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%.

Keywords: Chi-square, CK+ data set, Classification, Facial expression recognition, Relief-F

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1. INTRODUCTION

Facial 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 semantics 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 impacted 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 accuracy 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 textbed 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 expressions.
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

![Flowchart](image)

Figure 2. Dataset sample CK+ facial expression

| No. | Expression | 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              |

Table 1. CK+ dataset instances number of facial expression

2.2. Face 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 28x28 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]:

\[
x^2(t, c) = \frac{(AD-BC)^2}{(A+C)(B+D)(A+B)(C+D)}
\]

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 features from chi-square

| No. | 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   | 564      | 177     | 610  | 512   | 570    | 433 | 433      |
| 5   | 103   | 505      | 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 features from relief-F

| No. | 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      |

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. Naive 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 accuracy since they are based on Bayes’ hypothesis [37].

2.3.3. Multi layer perceptron (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].

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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 features determined as the most important for 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.

| Expression | TP | FP | 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 | 0.89      | 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    |

| Expression | TP | FP | Precision | Recall | F-measure | Accuracy |
|------------|----|----|-----------|--------|-----------|----------|
| 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    |

| Expression | TP | FP | 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    |
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%, which indicates that KNN is the best classifier for relief-F approach that shown in Figure 3(b).

Table 7. The chi-square performance result for the RF algorithm

| Expression | TP   | FP   | Precision | Recall | F-measure | Accuracy |
|------------|------|------|-----------|--------|-----------|----------|
| 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 | Accuracy |
|------------|------|------|-----------|--------|-----------|----------|
| 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.Range  | 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 | Accuracy |
|------------|------|------|-----------|--------|-----------|----------|
| 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      | 85.62    |
| 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.Range  | 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 | 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.Range  | 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 | 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.Range  | 0.98 | 0.39 | 1.00      | 0.98   | 0.97      | 93.95    |
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%     |
|      |                                |             |             |                   | Logistic   | 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        | 89.5%   |
|      |                                |             |             |                   | SVM        | 91.2%   |
| [13] | Cohn Kanade                    | 6           | -           | 2DPCA             | ED         | 95.12%  |
|      |                                |             |             |                  | LPB        | 95.83%  |
| This work | CK+                              | 8           | 6           | Chi-sq            | KNN        | 94.18%  |
|      |                                |             |             |                   | NB         | 89.01%  |
|      |                                |             |             |                   | MLP        | 92.09%  |
|      |                                |             |             |                   | RF         | 94.23%  |
|      |                                |             |             |                   | 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 classifier has the best accuracy ratio, 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.

REFERENCES

[1] H. Dino, et al., "Facial expression recognition based on hybrid feature extraction techniques with different classifiers," TEST Engineering & Management, vol. 83, pp. 22319-22329, 2020.
[2] Z. Xu, Y. Liu, H. Zhang, X. Luo, L. Mei, and C. Hu, "Building the multi-modal storytelling of urban emergency events based on crowdsensing of social media analytics," Mobile Networks and Applications, vol. 22, pp. 216-227, 2017, doi: 10.1007/s11036-016-0789-2.
[3] R. V. Petrescu, "Face recognition as a biometric application," Journal of Mechatronics and Robotics, vol. 3, no. 1, pp. 237-257, 2019, doi: 10.3844/jmrsp.2019.237.257.
[4] A. W. Alhtearer and A. H. Hussein, "Intelligent security system detects the hidden objects in the smart grid," Indonesian Journal of Electrical Engineering and Computer Science (IJEECS), vol. 19, no. 1, pp. 188-195, 2020, doi: 10.11591/ijeecs.v19i1.pp188-195.
[5] I. Abbaspournejad and D. Teney, "A hierarchical bayesian network for face recognition using 2d and 3d facial data," in 2015 IEEE 25th International Workshop on Machine Learning for Signal Processing (MLSP), 2015, pp. 1-6, doi: 10.1109/MLSP.2015.7324327.
[6] T. Yang, X. Zhao, X. Wang, and H. Lv, "Evaluating facial recognition web services with adversarial and synthetic samples," Neurocomputing, pp. 378-385, 2020, doi: 10.1016/j.neucom.2019.11.117.
[7] A. Rajawat, M. K. Pandey, and S. S. Rajput, "Low resolution face recognition techniques: A survey," in 2017 3rd International Conference on Computational Intelligence & Communication Technology (CICT), 2017, pp. 1-4, doi: 10.1109/100798-3-030-01132-1.11.
[8] M. Sajjad, et al., "Raspberry Pi assisted face recognition framework for enhanced law-enforcement services in smart cities," Future Generation Computer Systems, vol. 108, pp. 995-1007, 2020, doi: 10.1016/j.future.2017.11.013.
[9] H. I. Dino and M. B. Abdurahman, "Facial expression classification based on SVM, KNN and MLP classifiers," in 2019 International Conference on Advanced Science and Engineering (ICOASE), 2019, pp. 70-75, doi: 10.1109/ICOASE.2019.8723728.
[10] P. Wei, Z. Zhou, L. Li, and J. Jiang, "Research on face feature extraction based on K-mean algorithm," EURASIP Journal on Image and Video Processing, vol. 2018, p. 83, 2018, doi: 10.1186/s13640-018-0313-7.
[11] A. M. Nuruddin, X. Ding, and T. Page, "An integrated approach for face recognition using multi-class SVM," in 2020 IEEE 5th International Conference on Cloud Computing and Big Data Analytics (ICCCBDA), 2020, pp. 398-402, doi: 10.1109/ICCCBDA49378.2020.9056962.
[12] P. K. Jena, B. Khuntia, R. Anand, S. Patnaik, and C. Palai, "Significance of texture feature in NIR face recognition," in 2020 First International Conference on Power, Control and Computing Technologies (IPC2C), 2020, pp. 21-26, doi: 10.1109/IPC2C48082.2020.9071504.

---

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[25] F. W. Smith and S. Rossit, "Identifying and detecting facial expressions of emotion in peripheral vision," PloS one, vol. 13, no. 5, p. e0197160, 2018, doi: 10.1371/journal.pone.0197160.

[26] D. Ghimire, J. Lee, Z.-N. Li, and S. Jeong, "Recognition of facial expressions based on salient geometric features and support vector machines," Multimedia Tools and Applications, vol. 76, pp. 7921-7946, 2017, doi: 10.1007/s11265-016-3428-9.

[27] J. Kaur and A. Sharma, "Performance analysis of face detection by using Viola-Jones algorithm," International Journal of Computational Intelligence Research, vol. 13, no. 5, pp. 707-717, 2017.

[28] J. Ren, N. Kehtarnavaz, and L. Estevez, "Real-time optimization of Viola-Jones face detection for mobile platforms," in 2008 IEEE Dallas Circuits and Systems Workshop: System-on-Chip-Design, Applications, Integration, and Software, 2008, pp. 1-4, doi: 10.1109/DCAS.2008.4695921.

[29] T. Paul, U. A. Shammi, M. U. Ahmed, R. Rahman, S. Kobashi, and M. A. R. Ahad, "A study on face detection using Viola-Jones Algorithm in various backgrounds, angles and distances," International Journal of Biomedical Soft Computing and Human Sciences: the official journal of the Biomedical Fuzzy Systems Association, vol. 23, no. 1, pp. 27-36, 2018, doi: 10.24466/fbscs.23.1.27.

[30] M. R. Mahmood, A. M. Abdulazeez, and Z. Orman, "Dynamic hand gesture recognition system for Kurdish sign language using two lines of features," in 2018 International Conference on Advanced Science and Engineering (ICOASE), 2018, pp. 42-47, doi: 10.1109/ICOASE.2018.8548840.

[31] T. A. Assegie, R. L. Tulasi, V. Elanangai, and N. K. Kumar, "Exploring the performance of feature selection method using breast cancer dataset," Indonesian Journal of Electrical Engineering and Computer Science (IJEECS), vol. 25 No. 1, pp. 232-237, January 2022, doi: 10.11591/ijeecs.v25.i1.pp232-237.

[32] J. Sun, X. Zhang, D. Liao, and V. Chang, "Efficient method for feature selection in text classification," in 2017 International Conference on Engineering and Technology (ICET), 2017, pp. 1-6, doi: 10.1109/ICEngTechnol.2017.8308201.

[33] B. Venkatesh and J. Anuradha, "A review of face selection and its methods," Cybernetics and Information Technologies, vol. 19, no. 1, pp. 3-26, 2019, doi: 10.2478/cait-2019-0001.

[34] W. Li, Y. Chen, and Y. Song, "Boosted K-nearest neighbor classifiers based on fuzzy granules," Knowledge-Based Systems, p. 105606, 2020, doi: 10.1016/j.knosys.2020.105606.

[35] L. H. Lee, C. H. Wan, T. F. Yong, and H. M. Kok, "A review of nearest neighbor-support vector machines hybrid classification models," Journal of Applied Sciences, vol. 10, no. 17, pp. 1841-1858, 2010, doi: 10.3923/jas.2010.1841.1858.

[36] Y. Wu, "A new instance-weighting naive Bayes text classifiers," in 2018 IEEE international conference of intelligent robotic and control engineering (IRCE), 2018, pp. 198-202, doi: 10.1109/IRCE.2018.8492960.

[37] S. Shakya and S. Singhel, "An approach to develop a hybrid algorithm based on support vector machines and naive Bayes for anomaly detection," in 2017 International Conference on Computing, Communication and Automation (ICCCA), 2017, pp. 323-327, doi: 10.1109/ICCCA.2017.8229836.

[38] L. Weissbart, "Performance analysis of multilayer perceptron perceptron in profiling side-channel analysis," in International Conference on Applied Cryptography and Network Security, 2020, pp. 198-216, doi: 10.1007/978-3-030-61638-0_12.

[39] A. A. Hadadi, H. Faris, I. Aljarah, and S. Mirjalili, "An efficient hybrid multilayer perceptron neural network with grasshopper optimization," Soft Computing, vol. 23, pp. 7941-7958, 2019, doi: 10.1007/s00500-018-3424-2.

[40] T. M. Oshiro, P. S. Perez, and J. A. Baranauskas, "How many trees in a random forest?," in International workshop on machine learning and data mining in pattern recognition, 2012, pp. 154-168, doi: 10.1007/978-3-642-31537-4_13.

[41] Y. Elyusufi, Z. Elyusufi, and M. A. Khur, "Social networks fake profiles detection using machine learning algorithms," in The Proceedings of the Third International Conference on Smart City Applications, 2019, pp. 30-40, doi: 10.1007/978-3-030-37629-1_13.

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