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**Research Article**

# Face Recognition Using Histogram of Oriented Gradient Features and K-Nearest Neighbor Method

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***Abstract*** **–** Face recognition system is a technology of identifying people from facial images or video streams. In general, facial recognition applications are quite beneficial in the fields of security and identity verification. In this work, facial recognition systems have been implemented via Histogram of Oriented Gradient features and K-Nearest Neighbor machine learning technique. For this systems, the facial image dataset, which has four hundred facial images, has been adopted from the well-known data repository, Kaggle. In preprocessing stage, all the facial images have been applied by Gaussian filter due to reducing noise levels of the images. In feature extraction stage, The data set has been divided into training and testing sets via K-Fold-Cross-Validation. For various K values and distance metrics, the facial recognition systems have been developed with K-Nearest Neighbor using on the training dataset. For testing of the developed systems, Recall, Precision, Accuracy and F1-Score have been chosen from the classification metrics. It has been observed that the noise reduction filter improves the success of the systems.

*Keywords – Face Recognition, Histogram of Oriented Gradients, HOG, K-Nearest Neighbor, Machine Learning*

## I. INTRODUCTION

Face recognition is a biometric technology that uses advanced algorithms and machine learning techniques to identify and verify humans based on their face features [1-3]. This technology has gained widespread attention due to its applications in various sectors, including security, personal identification, and social media [1-11].

Face recognition systems typically involve the steps as detection, alignment, feature extraction and matching. In detection step, the system detects a face in an image or video stream. In alignment step, the detected face is aligned based on the position of key facial landmarks as eyes, nose, mouth. In feature extraction step, unique features of the face are extracted and converted into a numerical representation, known as a facial feature vector. In matching step, the extracted features are compared with the known face features. [1-4].

Face recognition applications have been generally used for security, authentication, social media and healthcare. For instance, these systems can be surveillance systems to enhance security and monitor suspicious activities, secure login for devices like smartphones and laptops, helping tag and organizing photos by identifying people automatically and assisting in patient identification and monitoring.

While face recognition studies provides a lot of benefits, furthermor it can bring up ethical issues such as privacy, consent, and potential biases. It's crucial to implement face recognition with proper regulations to ensure ethical and responsible use [1-3].

Face recognition continues to evolve, making it a powerful tool for identification and security, with potential for further innovations in the future.

Human beings are naturally very successful at identifying faces. However, it's a difficult task for machines. Problems arise from things like changes in lighting, different head positions, and if some parts of the faces are not seen. The scientists have developed many methods to assist computers recognize faces. The techniques involve the methods such as Principal Component Analysis, Discrete Wavelet Transform, and nowadays, state-of-the-art approaches like Convolutional Neural Networks. These developments have led to great improvements in how accurately and widely face recognition can be utilized in recent years [4-8].

The rest of the paper is structured as follows. Section two explains briefly the materials and methods that are used this study. Section three mentions the performances of the systems according to the metrics. Section four concludes the paper.

## II. Materials and Methods

K-Nearest Neighbors and Support Vector Machines have been used to develop machine learning systems in this work. The following subsections briefly explains the methods and how to extract HOG features from face images in face image dataset.

### A. *K-Nearest Neighbors (K-NN)*

K-NN algorithm is an effective machine learning technique utilized classification and regression problems. The K-NN algorithm works by identifying the K closest samples to given test samples and making predictions based on majority classes in classification tasks or mean of these neighbor samples in regression tasks [12-21].

KNN Algorithm for Classification

1. Data Preparation: Start with a dataset where each data sample has known features and a label of category.
2. Choosing K: Select the number of neighbors.
3. Calculating Distances: For a new test point, calculate the distance metric between this test point and all the points in the training dataset. (Manhattan metric in this study)
4. Finding Neighbors: Identify K samples in train set which are closest test samples.
5. Classification: Assign the closest class label among K nearest neighbor samples to the test point.

The advantages of KNN method are its simplicity and no assumptions. Namely, its implementation and understanding are quite easy. In addition, there is no need assumptions about the data distribution. On the other hand, there are some disadvantages for KNN. It is sensitive to irrelevant features and has computational cost when train sets are large. For that reason, the method can be slow with large datasets as it computes the distance between all data points in training set. In addition, the performance of the KNN system can be degraded if irrelevant features are included.

The applications of KNN method is usually used for image recognition such as handwritten digit recognition, medical diagnosis systems to classify diseases based on patient data and recommended systems to suggest items according to user preferences.

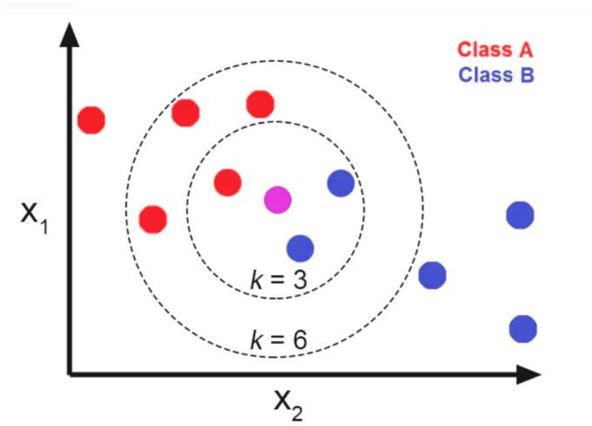


Fig. 1 The structure of K-Nearest Neighbor

### B. *HOG features*

The initials of HOG stand for "Histogram of Oriented Gradients". This feature is often chosen in the fields of image processing and computer vision to detect the objects in the image. The systems with HOG can calculate the occurrences of the orientations and gradients for some parts of the images. HOG can assist to localize and identify the objects in the images using edge and shape features. it is also a basic feature in computer vision and image processing. It can be said that continues to be a powerful tool for various image analysis tasks. It will continue to be a strong attribute in the future [22-30].

HOG Algorithm

1. Computing gradients in the image in tensity with the horizontal and vertical directions. In this stage, some edge detection operators are needed to detect the edges of the images.
2. The second stage is binning of the orientations of the image cells. Before the binning, the image is split into some cells. After computing histograms of gradients and orientations, the cells' binning has been implemented.
3. After binning operation, the block histograms of images are normalized to increase the contrast of the image. This process improves the robustness of the systems.
4. A feature vector is generated by adding the blocks of the image. The matrix form of the image is converted to one dimensional feature array or a feature vector.

HOG features have numerous benefits. It is robust and resistant to fluctuations in light with extracting edges. In addition, it can be implemented effectively. For that reason, HOG features can be used human or object detections in images or video streams. It is also effective to classify images.

## III. Results and Discussions

In this work, face recognition systems have been implemented by K-Nearest Neighbors classifier. The systems have been evaluated by the most preferred classification metrics such as Recall, Precision, Accuracy and F1-Score as shown in Equations 1, 2, 3 and 4. Precision is the rate of the detected positive samples to the total detected samples. Recall is the rate of the detected positive samples to the total samples in the actual category. Accuracy performance metric is the rate of correctly detected samples to the all samples. F1-Score can be stated as the weighted mean of Recall and Precision metrics. In the following formulas, the metrics can be calculated with TP, TN, FP and FN values (TP: True Positive, TN: True Negative, FP: False Positive, FN: False Negative).

$$\text{Precision} = TP/(TP + FP) \quad (1)$$

$$\text{Recall} = TP/(TP + FN) \quad (2)$$

Accuracy = (TP + TN) / (TP + TN + FP + FN) (3)

F1-Score= (2 x Precision x Recall)/(Precision + Recall) (4)

Confusion Matrix is the matrix table with TP, TN, FP and FN values to compute the success of the categorization systems. TP can be stated as correctly detected positive category whereas TN is correctly detected negative category. In the same way, FP is described as incorrectly detected positive class. But, FN is incorrectly detected negative category.

As displayed in Figure 2, Evaluating the performance of the systems has been based on K-Fold-Cross-Validation technique for better accuracy validation. With this technique, the dataset is divided into K equal sets and one of them is chosen for testing of the system. The other datasets are used for training operation. Every part of the dataset has been trained and tested for both training and testing operations. At the end, the performance values of the systems have been measured K times. The average of these K performance values is accepted as the system performance. Therefore, we obtain more accurate and effective evaluation with K-Fold-Cross-Validation although there are much more implementation costs and elapsed time. K has been selected as five. Namely, the dataset has been split into five segments, and after the rest of the first segment in the dataset is trained, it has been tested with the first segment dataset.

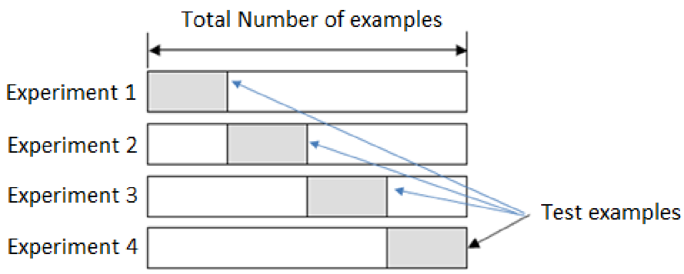


Fig. 2 K-Fold-Cross-Validation technique

The experiments has been performed on an Intel Core i7-12650H 2.30 GHz with 40 GB of RAM running Windows 11.

In this work, the systems, which is developed with K-NN machine learning method, utilized the Histograms of Oriented Gradient features. The distance metric for K-NN is preferred as Manhattan distance because of providing more accurate results than Euclidean distance. As shown in Table 1, 2, 3 and Figure 3, the best results of K-NN models have been obtained with K=1. When K is rising, the success scores are decreasing. According to folds of the dataset, it can be seen that the success scores do not change much among the folds of the dataset. It has been reached the highest average Accuracy and F1-Score as 95.6 percent.

Table 1. The results of face recognition systems with K-NN method for K=1.

| Fold | Precision | Recall | Accuracy | F1-Score |
|---|---|---|---|---|
| 1 | 0.95 | 0.94 | 0.94 | 0.94 |
| 2 | 0.97 | 0.95 | 0.95 | 0.95 |
| 3 | 0.97 | 0.95 | 0.95 | 0.95 |
| 4 | 1 | 1 | 1 | 1 |
| 5 | 0.95 | 0.94 | 0.94 | 0.94 |
| **Macro Average** | **0.968** | **0.956** | **0.956** | **0.956** |

Table 2. The results of face recognition systems with K-NN method for K=3.

| Fold | Precision | Recall | Accuracy | F1-Score |
|---|---|---|---|---|
| 1 | 0.91 | 1 | 0.95 | 0.95 |
| 2 | 0.9 | 0.9 | 0.9 | 0.9 |
| 3 | 0.94 | 0.94 | 0.94 | 0.94 |
| 4 | 0.96 | 0.96 | 0.96 | 0.96 |
| 5 | 0.91 | 0.91 | 0.91 | 0.91 |
| **Macro Average** | **0.924** | **0.924** | **0.932** | **0.932** |

Table 3. The results of face recognition systems with K-NN method for K=5.

| Fold | Precision | Recall | Accuracy | F1-Score |
|---|---|---|---|---|
| 1 | 0.86 | 0.99 | 0.91 | 0.91 |
| 2 | 0.86 | 0.86 | 0.86 | 0.86 |
| 3 | 0.93 | 0.93 | 0.93 | 0.93 |
| 4 | 0.95 | 0.95 | 0.95 | 0.95 |
| 5 | 0.86 | 0.86 | 0.86 | 0.86 |
| **Macro Average** | **0.892** | **0.918** | **0.902** | **0.902** |

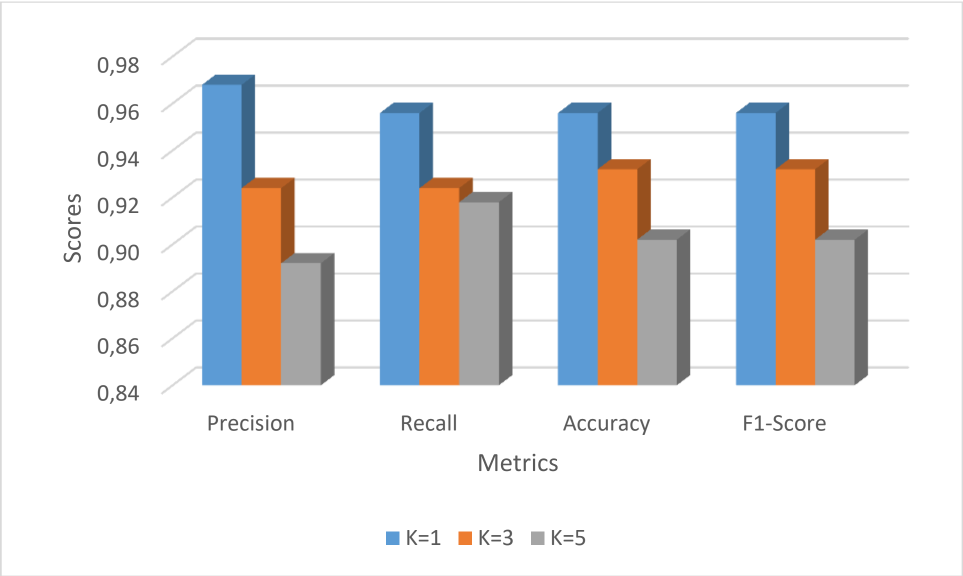


Fig. 3 The metric scores of K-NN method for K=1, 2 and 3

## IV. CONCLUSION

In this study, face recognition systems have been implemented with Histogram of Oriented Gradient features and K-Nearest Neighbor method. For training and testing of the systems, the face image dataset has been adopted from Kaggle repository. Before feature extraction phase, the face images have been filtered with Gaussian filter. And, with this operations, more smooth images has been obtained because of reducing the noise. After preprocessing, the HOG features are extracted from face images. Using K-Fold-Cross-Validation method, the systems' performances have been tested. The performance metrics as Recall, Precision, Accuracy and F1-Score have been chosen from the classification metrics for testing of the systems which have been developed by K-NN method with K=1, 3 and 5. After testing operation, the best performance score has been reached with K=1 as 95.6% Accuracy and F1-Score. In addition, it has been observed that the noise reduction filter improves the success of the systems.

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