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Enhancing Face Recognition Performance with Multispectral Imaging and Machine Learning: Comparison from Sift and Sift-Freak Feature Extraction

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Abstract— The development of modern societies faces many security and identification challenges. To meet this expectation, computer vision offers biometric solutions. Much research in recent years has focused on face recognition. Traditional facial recognition that uses color images has had many shortcomings, such as variation in illumination, smoke, rain, disguise, face concealment, makeup, etc. Light-insensitive infrared (IR) imaging is presented as an alternative to facial recognition in the visible to overcome the shortcomings of uncontrolled environments. However, IR also has weaknesses, such as facial occlusion by glasses, variation in body temperature, perfusion, etc. This paper proposes a new facial recognition architecture that uses several classification algorithms, detectors, and feature descriptors in multispectral imaging. A combination of SIFT and FREAK, feature extraction tools, was associated with classification algorithms such as SVM, logistic regression, and Random forest to conduct this study. Several experiments were made to evaluate the performance of the proposed recognition system. The validation process of the proposed multispectral face recognition method involved several important steps. First, experiments were carried out on visible and infrared spectrum images to measure the recognition system's performance. These experiments made it possible to compare the recognition performances between these two types of images. Then, fuse visible and infrared images were used to assess multispectral facial recognition. The goal was to maximize each spectrum's advantages while minimizing their disadvantages. Metrics were evaluated to measure the accuracy of the multispectral face recognition method. The performances were compared with classical facial recognition methods, such as facial recognition based on the visible spectrum or infrared imagery alone. The results showed that the proposed multispectral facial recognition method performed better than traditional methods, reaching a facial recognition score ranging from 76% to 95% in the IRIS database.

Keywords- Facial recognition; Multispectral Images; Infrared; Image fusion, Visible, Machine Learning.

I. INTRODUCTION

Face recognition is a growing area of artificial intelligence research, which has many practical applications, such as identity verification, security monitoring, and wanted person detection. Various factors can influence facial recognition, such as viewing angles, facial expressions, obstructions, and lighting variations. Recent studies have demonstrated that using infrared images is a reliable alternative to visible images for recognizing appearance differences due to lighting changes [1]. Thus, infrared facial recognition has advantages such as more straightforward, robust solutions and improved recognition performance in uncontrolled environments where fraudsters can conceal their faces. Although robust to changes in illumination, infrared imaging has shortcomings: temperature variation in an environment, stress, blood transfusion, thermal pattern variation, and glass opacity [2]. Beyond these weaknesses, infrared remains very insensitive to variations in illumination [3]. Several techniques have been developed to perform face recognition, each with advantages and disadvantages. For multispectral face recognition, it is important to use techniques that can work effectively with different types of spectra, such as infrared and ultraviolet [4]. Feature extractors are essential tools for multispectral face recognition. SIFT (Scale Invariant Feature Transform) and FREAK (Fast Retina Keypoint) methods are widely used. The SIFT method is known for its robustness to light, noise, and rotation variations, which makes it particularly useful for extracting multispectral face features. On the other hand, the FREAK method is a variant of SIFT that uses a more compact feature representation, thus providing a higher extraction speed for practical use. Therefore, using SIFT or

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FREAK will depend on the specific application needs and trade-offs between accuracy and processing time [5]. To design an efficient multispectral recognition system, we implemented an approach based on a combination of SIFT and FREAK feature extraction tools and classification algorithms such as SVM, logistic regression, and Random Forest. Combining these different elements, we have developed a recognition system that offers significant advantages over more traditional methods. To evaluate the performance of our recognition system, we conducted several experiments on images from two different sources: the visible spectrum and the infrared spectrum. This approach allowed us to compare and measure the efficiency of our system on different types of images. Then, we analyzed the performance of our multispectral recognition system using visible/infrared fusion images. This approach allowed us to take advantage of the advantages of each spectral band while minimizing their respective disadvantages. We were thus able to use significant metrics for multispectral facial recognition, confirming the effectiveness of our system. Our approach based on the combination of feature extraction tools and classification algorithms, combined with a rigorous evaluation of our method on different image sources, has made it possible to develop a robust and efficient multispectral recognition system. We have organized our article as follows:

In Section 2, we present a detailed analysis of the current state of face recognition, exploring the visible, infrared, and visible/infrared fusion domains. We also expose classification algorithms such as SVM, logistic regression, and Random Forest. In section 3, we describe the SIFT and FREAK feature extraction methods, which will be combined with the appropriate classification algorithms. We also present our study method, which consists of taking input data from the visible, infrared, and visible/infrared fusion bands and scaling them to extract features using SIFT and FREAK techniques. And their merging, then classify them using convolutional network algorithms SVM, logistic regression, and Random Forest in training and test sets.

In section 4, we will present the results of our experiments and the obtained results. We will validate these results using metrics and discuss the system's robustness.

Finally, in Section 5, we present our findings and discuss directions for future research.

II. RELATED WORK

SIFT (Scale-Invariant Feature Transform) and FREAK (Fast Retina Keypoint) algorithms are widely recognized as classic feature extraction algorithms in computer vision. Their popularity is due to their ability to extract robust and invariant features to scale, rotation, and illumination changes. Several authors have conducted studies on the classical feature extraction algorithm.

Yan et al. proposed the PCASIFT algorithm, which uses the Principal Component Analysis (PCA) algorithm to reduce the dimension of image feature descriptor sequences. The results of the experiment show that image matching [6]. Luka Daoud et al. proposed a fully pipelined hardware accelerator architecture for mapping SIFT key point descriptors to an accelerator core on an array of programmable gates. The results of this work yielded a reduction in resource consumption of up to 91% for LUTs and 79% for BRAMs [7]. Vision-based tracking is an essential prerequisite for a growing number of applications. Pareek et al. investigated feature detection, extraction, and matching in an object recognition system that uses image-matching techniques. In their work, they used the AKAZE, BRISK, DAISY, FREAK, ORB, SIFT, and SURF algorithms. The results showed that the most efficient algorithms for object tracking are ORB, SURF, and SIFT [8]. Stable detection and representation of local features are fundamental to many images registration and object recognition algorithms. Mohamad El-Abed et al. studied a method to quantify the quality of morphological biometric data. It is based on the joint use of two types of information, namely the quality of the image and the quality of the parameters extracted using the SIFT descriptor [9]. The scale-invariant feature transform (SIFT) algorithm remains one of the most reliable image feature extraction methods. Fan et al. proposed an analog signal processing architecture, Analog Signal Processing (ASP) SIFT. In ASP-SIFT, building the Gaussian pyramid, and locating key points, which are the main steps of the key point detection part of the SIFT algorithm, are performed directly with analog circuit networks [10].

III. MATERIALS AND METHODS

A. Dataset Description

The database used in this study is taken from the Imaging Robotics System (IRIS) database [11]. This database contains images of faces acquired simultaneously in the visible and infrared. The conditions for taking images are the variation in illumination, expression, and poses. Our experiments focused on the facial images in visible and infrared of 14 faces. The subjects posed in four directions, and the images were taken under four illuminations which are: Lon (Left Light On), Off (Left and Right Off), and Ron (Right Light On). In all, there are 336 facial images. After fusion, 168 fused images are obtained, and 504 images are manipulated. Fig. 1 presents an extract of the dataset used.

Figure 1. Extracted images from the database. From top to bottom: visible images in the first row, infrared images in the second row and visible/infrared fused images in the third row.

B. Features Extraction

Several types of research have explored the problem of facial recognition. One is based on facial properties characterized by unique traits per individual. According to the studies, the features studied are the organs of the face by representing their shape, the distance between them, their texture, etc. The feature extraction tools used are generally detectors, and descriptors for the detection of points of interest [12]. For texture, algorithms are used to determine the texture [13]. In this study, the interest point detection and description algorithms are SIFT, FREAK, and the two combined. These methods have the advantage of being invariant to affine transformations, and FREAK is a binary detector and descriptor, hence its speed of execution [14] [15].

- **SIFT**: The SIFT algorithm extracts points of interest, also called key points, from an image and computes a description of each point of interest invariant to scale rotation and illumination changes. This description is based on the image gradients and is calculated from a local region around each point of interest [16]. Points of interest extracted by SIFT can be used for tasks such as image matching, object recognition, and 3D reconstruction. The algorithm is also used in applications such as image search, augmented reality, and autonomous navigation [17].

- **FREAK**: The FREAK algorithm is based on using the artificial retina, a grid of Gaussian filters applied to the image. It extracts key points using a fast corner detector, then calculates a description of each ~~point of~~ interest point using a combination of binary descriptors based on artificial retina orientations and contrasts. The peculiarity of FREAK is that its descriptors are binary, which allows a quick and efficient comparison between ~~points of~~ interest points. Additionally, FREAK is designed to be robust to changes in scale, orientation, and [18] FREAK has been evaluated in different applications, including object recognition, autonomous navigation, and face detection. The results showed that FREAK is as efficient as SIFT and SURF in terms of accuracy but much faster in computation time [19].

C. Classification Algorithm

In machine learning, the choice of the appropriate classification algorithm is crucial for the model's performance. In our study, we chose to use three different classification algorithms: SVM (Support Vector Machine), Logistic Regression, and Random Forest. Each of these classification algorithms has its advantages and disadvantages, and we decided to combine them with feature extractors to improve the performance of our classification model [20].

- **SVM** is a supervised learning algorithm used for classification and regression. It is known for its ability to generalize data well and to separate classes linearly and nonlinearly. The SVM is beneficial for datasets with many variables and few observations.

- **Logistic regression** is a supervised learning algorithm used for binary classification, and it is widely used in statistical modeling and medical research. Logistic regression is robust to outliers and can provide probabilistic results for each class.

- **The Random Forest** is a supervised learning algorithm used for classification and regression, and it combines multiple decision trees to produce more accurate predictions. The Random Forest is useful for datasets with categorical or continuous variables and can handle missing data.

By combining these three classification algorithms with feature extractors such as SIFT, FREAK, or others, we hope to improve the accuracy and robustness of our classification model. Feature extractors are used to extract meaningful information from images, such as key points, edges, textures, and colors, and this information can then be used to train the classification models.

D. Methodology

The methodology of the facial recognition process adopted is divided into three main steps: data preparation, feature extraction, and face classification/recognition.

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In the first step, it is necessary to prepare the data for analysis. This involves the representation of visible and infrared data and the merging of images to enable a unified representation. It is also important to put the images in the same dimension to facilitate later manipulation.

The second step in image processing is to extract meaningful features that will serve as the basis for object recognition and classification. Using the SIFT (Scale-Invariant Feature Transform) algorithm is a standard method to extract these features. Indeed, SIFT can detect points of interest in the image that are robust to scale changes, making it a good choice for object detection in large-scale images.

In addition, we opted for a fusion of SIFT and FREAK (Fast Retina Key point) to combine the advantages of these two methods. Indeed, FREAK is a faster feature extractor than SIFT but less robust to scale changes. By merging these two feature extractors, we can benefit from the speed of FREAK and the robustness of SIFT, which significantly improves the accuracy of object detection and classification in images.

Figure 5 presents the synthesis of the methodology of our study.

E. Evaluation Metrics

In this study, we used several metrics to assess our results. We considered accuracy, precision, recall, F1 score, and Matthews Correlation Coefficient (MCC) among these. The differential equations are:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

$$Precison = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1\ score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

$$MCC = \frac{TP * TN - FP * FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (5)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Yi - \hat{Y}i)^2 \quad (6)$$

The Receiver Operating Characteristic (ROC) curve is a graph that represents the performance of a binary classification model. It plots the rate of true positives (sensitivity) as a function of the rate of false positives (1 - specificity) at different classification thresholds. An ideal ROC curve approximates the upper left corner of the graph, indicating high sensitivity and high specificity.

The confusion matrix is a table that summarizes the results of the predictions of a classification model. It compares the model's predictions with the actual values of the dataset and organizes them into four categories: true positives, true negatives, false positives, and false negatives. The confusion matrix is used to assess a model's precision, recall, specificity, and overall accuracy.

IV. RESULTS AND DISCUSSION

We will now present the experiment's results within the framework of our study. We will discuss the results of the three cases: visible, infrared, and visible/infrared fusion.

A. Case of infrared

TABLE I. TEST ACCURACY OF EACH MODEL IN THE INFRARED

Models	*Accuracy*
SIFT+SVM	0.88
SIFT+Logistic Regression	0.81
SIFT+Random Forest	0.74
SIFT+FREAK+SVM	0.92
SIFT+FREAK+Logistic Regression	**0.93**
SIFT+FREAK+Random Forest	0.88

Table 1 presents the different scores in the infrared of the models used, and the combinations of SIFT and FREAK with SVM and logistic regression algorithms give the best results, with accuracies of 0.93. Combining SIFT with the classification algorithms gives slightly less accurate results, with accuracies between 0.74 and 0.88.

Table 2 presents the value of metrics such as precision, F1 score, MSE, recall, and MCC are all used to evaluate the performance of the methods used in the infrared. These values consolidate the results obtained.

TABLE II. PERFORMANCE METRICS IN THE INFRARED

Methods	*Precision*	*F1 score*	*MSE*	*Recall*	*MCC*
SIFT+SVM	0.9365	0.8846	0.5714	0.8809	0.8745
SIFT+Logistic Regression	0.8265	0.7818	5.0	0.8095	0.7974
SIFT+ Random Forest	0.6900	0.6962	9.5238	0.7380	0.7194
SIFT+FREAK+SVM	0.9373	0.9272	1.7619	0.9285	0.9220
SIFT+FREAK+Logistic Regression	**0.9515**	**0.9223**	**1.5714**	**0.9285**	**0.9238**
SIFT+FREAK+Random Forest	0.9156	0.8845	6.0714	0.8809	0.8721

Table 2 shows performance results for different multispectral face recognition methods using SIFT and FREAK feature descriptors in combination with classification algorithms such as SVM, logistic regression, and Random Forest. Performance

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metrics include precision, F1 score, root mean square error (MSE), recall, and Matthews correlation coefficient (MCC).

The SIFT+SVM method presents the best performance in terms of precision (0.9365), F1 score (0.8846), and recall (0.8809), with a relatively low MSE of 0.5714 and an MCC of 0. ,8745.

The SIFT+FREAK+SVM method also showed remarkable performance with a precision of 0.9373, an F1 score of 0.9272, and an MCC of 0.9220. However, this method has a slightly higher MSE than the SIFT+SVM method, at 1.7619.

Methods using logistic regression and Random Forest generally performed less than SVM methods. The SIFT+Logistic Regression method has the lowest precision (0.8265) and F1 score (0.7818), while the SIFT+FREAK+Random Forest method has the highest MSE (6.0714). Table 8 details each model's ROC curves and confusion matrices in the infrared domain.

B. *Case of visible*

TABLE III. TEST ACCURACY OF EACH MODEL IN THE VISIBLE

Models	*Accuracy*
SIFT+SVM	0.69
SIFT+Logistic Regression	0.76
SIFT+Random Forest	0.55
SIFT+FREAK+SVM	**0.83**
SIFT+FREAK+Logistic Regression	0.81
SIFT+FREAK+Random Forest	0.71

Table 3 presents the different visible scores of the used models and the combinations of SIFT and FREAK with the SVM with a precision of 0.83. The variety of SIFT with Random Forest gets the lowest score, with 0.55.

Table 4 presents the value of metrics such as precision, F1 score, MSE, recall, and MCC are all used to evaluate the performance of the methods used in the infrared. These values consolidate the results obtained.

TABLE IV. PERFORMANCE METRICS IN THE VISIBLE

Methods	*Precision*	*F1 score*	*MSE*	*Recall*	*MCC*
SIFT+SVM	0.7508	0.6791	5.9761	0.6904	0.6731
SIFT+Logistic Regression	0.9171	0.7798	12.0238	0.7619	0.7567
SIFT+ Random Forest	0.7349	0.5553	17.0	0.5476	0.5229
SIFT+FREAK+SVM	**0.8916**	**0.8235**	**5.1428**	**0.8333**	**0.8242**
SIFT+FREAK+Logistic Regression	0.8218	0.7818	5.1190	0.8095	0.8024
SIFT+FREAK+Random Forest	0.7162	0.6857	5.1190	10.14	0.6984

The table provides evaluation measures for different facial recognition algorithms using the SIFT (Scale-Invariant Feature Transform) method in combination with classification algorithms such as SVM, Logistic Regression, and Random Forest. The FREAK (Fast Retina Keypoint) method is also combined with SIFT in some experiments. Assessment measures include precision, F1 score, mean square error (MSE), recall, and Matthews correlation coefficient (MCC).

We observe that the precision varies from 0.7162 to 0.9171 and the F1 score from 0.5553 to 0.8235 for the different methods. The results show that the SIFT+SVM method obtains the highest precision of 0.7508 and the F1 score of 0.6791, while the SIFT+FREAK+Logistic Regression method obtains the highest precision of 0.9171 and the F1 score of 0.7798. Mean squared error (MSE) results range from 5.0 to 17.0, with the lowest obtained by SIFT+FREAK+SVM and the highest by SIFT+Random Forest.

The recall results range from 0.5476 to 0.8333, with the SIFT+FREAK+SVM method obtaining the best result and SIFT+Random Forest the weakest. The Matthews Correlation Coefficient (MCC) ranges from 0.5229 to 0.8242, with the SIFT+FREAK+SVM method getting the best result and SIFT+Random Forest the lowest. Table 9 details each model's ROC curves and confusion matrices in the visible domain.

C. *Case of fusion visible and infrared*

TABLE V. TEST ACCURACY OF EACH MODEL IN FUSION VISIBLE AND INFRARED

Models	*Accuracy*
SIFT+SVM	0.81
SIFT+Logistic Regression	0.76
SIFT+Random Forest	0.74
SIFT+FREAK+SVM	**0.95**
SIFT+FREAK+Logistic Regression	0.86
SIFT+FREAK+Random Forest	0.76

Table 4 presents the different partitions of the fusion of the visible and the infrared of the models used, and it appears that the combinations of SIFT and FREAK with the SVM The combination of SIFT with Random Forest display the most miniature precision with a value of 0.55. Table 10 presents each implemented method's ROC curves and confusion matrix.

Table 5 presents the value of metrics such as precision, F1 score, MSE, recall, and MCC are all used to evaluate the performance of methods used in visible and infrared fusion. These values consolidate the results obtained.

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TABLE VI. METRICS PERFORMANCE IN FUSION VISIBLE AND INFRARED

Methods	*Precision*	*F1 score*	*MSE*	*Recall*	*MCC*
SIFT+SVM	0.8464	0.7864	5.9761	0.8095	0.8004
SIFT+Logistic Regression	0.8809	0.8022	2.5	0.7619	0.7472
SIFT+ Random Forest	0.8111	0.7342	5.9761	0.7380	0.7240
SIFT+FREAK+SVM	**0.9682**	**0.9507**	**0.2380**	**0.9523**	**0.9490**
SIFT+FREAK+Logistic Regression	0.8638	0.8490	5.3571	0.8571	0.8449
SIFT+FREAK+Random Forest	0.8242	0.7513	5.2857	0.7619	0.7465

The table presents the results of different methods used for object recognition using SIFT descriptor and key point detector on an image database. The five metrics used to evaluate the performance of each technique are precision, F1 score, MSE (Mean Squared Error), recall, and Matthew's correlation coefficient (MCC).

The first method presented is SIFT+SVM, which has a precision of 0.8464, an F1 score of 0.7864, an MSE of 5.9761, a recall of 0.8095, and an MCC of 0.8004. The second method is SIFT+Logistic Regression, which has a precision of 0.8809, an F1 score of 0.8022, an MSE of 2.5, a recall of 0.7619, and an MCC of 0.7472. The third method is SIFT+Random Forest, which has a precision of 0.8111, an F1 score of 0.7342, an MSE of 5.9761, a recall of 0.7380, and an MCC of 0.7240.

The last three methods use the SIFT descriptor and the FREAK descriptor. The fourth method is SIFT+FREAK+SVM, which has a precision of 0.9682, an F1 score of 0.9507, an MSE of 0.2380, a recall of 0.9523, and an MCC of 0.9490. The fifth method is SIFT+FREAK+Logistic Regression, which has a precision of 0.8638, an F1 score of 0.8490, an MSE of 5.3571, a recall of 0.8571, and an MCC of 0.8449. The sixth and final method is SIFT+FREAK+Random Forest, which has a precision of 0.8242, an F1 score of 0.7513, an MSE of 5.2857, a recall of 0.7619, and an MCC of 0.7465. Table 8 details each model's ROC curves and confusion matrices in the fusion and infrared domain.

D. Comparison between electromagnetic spectrum

We will compare the different electromagnetic spectra of our study. We will use the best accuracies of each case: the visible, the infrared, and the fusion of the visible and the infrared.

TABLE VII. COMPARISON OF THE DIFFERENT SPECTRA OF OUR STUDY

Spectre	*Methods*	*Accuracy*
Infrarouge	SIFT+FREAK+Logistic Regression	0.93
Visible	SIFT+FREAK+SVM	0.83
Fusion visible Infrarouge	**SIFT+FREAK+SVM**	**0.95**

Table 8 compares the different spectra, and we find that the visible/infrared fusion using the SIFT+FREAK+SVM method achieves the best accuracy in our study.

The table provides accurate results for three image recognition methods using different spectra (infrared, visible, and visible-infrared fusion). The methods are SIFT+FREAK+Logistic Regression for infrared, SIFT+FREAK+SVM for visible, and SIFT+FREAK+SVM for visible-infrared fusion.

The SIFT+FREAK+Logistic Regression method on infrared images has the best accuracy with 0.93, followed by the SIFT+FREAK+SVM method on visible-infrared fused images with 0.95. The SIFT+FREAK+SVM method on visible images has a lower accuracy than the other two methods, with 0.83.

These results suggest that merging visible and infrared images can improve facial recognition performance compared to using a single spectrum. The SIFT+FREAK+SVM method is efficient for visible/infrared fusion, while the SIFT+FREAK+Logistic Regression method is more efficient for infrared images.

V. DISCUSSION

In our study, we can note the following three points:

These are the performance results of a model for face recognition using image processing techniques. SIFT and FREAK are visual landmark detection algorithms that extract features from an image. SVM, Random Forest, and Logistic Regression are algorithms used to perform face recognition based on their extracted features.

First, for infrared, the results indicate that using SIFT alone with SVM gave an accuracy rate of 0.88 while using SIFT with logistic regression gave an accuracy rate of 0 81. Using SIFT with random forest gave an accuracy rate of 0.74. In this first phase, the SVM obtained the best precision than the others. Using SIFT and FREAK together with SVM gave an accuracy rate of 0.92. Using SIFT and FREAK together with logistic regression yielded an accuracy rate of 0.93, while using SIFT and FREAK together with random forest paid an accuracy rate of 0.88. In this second phase, the logistic regression obtains the best precision of the other models, and in general, the couple SIFT + FREAK + Logistic Regression obtains the best precision in the infrared spectrum and our study of the figure 2 of the precision histograms of the different methods.

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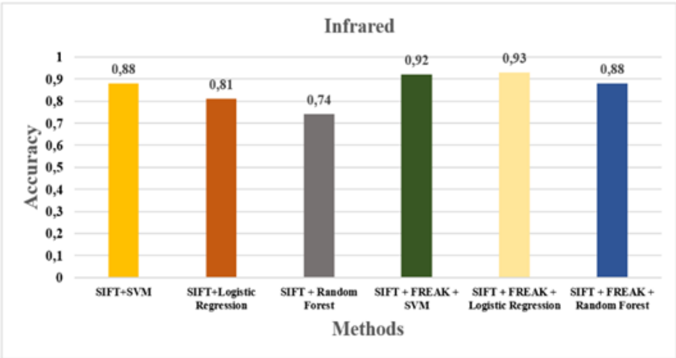

Figure 2. Histogram of the accuracies of each infrared method

Then concerning the visible, the results indicate that using SIFT alone with SVM gave an accuracy rate of 0.69 while using SIFT with logistic regression gave an accuracy rate of 0.76. Using SIFT with random forest gave an accuracy rate of 0.55. In this first phase, the logistic regression obtains the best precision than the others.

Using SIFT and FREAK together with SVM gave an accuracy rate of 0.83. Using SIFT and FREAK together with logistic regression yielded an accuracy rate of 0.81, while using SIFT and FREAK together with random forest paid an accuracy rate of 0.71. In this second phase, the SVM obtains the best accuracy of the other models, and in general, the SIFT+ FREAK SVM pair obtains the best accuracy in the visible spectrum; it should be noted that the methods are less effective in the visible spectrum. The figure 3 of the precision histograms of the different techniques.

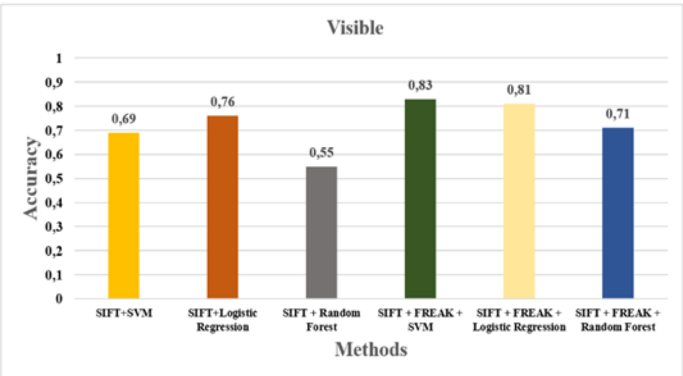

Figure 3. Histogram of the accuracies of each visible method

Finally, for the visible and infrared merging cases, the results indicate that using SIFT alone with SVM gave an accuracy rate of 0.81. In contrast, using SIFT with logistic regression gave an accuracy rate 0.76. Using SIFT with random forest gave an accuracy rate of 0.55. In this part, the SVM obtained the best precision than the others.

Using SIFT and FREAK together with SVM gave an accuracy rate of 0.95. Using SIFT and FREAK together with logistic regression yielded an accuracy rate of 0.86, while using SIFT and FREAK together with random forest paid an accuracy rate of 0.76. In this second phase, the SVM is always above the other models, and in general, the couple SIFT + FREAK + SVM obtains the best precision in the spectrum of the fusion of the visible and the infrared in our study. The figure 4 of the precision histograms of the different methods in the fusion of the visible and the infrared.

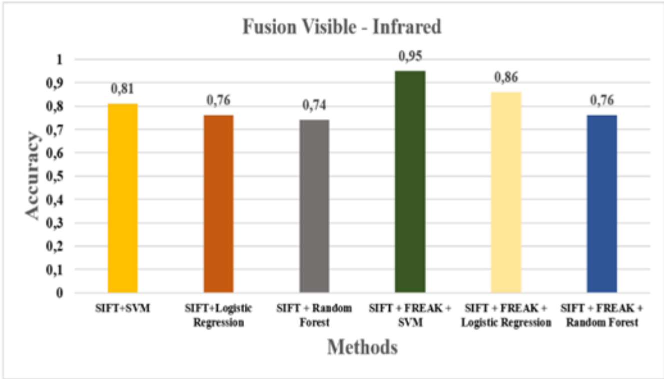

Figure 4. Histogram of the accuracies of each visible-infrared fusion method

However, it is essential to note that these results may vary depending on many factors, including the quality and diversity of the training data, the hyperparameters used for each algorithm, and the validation method used.

VI. CONCLUSION

Overall, this work shows that multispectral facial recognition effectively addresses security and identification challenges in uncontrolled environments. Combining SIFT and FREAK feature extraction tools with classification algorithms such as SVM, logistic regression, and Random forest has yielded powerful results. The fusion of visible and infrared images made maximizing each spectrum's advantages possible while minimizing their disadvantages. The results showed that the proposed multispectral facial recognition method performed better than traditional methods, reaching a facial recognition score ranging from 76% to 95% in the IRIS database. This opens many prospects for applying this technology in various fields, such as security, identification of people, surveillance, etc.

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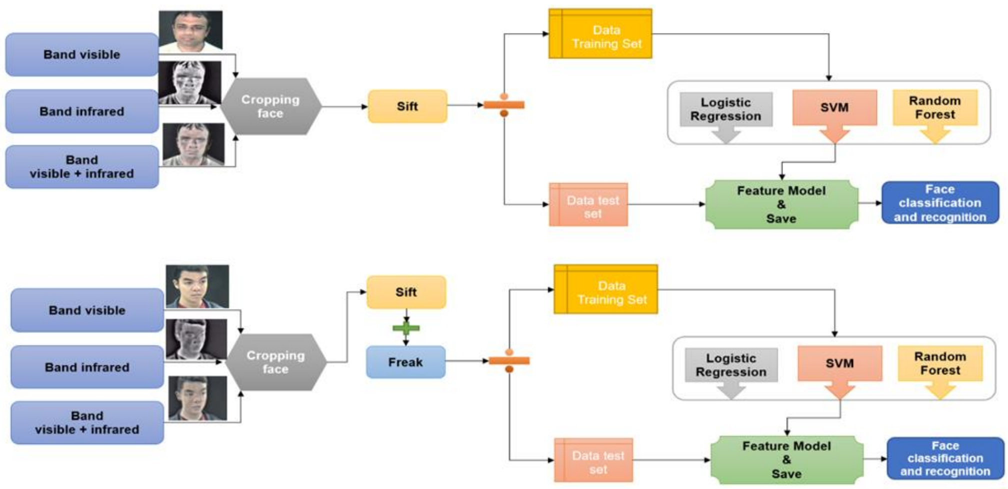

Figure 5. Summary diagram of our methodology

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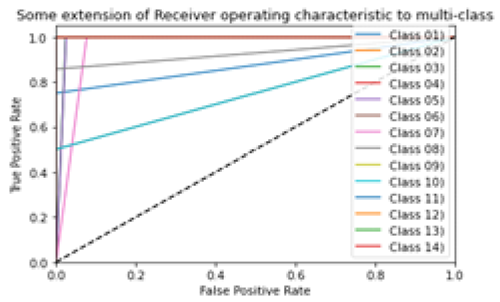
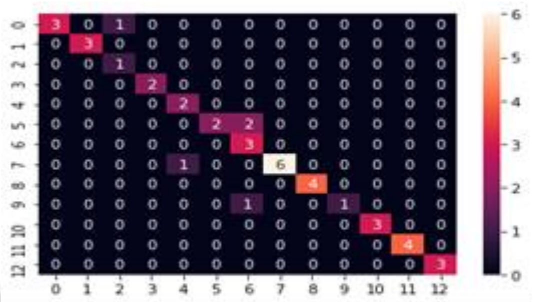
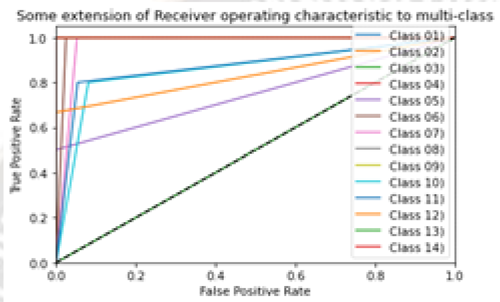
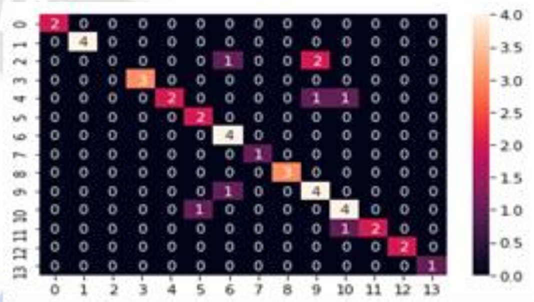
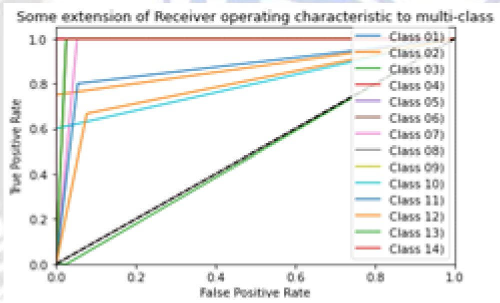
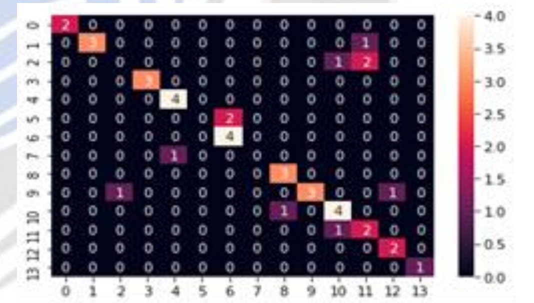
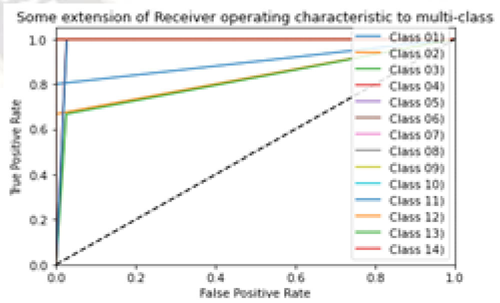
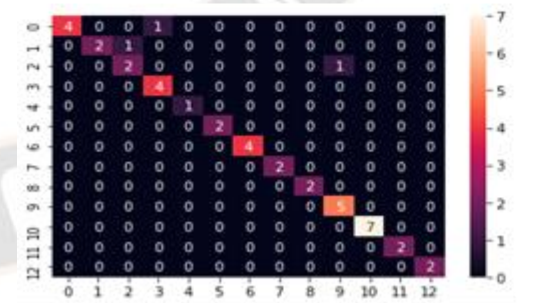
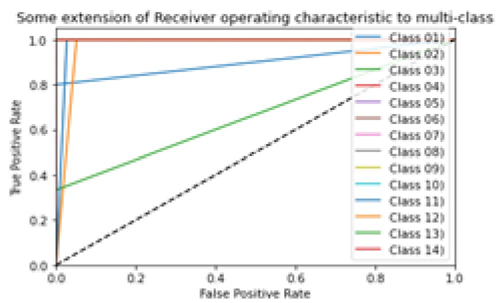
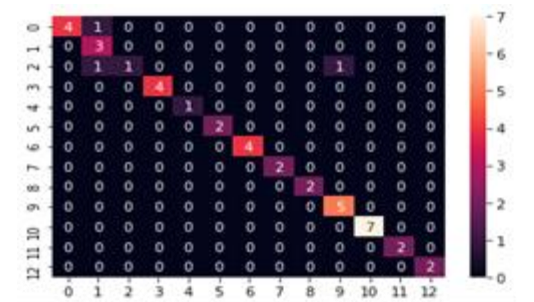
Roc Curve And Confusion Matrix Of Each Model in infrared

Models	**ROC curve**	**Confusion Matrix**
SIFT+SVM		
SIFT+Logistic Regression		
SIFT+ Random Forest		
SIFT+FREAK+SVM		
SIFT+FREAK+ Logistic Regression		

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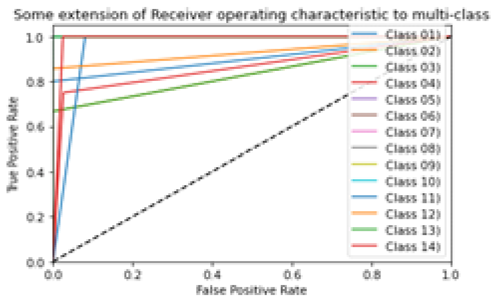
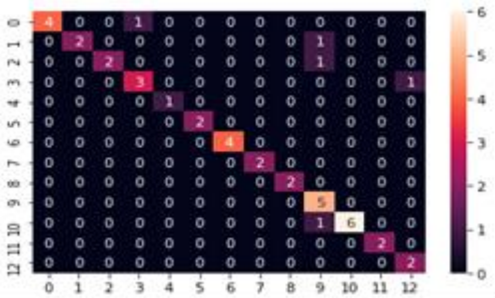
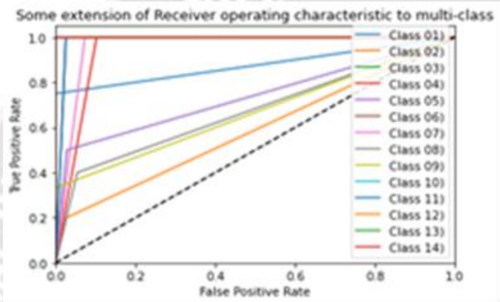
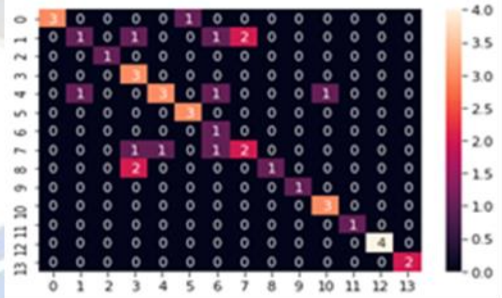
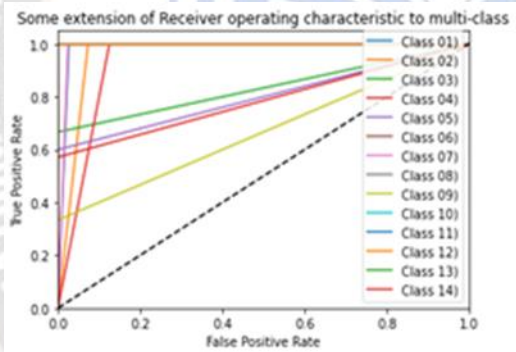
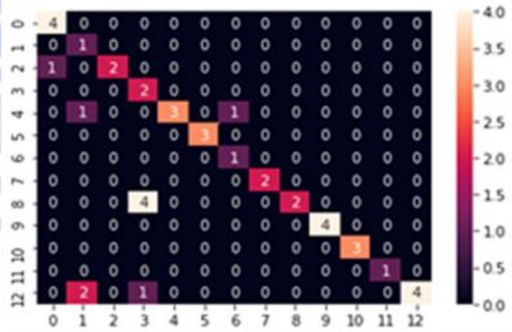
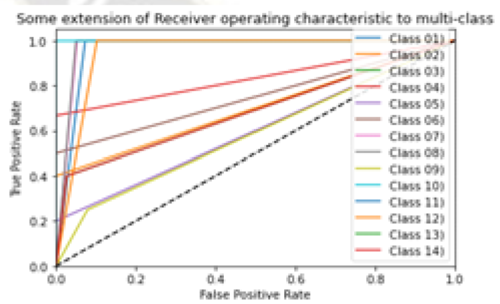
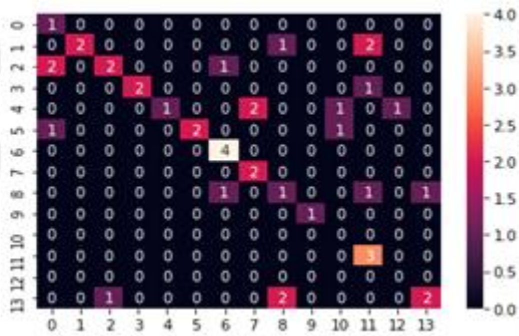
SIFT+FREAK+ Random Forest		

TABLE VIII. ROC CURVE AND CONFUSION MATRIX OF EACH MODEL IN VSIBLE

Models	**ROC curve**	**Confusion Matrix**
SIFT+SVM		
SIFT+Logistic Regression		
SIFT+Random Forest		

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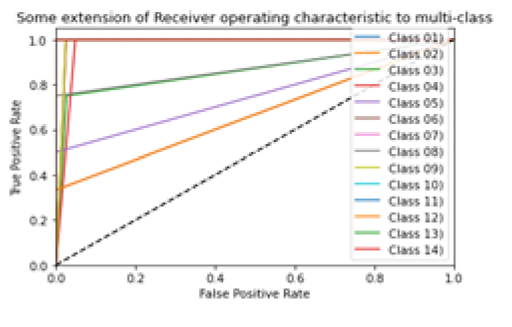
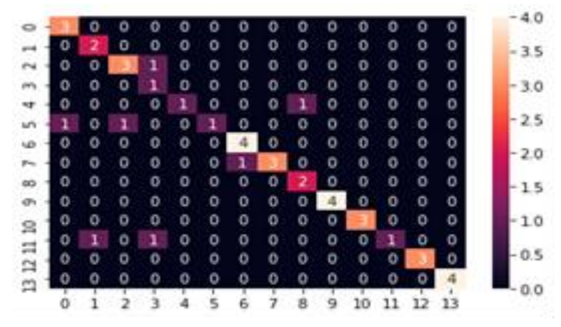
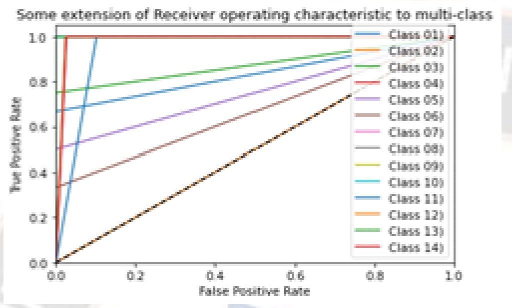
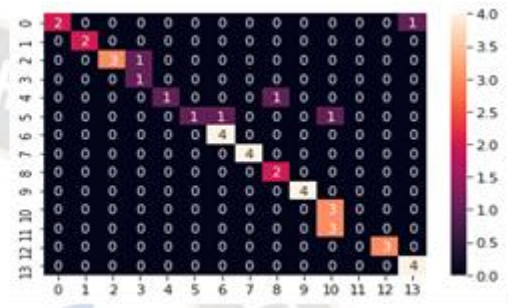
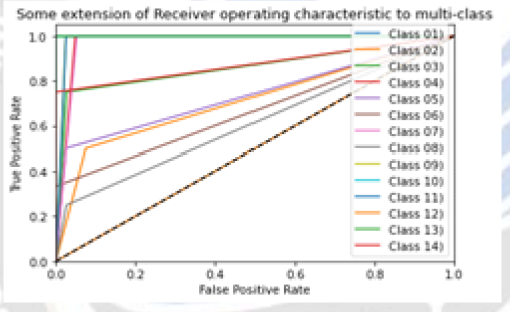
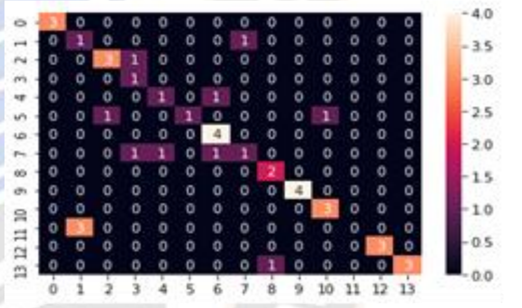
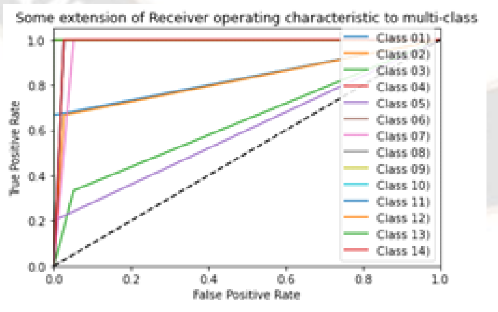
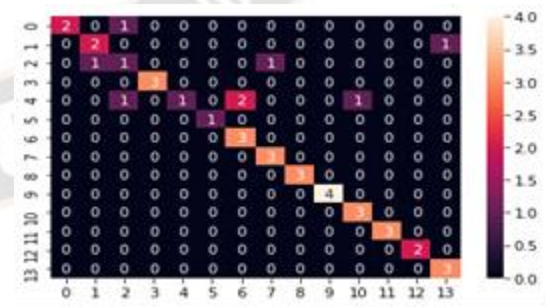
SIFT+ FREAK+ SVM		
SIFT+FREAK+Logistic Regression		
SIFT+FREAK+Random Forest		

TABLE IX. ROC CURVE AND CONFUSION MATRIX OF EACH MODEL IN FUSION VISIBLE AND INFRARED

Models	**ROC curve**	**Confusion Matrix**
SIFT+SVM		

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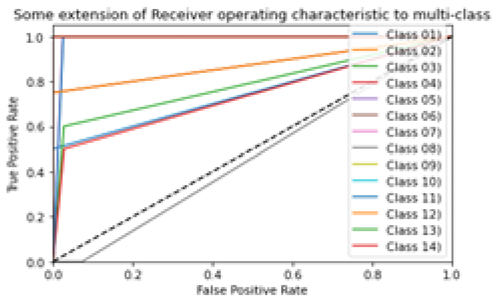
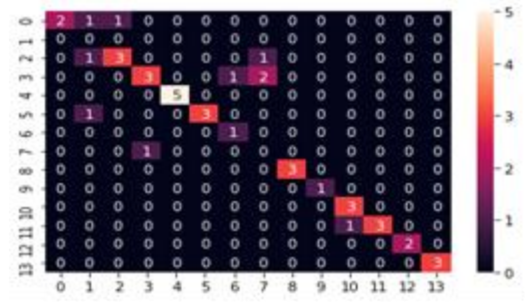
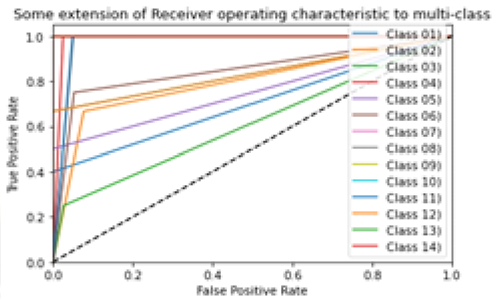
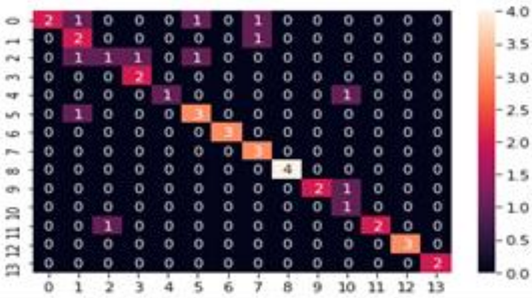
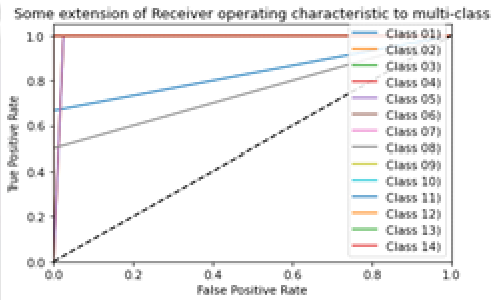
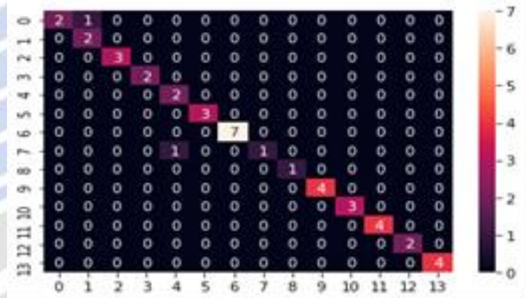
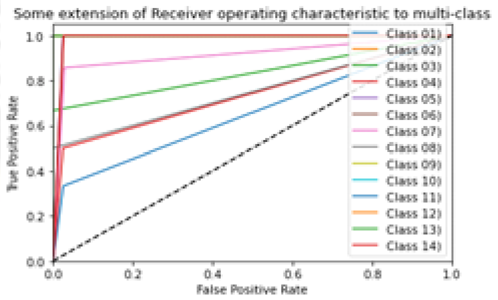
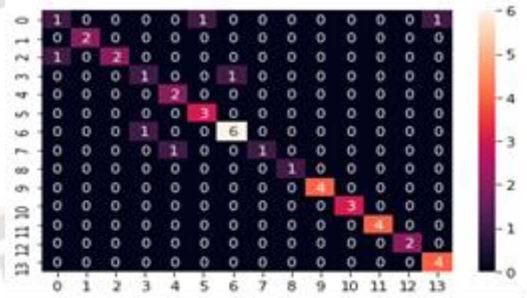
SIFT+Logistic Regression		
SIFT+Random Forest		
SIFT+FREAK+SVM		
SIFT+FREAK+Logistic Regression		
SIFT+FREAK+Random Forest