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ENHANCING SIGNATURE RECOGNITION PERFORMANCE THROUGH CONVOLUTIONAL NEURAL NETWORK AND K-NEAREST NEIGHBORS

O. El Melhaoui [1] S. Benchaou [2] R. Zarrouk [3] A. Bouzidi [1]

1. Research Center, High Studies of Engineering School, EHEI, Oujda, Morocco - Laboratory of LETSER, Faculty of Sciences, Mohammed I University, Oujda, Morocco, wafa19819@gmail.com, afaf.bouzidi9@gmail.com
2. Laboratory of MATSI, Faculty of Sciences, Mohammed I University, Oujda, Morocco, soukaina.benchaou@gmail.com
3. Laboratory of Electronics and System, Faculty of Sciences, Mohammed I University, Oujda, Morocco zarroukredouan1@gmail.com

Abstract- The current study presents an offline signature identification system which uses machine learning algorithm. The proposed system consists of four fundamental operations; data acquisition, preprocessing, feature extraction and classification. Initially, various image preprocessing algorithms are employed to segregate signature pixels from the background or noise pixels. The convolutional neural network (CNN) is applied as feature extraction method with careful consideration of appropriate parameter selection. The determined attributes are collected in a vector and used to feed K nearest neighbors (KNN) instead multilayer perceptron (MLP). In this context a thorough studies of numerous distance metrics are carried out, and the Manhattan distance was found to be robust in distinguishing between signatures. To evaluate the proposed system, three models containing the most widely used techniques, including convolutional neural network (CNN), profile projection-kNN, and loci characteristics-KNN, are compared. The best result is achieved with the proposed system.

Keywords: Machine learning, CNN, KNN, MLP

1. INTRODUCTION

Signature recognition is a biometric security that involves the automated verification and authentication of an individual's signature to establish their identity. The signature recognition task is typically used in areas such as banking, legal documents, and government identification [1] to ensure that the signature is genuine and has not been forged. Signature recognition can also be used for other purposes such as biometric identification, document verification, and fraud detection [2].

Signature recognition technology employs various techniques, such as image processing, machine learning, and artificial intelligence, to capture and analyze the signature's unique characteristics. The use of these advanced algorithms and technologies is driving its development and deployment in various industries. Within the signature recognition task; there are two main methodologies:

The first methodology is commonly known as dynamic signature recognition. This method involves capturing the dynamic features of a signature, such as the speed, pressure, and direction of the strokes made by the signer [17]. Dynamic signature recognition systems require a signature to be captured in real-time using a digital tablet or similar device [1]. The system then analyzes the captured data to extract the relevant features and build a model of the signer's signature.

The second methodology is known as offline signature recognition. This method involves capturing a signature as a two-dimensional image and then analyzing it to extract features such as the shape and size of the letters, the angles between the strokes, and the overall layout of the signature. In summary, both online and offline signature recognition methods have their own strengths and weaknesses, and the choice of method depends on the particular application and level of security required.

Many techniques are used for offline signature recognition problem. In [1] a system for identifying a subject's signature utilized the spatial distribution of signature, along with two measures of Euclidean distance that have been normalized. In [15] the invariant moments take place and are used as features to feed a fuzzy Kohonen clustering network. A new system was proposed also in [8], it used the wavelet average framing entropy as features and a neural network as classifier. With the same classifier, geometric features are used in [11]. Several studies have employed the Hough transform as a feature extraction method due to its high efficiency [10, 9, 2]. However, when it comes to classification, some studies have utilized artificial neural networks [10,7], while others have employed support vector machines [9].

The target of this study is to build a system for recognizing offline handwritten signature by utilizing features obtained from a convolutional neural network (CNN), with careful consideration of appropriate parameter selection. The resulting features are then used to feed a K-nearest neighbors (KNN) classifier. The study includes an assessment of various distance metrics to identify the most efficient metric for accurate signature recognition.

This work is organized as follows; proposed methodology is outlined in section 1, including preprocessing, feature extraction and classification. In section 2, a thorough investigation was carried out during the feature extraction phase to determine which parameters may have an effect on the performance of recognition system. Likewise, during the classification stage, comprehensive research was conducted to assess the impacts of different distance metrics, subsequently, a comparative analysis is conducted. At last, concluding remarks are given.

2. PROPOSED METHODOLOGY

The framework for signature recognition is divided into four main parts: data acquisition, preprocessing, feature extraction, and classification [14]. This structure is illustrated in Figure 1.

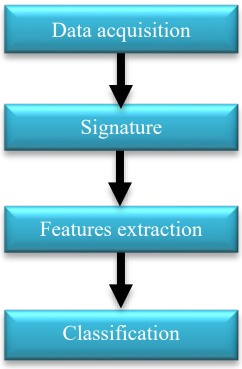

Figure 1. Different operations of proposed system [14]

2.1. Data Acquisition

In this paper, we have used a database formed of 240 signatures [2]. Signatures were collected from a total of 12 individuals, with 20 signatures collected from each individual. To train the system, a subset of 120 signatures was selected, while the remaining signatures were employed for testing. The sample of signature images is shown in Figure 2.

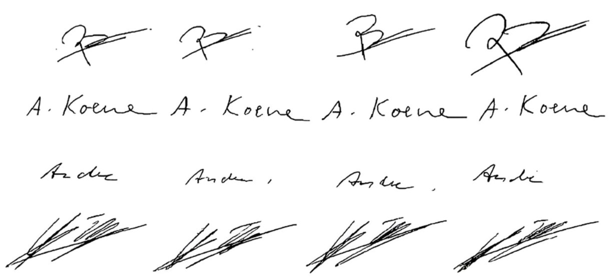

Figure 2. A sample of signature images [2]

2.2. Signature Preprocessing

Preprocessing is the primary stage for pattern recognition, to ensure scale and translation invariance and remove the noise such as isolated pixels and blurred images [2]. Thus, it is important to perform preprocessing processes to enhance both the effectiveness and the performance of signature recognition.

The different steps of preprocessing phase include binarization, cropping and normalization, which are identical to that mentioned in [2, 3]. These processes are explained as:

Binarization is the procedure of transforming a color image into a binary form (black and white) by applying a global threshold to the whole image. If a pixel's value exceeds the threshold, it is assigned a value of one, otherwise, it is assigned a value of zero [14].

Cropping consists of preserving the interest area from the background image. Normalization consists of applying a transformation to the cropped signature image to adjust its size to the predefined dimensions.

2.3. Feature Extraction

Feature extraction is the main motivation behind the improvement of an offline signature recognition system. In order to distinguish individuals from others, it is necessary to extract the most relevant characteristics that define their unique pattern. These features are then flattened into a feature vector. In this research a deep learning algorithm was used. A CNN is a powerful deep learning technique that has proven to be highly effective performer in numerous computer vision applications [10, 11]. The CNN training process for image recognition involves a multiple operations including convolution, activation function, padding, pooling, flattening. These operations are performed iteratively and mentioned in Figure 3.

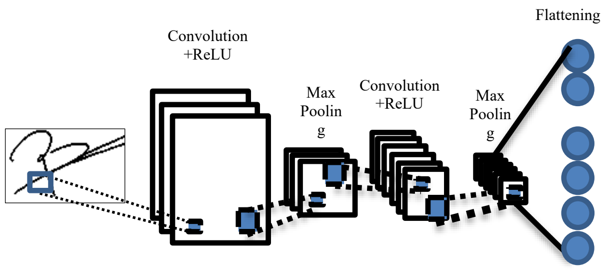

Figure 3. Different operations of CNN [18]

The convolution process involves by shifting the convolution filter K over the image with a particular stride. At each position the elements of the convolution filter and the corresponding image are multiplied, the resulting products are summed up. The basic convolution process is presented in Figure 4, basic formulation of the convolution operation has been given in Equation (1) [19].

$$y_n = \sum_{i=1}^{9} x_i w_i \tag{1}$$

where, y, x and w are respectively pixels of the output image, the input image and the filter.

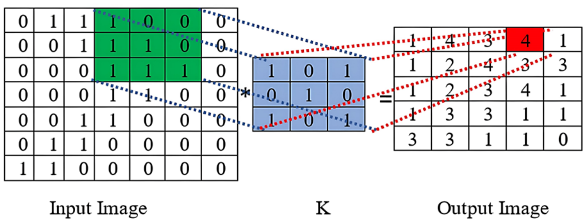

Figure 4. The convolution operation [9]

Then, the nonlinear activation function ReLU is applied, it consists of discarding the negative values and replace them by zero. The main operation ReLU was depicted in Equation (2) [19].

$$\mathrm{ReLU}(x) = \begin{cases} 0 & \text{if } x < 0 \\ 1 & \text{if } x > 0 \end{cases} \quad (2)$$

The next step includes a padding procedure, it consists of appending p zeros on each side of the boundaries of the image portion. The pooling is the last step in the convolutional process, it responsible for reducing the spatial size of the convolved feature [12]. It consists of sweeping the filter across the entire input and choosing the maximum pixel value to be sent to the output array. The mathematical expression for the max filter function is represented in Equation (3) [19].

$$f(x, y) = \max_{x,y}(image(i, j)) \quad (3)$$

After the final convolution, padding and pooling process, the resulting features are flattened into a vector, which is then fed into a K-nearest neighbors instead multilayer perceptron which takes almost hours to train, even with a small number of signature data.

2.4. Classification Method

In order to determine the rightful owner of an unknown signature image, the feature vector obtained from convolutional neural network operations including convolution, ReLU, padding and pooling is utilized as input for the KNN classifier rather than an MLP.

The KNN is a type of machine learning algorithm, commonly used in data analytics, visual computing, information analysis [4]. The KNN algorithm works by calculating the distance between a test data and the various learning data samples [16], and then using this information to envisage the label of an unlabeled pattern as mentioned in Algorithm 1.

Algorithm 1. The KNN algorithm

<u>Input</u>
X: a matrix containing the training data features.
x_test: a vector containing the features of the test observation
K: the number of neighbors to consider

<u>Output</u>
x_pred: the predicted class label for the x_test

- For each observation in X, calculate the distance between that observation and x_test using a distance metric
- Select the K nearest neighbors from X matrix which have the lower distance with x_test
- Determine the majority class label among the K neighbors
- Assign this class label x_pred to x_test

The KNN is very simple and strongly depends on two parameters which are the value of K and the distance metric between the test object and the various training objects [14]. The K is a hyperparameter that need to be set previously, the choice of K can significantly affect the performance of the algorithm.

The distance metric is a key metric in many machine learning algorithms, it characterized as a quantitative measure of the distance between two objects [4]. A good distance metric helps to improve the accuracy of the model developed and also provides correct predictions, the most commonly used metric is the Euclidian distance [3,4]. Our study included a presentation of a survey and an analysis of the performance of various distance metrics and how do they contribute to the machine learning model. The distance metrics are; Euclidian [5], Manhattan [6], Minkowski which include an exponent p in its formula, he combines both Manhattan ($p = 1$) and Euclidean ($p = 2$) distances [4].

When p goes to positive infinity, the Chebyshev distance is gotten [4]. These four-distance metrics, Euclidean, Manhattan, Minkowski, and Chebyshev, are the most commonly used in many studies [4]. Another's version of distance metrics is used called Canberra distance [7], Normalized Mean Absolute Differences, Normalized Mean Square Differences [1], Cosine's distance and finally, Rodrigues distance [4] which is a mixture of Minkowski and Chebyshev distances. The formulas of different distance metrics between $A = (x_1, x_2, x_3, ...x_n)$ and $B = (y_1, y_2, y_3, ...y_n)$ vectors are given in Table 1 [4].

Table 1. The formulas of different distance metrics [1, 4]

distance Metrics	Formulas
Euclidian distance	$d_1 = \sqrt{\sum (x_i - y_i)^2}$
Manhattan distance	$d_2 = \sum \lvert (x_i - y_i) \rvert$
Minkowski distance	$d_3 = \sqrt[p]{\sum (x_i - y_i)^p}$
Chebyshev distance	$d_4 = \max_{i=1:n} \lvert (x_i - y_i) \rvert$
Canberra distance	$d_5 = \sum \frac{\lvert (x_i - y_i) \rvert}{\lvert x_i \rvert + \lvert y_i \rvert}$
Cosine's distance	$d_6 = \frac{\sum x_i \times y_i}{\lvert x_i^2 \rvert \times \lvert y_i^2 \rvert}$
Normalized Mean Absolute Differences	$d_7 = \frac{\sum \lvert (x_i - y_i) \rvert}{\sum x_i}$
Normalized Mean Square Differences	$d_8 = \frac{\sum (x_i - y_i)^2}{\sum x_i^2}$ $\frac{\sum (x_i - y_i)^2}{\sum x_i^2}$
Rodrigues distance	$d_9 = d_3 + d_4$

3. EXPERIMENTAL RESULTS AND COMPARATIVE STUDY

We employed a database of 240 signatures from diverse signers to validate our contributions in the experiments. The database was partitioned into two groups, where one is utilized for the training stage and the other for the testing stage. A subset of the database is illustrated in Figure 2.

A thorough investigations were carried out during the feature extraction phase to determine which parameters may have an effect on the performance of recognition system. Likewise, during the classification stage, a detailed experimentation was conducted to assess the impact of different distance metrics on the recognition rate.

For the features extraction phase; the CNN depends strongly on a number of user-defined hyper-parameters, which can have a notable effect on the result of the convolution operation and the accuracy of recognition system, that need to be set before the classification begins. These include: number of convolution filters and choice of stride value. In this case, multiple experiments were conducted to determine these numbers that obtain the best performance of the system.

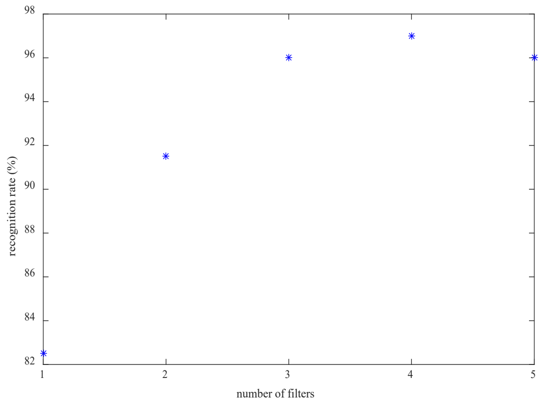

Figure 5. The impact of convolution filter number on the recognition rate

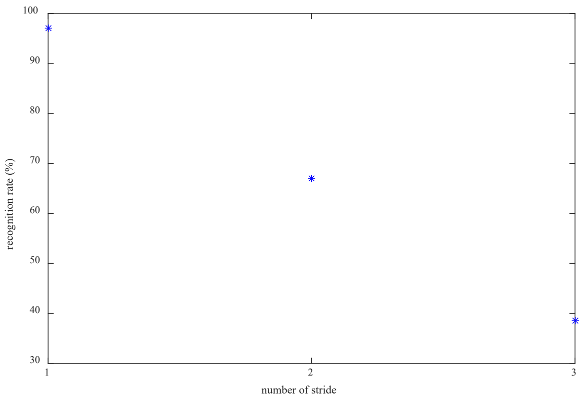

Figure 6. The impact of stride value on the recognition rate

In Figures 5 and 6, it is observed that the utilization of an ideal filter number of 4 and a stride value of 1 give a high recognition rate.

Another hyperparameter that needs to be tuned, is the number of zero padding p. Several experiments were conducted to determine the optimal value for p as mentioned in Figure 7.

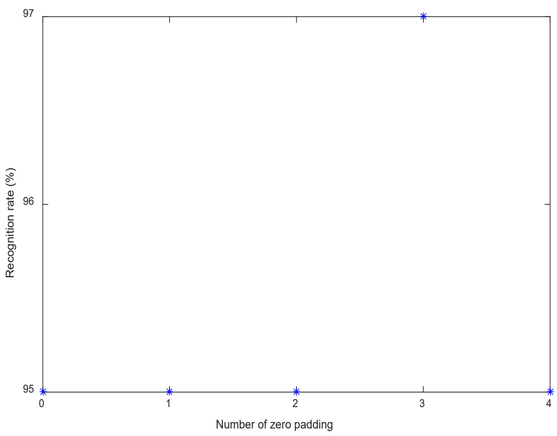

Figure 7. The impact of zero padding number on the recognition rate

According to Figure 7, incorporating 3 additional rows of pixels with zero values on each side of the image results a higher recognition rate.

After the feature extraction process, our major goal is to provide an adequate metric distance that is especially effective to classify the unknown signature. In this case, an evaluation of the performance of the previously discussed distances is conducted. By varying the parameter K between 1 and 7, the recognition rate (RR) is determined in Table 2. The recognition rate RR is calculated using Equation (4) [21].

$$RR = \frac{\text{number of correct predictions}}{\text{total number of examples}} \times 100 \quad (4)$$

Table 2. Different RR obtained by different distance metrics

Distance Metrics	K=1	K=3	K=5	K=7
Euclidian Distance	95%	84.16%	80.33%	72.5%
Manhattan distance	**96.67%**	85%	83.3%	75.83%
Chebyshev distance	66.67%	37.5%	27.5%	20.83%
Minkowski distance (p=0.5)	95.83%	86.67%	80%	75.83%
Minkowski distance (p=0.75)	**96.67%**	85%	83.3%	75.83%
Minkowski distance (p=3)	94.16%	84.16%	78.33%	69.16%
Canberra distance	8.3%	8.3%	8.3%	8.3%
Cosine's distance	95.83%	86.67%	79.16 %	70%
Normalized mean absolute differences	94.16%	86.67 %	81.67%	75.83%
Normalized mean square differences	94.16%	85.83	76.67%	69.16%
Rodrigues distance (p=0.5)	95.83 %	86.67 %	80 %	75.83%
Rodrigues distance (p=0.75)	95.83%	86.67%	82.5%	75.83%
Rodrigues distance (p=1)	**96.67%**	85%	83.3%	75.83%
Rodrigues distance (p=2)	94.16%	84.16%	80.83%	71.66%
Rodrigues distance (p=3)	91.67%	79.16%	70.83%	60.83%

From this table we notice that the highest recognition rates are obtained with K=1 and we also observe that the most efficient metric distances for achieving high recognition rates are the Manhattan distance and Minkowski distance with p=0.75. These two metrics yield a recognition rate of 96.67%, which is higher than the rates achieved by other metric distances.

The second test, multiple simulations were conducted to determine the correlation between the recognition rate and the size normalization of the signature, using Manhattan distance as metric distance as shown in Table 3 and Figure 8.

The data presented in the table 3 and figure 8 suggests that recognition rates are strongly influenced by size normalization, and the optimal recognition rate is achieved when using a size of 102×80. If an image is resized beyond this size, it may result in a decrease in image quality and loss of information, as mentioned in reference [3].

Table 4 compares the results obtained by our recognition system and others methods using the size normalization 102×80.

Table 3. The influence of signature size normalization on *RR*

Size normalization	*RR* (%)	Misclassified signatures
100×40	94.16%	7
100×60	94.16%	7
100×80	95.83%	5
100×100	95%	6
...	...	...
101×80	95%	6
102×80	**96.67%**	4
104×80	95.83%	5
110×80	95%	6
120×80	94.16%	7

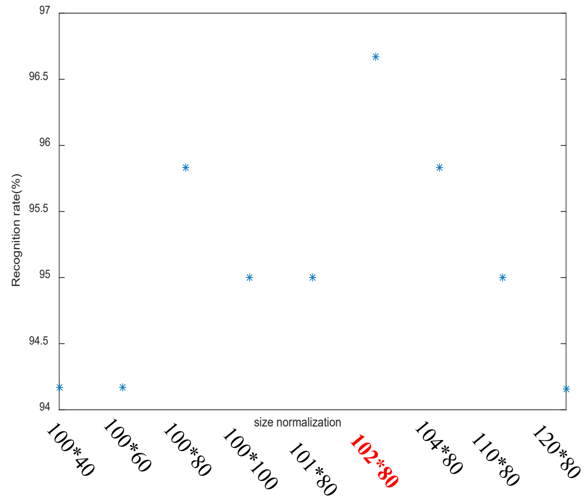

Figure 8. The impact of size normalization on the recognition rate

The first system employs profile projection for feature extraction, wherein the number of background pixels is computed between each image edge and the first foreground pixel encountered on the corresponding row or column as depicted in Figure 9 [2].

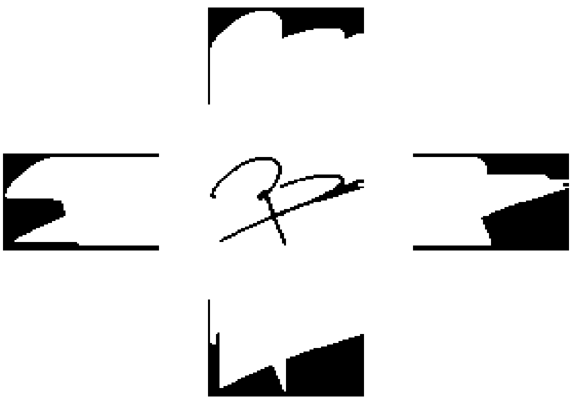

Figure 9. The four profile projections of the signature image [20]

The second approach utilizes Loci characteristics for feature extraction, wherein the number of transitions in both the horizontal and vertical directions is computed for each background pixel, in all four directions as presented in Figure 10 [2].

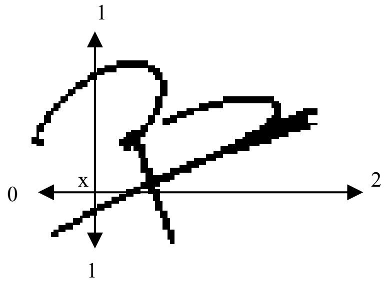

Figure 10. The code of x pixel is (1,0,1,2) [14]

Both of the systems offer internal and profile details about the image. However, they prioritize the use of convolutional operations for features extraction.

The third model; convolutional neural network (CNN) uses convolution operation for extracting features and MLP for classification, this model is designed to prioritize KNN than multilayer perceptron for classification.

Table 4. The *RR* obtained by different techniques

Recognition system	*RR* (%)
Loci characteristics + KNN	93%
Profile projection +KNN	78.5%
CNN	78%
Proposed system: CNN+KNN	**96.67%**

Table 4 notices that the better recognition rate (*RR*) is achieved by our recognition system, the other systems have a lower recognition rate.

The CNN-KNN model considers the resilience of both feature extraction and classification techniques. In one hand, the convolution ReLU+ padding+ Pooling operations used for features extraction, with the adequate choice of parameters, take into account local details that provide additional information to the attribute vector [2]. On the other hand, the classifier KNN uses a simple architecture and an adequate metric distance which provides an efficient recognition rate.

The use of the traditional CNN is restrained by the use of MLP, which takes almost hours to train, even with a small number of signature data.

Overall, careful consideration of parameter selection for feature extraction and choice of metric distances for classification notably enhance the performance of recognition system.

4. CONCLUSION

This study introduces a novel signature recognition system that emphasizes the effectiveness of combining a convolutional neural network (CNN) for feature extraction and K nearest neighbors (KNN) for classification.

The system passes through a several processes; in the preprocessing stage, the color images are binarized, cropped and normalized to prepare them for further analysis. Then a CNN is applied to these preprocessed images, the resulting features are flattened into a vector, which are fed into a KNN instead of using multilayer perceptron.

During the feature extraction phase, a detailed analysis and experimentation were conducted to explore the impact of various factors on the recognition system performance, such as the number of convolution filters, the choice of stride value, and the number of zero padding.

Similarly, in the classification stage, an extensive experimentation was carried out to evaluate the influence of different distance metrics on the recognition rate.

The results of the study revealed that using the Manhattan metric as a similarity criterion leads to a significant improvement in performance. It is also noted that careful parameter selection for feature extraction plays a crucial role in achieving better results.

To evaluate the effectiveness of the proposed system, a comparative analysis was conducted with three commonly used models: CNN, profile projection-KNN, and loci characteristics-KNN.

The first model, CNN, is commonly used for feature extraction and classification. In this study, the proposed system prioritizes the KNN algorithm instead the multilayer perceptron for classification. The second and third models, profile projection-KNN and loci characteristics-KNN, are used to prioritize the convolution and pooling operations for feature extraction.

The results of the comparative analysis demonstrate that the proposed system outperforms the other models, achieving the best recognition rate which is 96.67%. These results emphasize the superiority of the proposed approach for signature recognition.

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BIOGRAPHIES

Name: **Ouafae**
Surname: **El Melhaoui**
Birthday: 14.01.1981
Birthplace: Oujda, Morocco
Bachelor: Electronics, Physics, Faculty of Science, University of Mohamed I, Oujda, Morocco, 2004
Master: Physics and Technology of Microelectronic Devices and Sensors, Faculty of Science, University of Cadi Ayyad, Marrakech, Morocco, 2006
Doctorate: Classification of Data with New Signal Processing Techniques, Concept and Applications, Physics, Faculty of Science, University of Mohamed I, Oujda, Morocco, 2013
The Last Scientific Position: Assoc. Researcher and Part-Time Teacher, FSO, ENSAO, ESTO, University of Mohamed I, Oujda, Morocco, Since 2018
Research Interests: Image Analysis, Pattern Recognition, Computer Vision
Scientific Publications: 17 Papers, 16 Communications, 1 Thesis
Scientific Memberships: Research Center, High Studies of Engineering School, EHEI, Oujda, Morocco - LETSER Laboratory, Faculty of Sciences, Mohammed First University, Oujda, Morocco

Name: **Soukaina**
Surname: **Benchaou**
Birthday: 28.11.1989
Birthplace: Oujda, Morocco
Bachelor: Computer Engineering, Faculty of Sciences and Techniques, University of Sidi Mohamed Ben Abdellah, Fes, Morocco, 2010
Master: Intelligent Systems and Networks, Computer Engineering, Faculty of Sciences and Techniques, University of Sidi Mohamed Ben Abdellah, Fes, Morocco, 2012
Doctorate: Computer Science, Contributions to Character Recognition Using Statistical, Structural and Evolutionary Approaches, Faculty of Science, University of Mohamed I, Oujda, Morocco 2018
Research Interests: Image Analysis, Pattern Recognition, Computer Vision
Scientific Publications: 14 Papers, 10 Communications, 1 Thesis

Name: **Redouan**
Surname: **Zarrouk**
Birthday: 13.05.1986
Birth Place: Targuist, Morocco
Bachelor 1: Physics and Electronics, Department of Physics, Faculty of Sciences, University of Mohamed I, Oujda, Morocco, 2008
Bachelor 2: Applied Electronics, Department of Electronics and Systems, Faculty of Sciences, University of Mohamed I, Oujda, Morocco, 2012
Master: Electronics and Applied Computer Science, Department of Electronics and Systems, Faculty of Sciences, University of Mohamed I, Oujda, Morocco, 2014
Doctorate: Electronic and Signal Processing, Department of Electronics and Systems, Faculty of Sciences, University of Mohamed I, Oujda, Morocco, 2020
The Last Scientific Position: Assoc. Researcher and Part-Time Teacher, FSO, ENSAO, ESTO, University of Mohamed I, Oujda, Morocco, Since 2018
Research Interests: Maintenance of Complex Industrial Facilities through Vibration Analysis, Artificial Intelligence
Scientific Publications: 3 Papers, 7 Communications, 1 Thesis
Scientific Memberships: Laboratory Electronic and System (LES), Faculty of Sciences, University Mohamed I, Oujda, Morocco

Name: **Afaf**
Surname: **Bouzidi**
Birthday: 29.07.1985
Birthplace: Oujda, Morocco
Bachelor: Electronics, Physics, Faculty of Science, University of Mohamed I, Oujda, Morocco, 2004
Master: Electronics and Applied Computer Science, Physics, Faculty of Science, University of Mohamed I, Oujda, Morocco, 2006
Doctorate: Sensors and Biosensors Based on 1D, Physics, Faculty of Science, University of Mohamed I, Oujda, Morocco, 2017
Research Interests: Functional Materials, Photonics, Sensors and Biosensors Based on 1D
Scientific Publications: 17 Papers, 16 Communications, 1 Thesis
Scientific Memberships: Research Center, High Studies of Engineering School, EHEI, Oujda, Morocco