions. The SVM classifier has an accuracy recognition rate of 93.53%, while the MLP classifier has an accuracy recognition rate of 82.97% and the KNN classifier has an accuracy recognition rate of 79.97%. This means that the research shows that SVM as a classifier gives better results than the other classifiers.

In order to understand the six fundamental emotional expressions, Bilkhu *et al.* [10] proposed another model of facial expression recognition. This approach applies cascade regression to derive characteristics. The approach uses three machine learning algorithms to classify the features and carry out this mission. Logistic regression, vector support, and NN were added to the technique. The data set for this method was CK+, and the results obtained were matched for each algorithm. The result shows 89% of the SVM accuracy, 80% of the neural network (NN), and 77.06% of the logistic classification accuracy.

In the context of generalization, limited sampling, and highly dimensional data handling, Pk *et al.* [11] suggested methods provide high efficiency. In the context of these advantages of the SVM, an optimal, new way of recognizing a face is suggested employing multi-class SVM. The histogram of oriented gradients (HOG), an extraction process, is employed in this facial recognition technology for extracting facial pictures. The one-on-one SVM approach is then followed to achieve a multi-class grouping on facial expression attribute vectors. For experimentation, the ORL dataset, the YALE dataset face, then self-created databases. The experimental findings demonstrate the consistency of the two datasets and the self-created database, which was over 96% identification.

Jena *et al.* [12] focused on content-based image retrieval (CBIR) as the high-level sémantics of multiple people's faces are the same. The uniqueness of the particular image needs to be found in the algorithm. This is harder due to poor resolution picture quality with the NIR face recognition. The aim is to determine the importance of the near-infrared (NIR) faces recognition texture function. He has been using the S-Subband of the singular value decomposition (SVD) function and the local binary pattern (LBP) texture feature of the original picture. A combined feature vector is used. The efficiency of the integrated function is compared to the value of the global SVD feature. They used the help SVM and KNN classifier for analysis in addition to the minimal distance classifier (MDC).

In order to reduce computational complexity, Bagga *et al.* [13] used 2DPCA to input images. Very poor precision and time. The completion of their procedure was completed. This technology is designed for implementation in real-time. 2DPCA has been used on LBP images instead of the initial images to increase the device's performance. Based on their precision and time complexity, the comparative study is achieved through experimental results. An acceptance rate of 95.83% for LBP+2DPCA and 95.12% for 2DPCA was given for the proposed scheme. In comparison with other contemporary approaches, the time taken to consider 2DPCA is much less.

Face detection, feature extraction, and face recognition are all part of facial emotion recognition task (FERT) [14]. Feature selection is used to reduce dimensionality even further by picking the features that describe the image face in relation to all the face images [15], which is impaced by the classification quality and computational complexity [16]. Therefore, the relevant rundown together with the elicited qualities is sufficient for determining the input class accurately. A large number of duplicate attributes adds to the complexity of the classification process and training. Overlapping edges with classification tasks and increasing complex distribution fail feature selection approaches that are helpful in dividing patterns having a location with the diverse classes. Correlation techniques, for example, assume linear data conditions that cannot deal with self-assertive relationships between separate classes and pattern coordinates. When data is subjected to linear changes, such as data scaling in the pre-processing stage [17], most prevalent data reduction strategies are not invariant. The chi-square and relief-F features selection methods are used in the proposed strategy to identify the highest rank six features. The previously elicited properties will be employed in the training and testing of the CK+ dataset to use the classifiers KNN [18], naive Bayes (NB) [19], MLP [20], and random forests (RF) [21].

This paper aims to test the accuricy of the chosen classifiers by using a range of facial images to assess the performance of two functional sorting techniques, chi-square and relief-F. In this article, the function collection then classification FER from facial images are computed efficiently.

2. METHOD

The basic strategy of this paper is to recognize human facial expressions in four steps. As shown in Figure 1, there are four steps: first data preprocessing, then face detection, third feature selection, and finally classification (training and testing). The ten fold validation used for training and testing. The CK+ dataset used in this paper consists of eight expressions.

2.1. Data preprocessing

The Cohn-Kanade (CK) database was made public to encourage research on detecting particular facial expressions automatically. The CK database has grown in popularity as a testbed for algorithm creation and evaluation [22]. The CK+ dataset is well-known and widely used, with 210 adult adults of both genders participating [23]. Surprising, sad, glad, afraid, disgusted, contemptuous, angry, and neutral are the eight basic facial expressions [24]. The dataset contains 31% males and the rest are females [25]. Figure 2 shows samples from the CK+ dataset.

Individuals of many nationalities, including European-Americans, are included in the dataset [22]. This dataset includes 593 sequences from 123 individuals. The picture sequence lasts between 7 and 60 frames and includes the onset (also known as the neutral face) and peak creation of the facial expression. Image sequences were digitized into (640,480) or (640,490) pixel arrays from neutral to target display. Only 327 of the 593 sequences have been classified as emotional [26]. This paper uses 4,090 randomly chosen samples from the given dataset. Table 1 lists all of the emotions and faces that apply to the algorithms of chi-square and relief-F. The standardization of the photos, which includes noise reduction, scaling, and modification, is the first step. Viola-Jones used the CK+ dataset to create the black and white images.

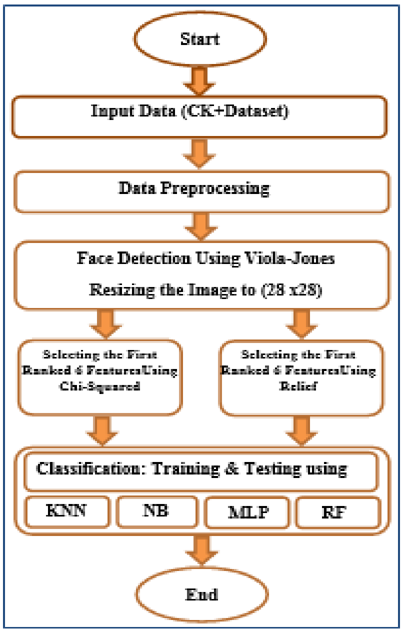


Figure 1. The main steps of the system

Figure 2. Dataset sample CK+ facial expression

Table 1. CK+ dataset instances number of facial expression

No.	Expression	No. of instances
1	Angry	527
2	Contemptt	47
3	Disgust	389
4	Fear	458
5	Happy	614
6	Normal	913
7	Sad	540
8	Surprised	602

2.2. Fase detection and feature selection

Face recognition from images, the Viola-Jones algorithm [27], one of the most well-known face recognition algorithms, is utilized. It is utilized for real-time detection [28]. Viola-Jones is often used for face detection because of its consistency in face detection rate and outstanding accuracy [29], among other techniques. It also has a tool for identifying in real time [27]. Integral picture generation, Adaboost training, then cascading classifiers comprise the attentional cascade structure [29]. The faces of Viola-Jones have been cropped and reduced to a size of 28×28 pixels. The relief-F feature selection technique uses the 784 attributes to rank the features according to their positional significance. The much more prominently ranked features will be isolated from the others and used in four classifiers to determine which is the most accurate. Feature selection is a method of selecting features based on their ranking [30]. There are two types of fear used in this paper.

2.2.1. Chi square feature selection

The chi-square method equation is a powerful machine learning technique [31]:

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

when A represents the variant frequency of the document that contains t and belongs to class c, B represents the frequency of the document that does not contain t and does not belong to class c. C denotes the frequency of documents that are missing and don't belong to class C, whereas N denotes the document's bravery [32]. The approach was applied to the CK+ dataset, and then the best six characteristics were selected, as shown in Table 2.

Table 2. The six highest rank featurs from chi-square

No.	Anger	Contempt	Disgast	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	564	177	610	512	570	433	433
5	103	565	178	623	526	571	137	634
6	130	592	179	637	527	572	601	655

2.2.2. Relief feature selection

For selecting near-hit as well as near-miss, relief-F employs Euclid distance. Based on the average near-hit plus near-miss, the relief-F method derives feature weight. It chooses features that have a high feature weight [33]. The relief-F approach is used on the CK+ dataset. Table 3 shows the top six features that are found.

Table 3. The six highest rank featurs from relief-F

No.	Anger	Contempt	Disgast	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

2.3. Classification

The categorization of six features generated by relief-F and chi-square is based on the use of the four classifiable KNN, NB, MLP, and RF. Training and testing procedures used the ten-fold validation methodology. That means always taking 90% (3681 instances) for training and 10% for testing (409 instances).

2.3.1. Kindest nearest neighbors (KNN)

The KNN classification [34], in which K stands for the closest neighbors, is used to determine the class based on distance measurements. Run-time training is required (they need to be in memory at run-time). Memory-based classification [35] is the name of the technique. The number of categories in the domain is represented by K. This classifier examines the unlabeled X to determine which category it belongs to.

2.3.2. Naïve Bayes (NB)

Naive Bayes is a widely used classification algorithm with significant influence [36]. Bayesian classifiers (BC) are classifiers that can be measured. They're used to anticipate class enrolment probabilities, or how likely an instance is to be assigned to a given class. Bayesian classifiers have great speed and accuricy since they are based on Bayes' hypothesis [37].

2.3.3. Multi layer perseptron (MLP)

The MLP is a feed-forward neural network that links inputs to outputs. MLP contains three layers: input, hidden, and output, each of which is completely functional [38]. The number of output nodes is equal to the number of classes [30]. Nodes in MLP can accomplish two tasks: initiating and aggregating. While performing the accumulation work, prejudice, heaviness, and inputs accumulated. MLP may benefit from several types of initiating roles [39].

2.3.4. Random forest (RF)

Random forest is a fast, computationally accurate approach for processing huge datasets. It's been used in a number of recent research projects as well as real-world applications [40]. To attain a high classification rate, this approach generates a forest by merging numerous decision trees. The ultimate goal of using this classifier is to avoid being too reliant on a single learning model. The main difference between this new approach and a traditional classifier like a decision tree is that the root nodes are made up of split nodes that are connected in a way that doesn't make sense [41].

3. PERFORMANCE EVALUATION AND RESULTS

A confusion matrix is used to investigate and assess each classifier's performance on the same set of six features determined as the best qualities of face expression by the two methods: In seconds, the average weighted TP, FP, precision, F-measure, recall and processing time. The major goal of this study is to examine how well the four classifiers performed on a few features that were deemed the most important for the two techniques used. The experimental results obtained from the classification process at the level of the four classifiers, using the attributes extracted from the chi-square method show that. The KNN classifier achieves the highest recognition rate of 94.18%, NB achieves the lowest recognition rate of 89.01%, MLP achieves 92.09%, and RF achieves 94.23%, Tables 4-7 illustrate the results, accordingly.

The chi-square approach result is used to identify the eight different types of facial recognition. Using the RF classifier, the greatest accuracy rate for contempt is 99.19%; fear is 92.79%; happy is 97.07%; sad is 90.91%; surprised is 97.09%; anger is 94.48%; disgust is 96.14%; and normal is 87.95%. Because the top three results recognized by it are merely anger, disgust, and normality, as detected by KNN, it is the best classifier for chi-square that shown in Figure 3(a).

Using the relief-F approach, KNN has the highest identification rate of 94.93%, NB has the lowest recognition rate of 87.07%, MLP has an 89.89% recognition rate, and RF has a 93.95% recognition rate utilizing the relief-F method with six features. Tables 8-11 illustrate the accuracy of each classifier.

Table 4. The chi-square performance result for the KNN algorithm

Expression	TP	FP	Precision	Recall	F-measure	Accuricy
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	0.89	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. The chi-square performance result for the NB algorithm

Expression	TP	FP	Precision	Recall	F-Measure	Accuricy
Anger	0.99	0.35	0.95	0.99	0.97	94.47
Contempt	0.98	0.62	0.99	1.00	0.99	97.43
Disgust	0.90	0.48	0.95	1.00	0.92	86.41
Fear	0.94	0.55	0.93	1.00	0.94	88.68
Happy	0.97	0.21	0.96	0.99	0.97	94.18
Normal	0.85	0.63	0.82	0.96	0.84	74.08
Sad	0.91	0.65	0.90	0.99	0.91	83.74
Surprise	0.95	0.18	0.97	1.00	0.96	93.08
Avg.Rate	0.94	0.46	0.94	0.94	0.94	89.01

Table 6. The chi-square performance result for the MLP algorithm

Expression	TP	FP	Precision	Recall	F-measure	Accuricy
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 7. The chi-square performance result for the RF algorithm

Expression	TP	FP	Precision	Recall	F-measure	Accuricy
Anger	0.97	0.27	0.96	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

Table 8. The performace accuracy for KNN algorithm using relief-F

Expression	TP	FP	Precision	Recall	F-measure	Accuricy
Anger	0.99	0.12	0.98	0.99	0.97	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 9. The performace accuracy for NB algorithm using relief-F

Expression	TP	FP	Precision	Recall	F-measure	Accuricy
Anger	0.84	0.50	0.92	0.84	0.88	93.30
Contempt	0.26	0.02	0.13	0.26	0.17	97.19
Disgust	0.87	0.47	0.95	0.87	0.91	83.62
Fear	0.91	0.64	0.92	0.91	0.91	84.43
Happy	0.92	0.27	0.95	0.92	0.93	88.88
Normal	0.86	0.66	0.82	0.86	0.84	74.40
Sad	1.00	1.00	0.87	1.00	0.93	86.75
Surprise	0.90	0.26	0.95	0.90	0.93	87.97
Avg.Rate	0.82	0.48	0.81	0.82	0.81	87.07

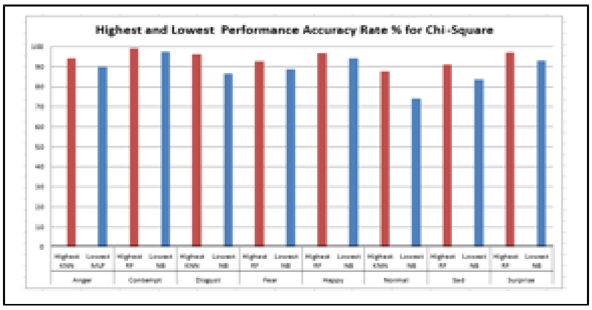
Table 10. The performace accuracy for MLP algorithm using relief-F

Expression	TP	FP	Precision	Recall	F-measure	Accuricy
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

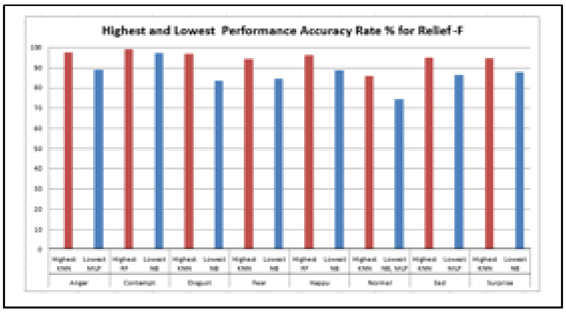
Table 11. The performace accuracy for RF algorithm using relief-F

Expression	TP	FP	Precision	Recall	F-measure	Accuricy
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

The relief-F attribute selection result is utilized for eight various forms of face detection. Using the KNN classifier. Anger gets the highest score 97.58%, disgust is 94.77%, fear is 94.25%, normal is 85.92%, sad is 94.96%, and surprise is 94.74%, while contempt and happiness are 99.22% and 96.43%, respectively. Because the greatest results recognized from it are merely contempt and happiness, detected from RF, KNN is the best classifier for relief-F approach that shown in Figure 3(b).



(a)



(b)

Figure 3. Selection high and low accuracy in feature (a) chi-square and (b) relief-F

The optimum classified facial emotion, based on the results of each classifier's performance evaluation, is disdain, with a ratio of 99.19%. Concurrently, with a ratio of 74.08%, the minimal recognition rate is normal. A comparison summary of the pertinent research is shown in Table 12. Other related studies have used alternative approaches to classification and feature selection on diverse datasets with varying volumes of facial expressions. The proposed method makes it possible to identify people with a high rate using faces with fewer features and more expressions than previous research. Researchers in [9] and [11] used SVM classifiers with HOG feature selection to get good recognition rates (93.53% and 96%, respectively). Researchers [9] and [10] employed various numbers of characteristics (247,68), yet research [9] was more accurate for SVM than research [10]. It’s (93.53%). For research [9], the MLP classifier had a greater accuracy than [10]. (82.97%). Researchers in [12] employed Euclidian Distance with 2DPCA and 2DPCA+LBP to reach high accuracy (95.12% and 95.83%, respectively), but in [9], they used HOG+PCA feature selection with SVM to get lower accuracy (95.12% and 95.83%, respectively) (93.53%). The accuracy of the KNN classifier in research [13] was 89.5%, which was lower than the accuracy of KNN with six feature selection by relief-F in this study (94.93%). Researchers [9] and [10] employed MLP with an accuracy of 82.97% and NN with an accuracy of 77.06%, while this work uses chi-square feature selection, which has a higher accuracy (good) of 92.09%.

Table 12. Comparison table

Ref.	Dataset	Emotion No.	Feature No.	Feature selection	Classifier	Result
[9]	CK+	8	247	HOG	SVM	93.53%
				PCA	KNN	79.97%
[10]	CK+	5	68	FER	MLP	82.97%
					SVM	89%
					Logestic	80%
					NN	77.06%
[11]	ORL, YALE, and FACE self database	6	-	HOG	SVM	96%
[12]	CASIA-NIR	4	-	S-Sub	KNN	86.2%
					SVM	86.3%
				LPB	KNN	89.5%
					SVM	91.2%
[13]	Cohn Kanade	6	-	2DPCA	ED	95.12%
				LPB		95.83%
This work	CK+	8	6	Chi-squ	KNN	94.18%
					NB	89.01%
					MLP	92.09%
					RF	94.23%
				Relief-F	KNN	94.93%
					NB	87.07%
					MLP	89.89%
					RF	93.95%

4. CONCLUSION

Researchers are becoming increasingly more interested in feature selection methods, which is important because it is one of the most efficient ways to classify data with high discrimination accuracy while reducing processing time. In feature selection methods, chi-square and relief-F are both rigorous approaches to feature selection. Using both approaches, the chi-square and relief-F algorithms, the six highest-scoring features from the input image with 784 attributes were selected for utilization by four classifiers in this research. The findings of the experiment indicate that RF is the most accurate classifier among the four classifiers that use the highest features from chi-square and KNN for relief-F. When the four classifiers are trained and tested on the dataset, they generate various outputs. The RF classifer has the best ratio of accuracy, with a percentage of 94.23%, whereas relief-F has a total percentage of 94.93%, based on chi-square and KNN. NB has an accuracy ratio of 89.01% when it comes to chi-square and an accuracy ratio of 87.07% when it comes to relief-F.

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