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# Efficient feature descriptor selection for improved Arabic handwritten words recognition

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**ABSTRACT**

Arabic handwritten text recognition has long been a difficult subject, owing to the similarity of its characters and the wide range of writing styles. However, due to the intricacy of Arabic handwriting morphology, solving the challenge of cursive handwriting recognition remains difficult. In this paper, we propose a new efficient based image processing approach that combines three image descriptors for the feature extraction phase. To prepare the training and testing datasets, we applied a series of preprocessing techniques to 100 classes selected from the handwritten Arabic database of the *Institut Für Nachrichtentechnik/Ecole Nationale d'Ingénieurs de Tunis* (IFN/ENIT). Then, we trained the k-nearest neighbor's algorithm (k-NN) algorithm to generate the best model for each feature extraction descriptor. The best k-NN model, according to common performance evaluation metrics, is used to classify Arabic handwritten images according to their classes. Based on the performance evaluation results of the three k-NN generated models, the majority-voting algorithm is used to combine the prediction results. A high recognition rate of up to 99.88% is achieved, far exceeding the state-of-the-art results using the IFN/ENIT dataset. The obtained results highlight the reliability of the proposed system for the recognition of handwritten Arabic words.



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## 1. INTRODUCTION

The objective of handwriting recognition is to transform a character, word, or text into a habitual representation that can be easily processed by the machine. Many applications can take advantage of the progress made in the field of automatic handwriting recognition [1], such as reading postal or bank checks, reading postal addresses, office automation, and automatic exam copy correction. Few works have been done on the recognition of Arabic text writing, unlike other handwriting languages. Although more than 300 million people in more than 20 countries practice the Arabic language. In addition, the handwriting Arabic characters are used in the writing of several historical documents. The complexity of the Arabic script form and its cursivity is a very broad field of study and has made great strides.

The variety of Arabic styles and the complexities of letter morphology make selecting and describing extracted features more difficult. In practice, there are two major techniques for handwriting recognition. The analytical approach, for example, is based on word segmentation [2]. This method divides the handwritten text into graphemes, which are the bottom sections of the letters [3]. In the case of extensive vocabulary, the analytical technique is the only viable solution. On the other hand, the global approach is based on a unique description of the word as an undivided unit. This method is far more successful than the analytical one because it allows for the development of more interesting recognition systems [4].

In recent years, many researchers have attempted to create a system for identifying Arabic words [5]–[7]. Almodfer *et al.* [8] realized a handwritten Arabic recognition system using deep multi-column neural networks (DMNN). This system used the *Institut Für Nachrichtentechnik/Ecole Nationale d'Ingénieurs de Tunis* (IFN/ENIT) database and reached an accuracy of 91.5% using a DMNN with three columns. In another study Parvez and Mahmoud [9] developed a system that recognizes Arabic handwriting using several approaches. This system is based on the text's structural features as well as the syntactic interactions that exist between the various elements of an Arabic word. Using the whole IFN/ENIT database, a recognition rate of 79% was achieved. Recently, Alyahya *et al.* [10] created four deep learning models. After all convolutional layers, the first two models employed a fully connected layer with/without a dropout layer. Two completely linked layers with or without a dropout layer were utilized in the second two models. The authors used the Arabic handwritten characters dataset (AHCD) dataset to train and validate the CNN-based ResNet-18 model. The highest accuracy of the results achieved was 98.30%. Alalshekmubarak *et al.* [11] proposed a new recognition system that applies a technique for extracting grid features by using a support vector machine (SVM) with a standardized polynomial kernel. The authors used the IFN/ENIT database to evaluate the performances. The experiments show that the suggested system achieved a 95.27% recognition accuracy in a subset of 24 classes using 7971 instances, while 56 classes utilizing 12217 instances achieved a 92.34% recognition rate.

By comparing these studies, it turns out that the majority of the proposed systems are faced with some problems in the feature extraction step. Therefore, this step affected the results obtained by these studies. To overcome this problem, we used in the feature extraction phase a selective feature extraction method based on three image descriptor architectures to increase the accuracy of our cursive Arabic word recognition system.

This paper uses the global recognition approach to extract primitives from handwritten Arabic word images. The aim is to build a new prediction system capable to recognize handwritten Arabic words vocabulary with enhancing recognition rate [12], [13]. We develop an effective selection approach based on three image feature descriptors: the histogram of oriented gradients (HOG), the Gabor filter (GF), and the local binary pattern (LBP). Indeed, the proposed recognition system is based on the selection of the optimal descriptor from three used descriptors to make an accurate prediction. The best feature descriptor is selected based on one of the well-known machine learning (ML) algorithms using the k-nearest neighbor’s algorithm (k-NN). The best-generated k-NN model is chosen using the majority voting technique combining and comparing the performance of the three k-NN models related to the 3 considered feature descriptors. Note that the training and testing process was done using the handwritten Arabic IFN/ENIT database.

The rest of this paper is structured as follows: section 2 provides the dataset, feature extraction methods, and the combination method used. The proposed handwriting recognition system's architecture is explored in section 3. Experimental results and discussion are given in section 4. In section 5, we summarize our study and present some perspectives on this work.

## 2. PROPOSED RECOGNITION SYSTEM ARCHITECTURE

First, we explore the IFN/ENIT dataset and start by extracting the 100 classes that have a large occurrence. Following that, we performed a variety of pre-processing operations on the word images to increase prediction accuracy. Indeed, it is essentially a question of reducing the noise superimposed on the images because the reliability of the recognition is deeply linked to the quality of the word to be processing and to the lack of noise [14], [15]. In this work, we were interested in the normalizing procedure since it compresses word images to standard sizes (40, 150) and reduces all forms of variances. All images are converted to binary format. A pixel can only take black or white values. Moreover, we applied smoothing algorithms to increase image quality. This technique examines a pixel's neighbor and assigns it a value of 1 if the number of black pixels in this area exceeds a threshold. In Figure 1, we illustrate the overall diagram of the modeled system. In addition, we applied a skeletonization preprocessing method to reduce the width of the lines. This process is performed on all handwritten word images [16]. We divided the entire dataset into two sections, with 80% of the data picked for training and 20% of the data selected for testing. The next step is to specify the primitives in a numerical or symbolic form called encoding. One of the most critical processes in any recognition system is the feature extraction phase. It involves extracting significant information from an image of a specific class to differentiate it more clearly from other classes. A feature vector summarizes the information included in the full word in digital image descriptions. The oriented gradient histogram, the Gabor filter, and the LBP technique were employed as descriptors. The values of this pertinent information could be real, entire, or binary, depending on context. A vector of features summarizes the information included in entire word in numerical descriptions.

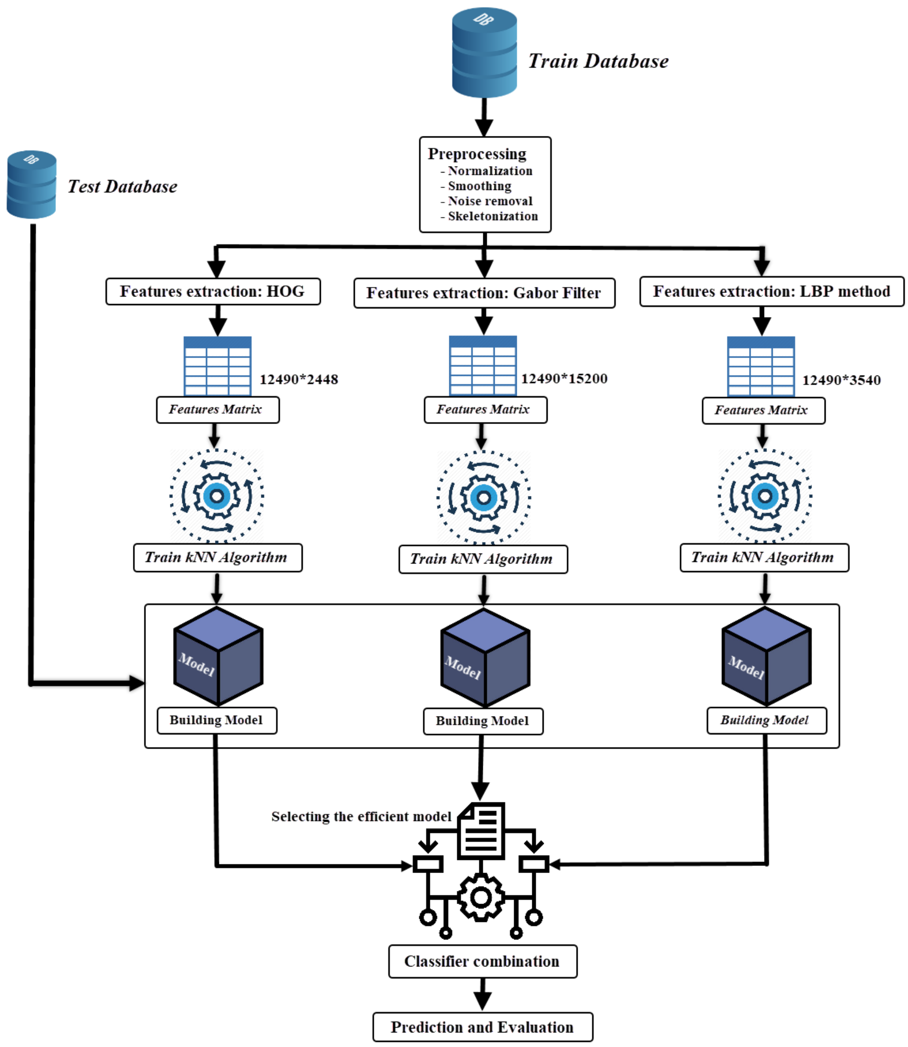


Figure 1. Model construction overview

In this work, we used the extraction features results obtained by the three studied descriptors. The HOG descriptor generates a matrix, which contains 6,047 images; each image is represented on 2,448 values. The Gabor filter provided a matrix containing 6,047 images represented on 15,200 values. The LBP method converts each image into a vector of 3,540 values. The objective behind the choice of these three feature extraction methods is to ensure an improvement in the final precision of the proposed system. On the other hand, each of the implemented descriptors uses a particular architecture to generate a vector of features. Consequently, these feature vectors' diversity will increase the efficiency of a prediction system. Indeed, the features extraction phase has an indirect impact on the learning model's performance. In the result section, we will demonstrate our interest in this choice. The obtained vectors by the descriptors represent the discriminating and relevant features of each image. In the next step, we have exploited these features to build and train the three models using the k-NN algorithm. This training step makes it possible to compare the features of the image with the references. For each test input, it is required to characterize the impact of adjacent values on target prediction for each test input. The algorithm finds the k closest neighbors consistent with a metric determining how similar the inputs are. The k-NN algorithm Tuning is done by using optimization methods to determine the optimal hyperparameters. Then, we used the majority voting method to combine the classification result obtained by the three models. Finally, the system predicts the correct class based on the obtained result given by the majority voting method.

## 3. MATERIALS AND METHODS
### 3.1. Dataset description
The current version 2.0 of the IFN/ENIT dataset is a handwritten Arabic database of Tunisian city names. This dataset contains 32,492 images for 937 Tunisian cities provided by over 1,000 authors. The database is small in comparison to other language databases. For example, the identity and access management (IAM) dataset for the English language comprises over 100,000 instances. The occurrence of each city name varies considerably [17]. The variability of occurrence classes influences the performance of any system's recognition rate. In this research, we identified 100 classes with occurrences ranging from 60 to 350. This dataset comprises 15,613 images from 100 different classifications. We divided the created dataset into two parts: 12,490 images for training (80%) and 3123 images for testing and validation (20%). Figure 2 illustrates various images samples from the IFN/ENIT dataset.

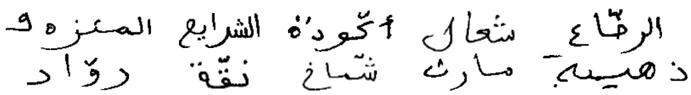

Figure 2. Some word images samples from the IFN/ENIT database

### 3.2. Feature extraction methods
#### 3.2.1. Oriented gradient histogram
The selection of a descriptor is critical to the success of a classification model. The descriptor must be representative, discriminating, and fast to accurately predict [18]. The basic principle behind the directed gradient histogram is that the distribution of gradient intensity or contour direction may define the local shape and form of an item in an image [19]. The HOG descriptor is implemented by splitting the image into small-connected sections called cells, and then calculating a histogram of the gradient directions or outline orientations for the pixels in each cell. The descriptor is represented by the combination of these histograms.

#### 3.2.2. Gabor filter
A Gabor filter (GF) is a sinusoidal function modulated by a Gaussian envelope. The sinusoidal function is distinguished by its direction and frequency. Furthermore, a GF may be thought of as a detector of edges with a specific orientation. It responds at edges perpendicular to the sinus's propagation direction [20]. This sinusoidal function in two dimensions is the sum of two sinusoidal functions, the first pair and real, and the second odd and imaginary. We employed two functions: the Gabor filter bank and the Gabor features. Gabor Array was obtained using the Gabor filter bank function. This array was passed to the Gabor features method as an argument. It constructs a table u by v cells and a bank of Gabor custom filters. The Gabor filter bank extracts texture-related information from the examined image in terms of both space and frequency.

#### 3.2.3. Local binary pattern
The LBP has been frequently used to analyze image texture [21], [22]. They are basic but efficient texture operators that identify pixels in an image depending on their surroundings and are insensitive to monotonic changes in illumination. Each label is represented by a binary index. LBPs were extended in [23] to allow the usage of neighborhoods of varied sizes. This allows us to compare the central pixel to the *P* evenly dispersed points located on a circle of radius *R* centered on the central pixel. The gray level values of these *P* points are bilinearly interpolated, allowing us to analyze all conceivable radius and point combinations in the neighborhood.

In an image, we inspect each pixel (x, y) and then select *P* pixels with radius *R*. Following that, we compute the difference in current intensity between the pixels and the *P* neighboring pixels. The intensity difference threshold is determined by assigning all negative differences to zero and all positive differences to one, resulting in a bit vector. Finally, we transform the bit vector to its appropriate decimal value and replace it with the pixel intensity value at (x, y). The equation (1) gives the LBP description for each pixel:

$$LBP_{P,R}(x_c , y_c) = \sum_{P=0}^{P-1} S(g_P - g_c) 2^P \tag{1}$$

with $g_c$ and $g_n$ denote respectively the intensity of the gray level of the central current and the neighboring pixels [24]. *P* is the number of neighboring pixels chosen at a radius *R*, and the function S(x) is defined as (2):

$$S(x)= \begin{cases} 1 \text{ if } x \geq 0 \\ 0 \text{ if } x < 0 \end{cases} \tag{2}$$

### 3.3. Majority voting method

Humans cannot detect a texture based on a particular contact. If a person is given a material to categorize, he or she will attempt multiple investigations of the substance's surface before making a decision. We employ a majority voting approach that replicates this behavior, but more importantly, majority voting significantly enhances the robustness of the classifier, as seen by the experimental findings. The application of the majority voting technique is described in algorithm 1.

Algorithm 1. Majority voting method

```
Begin
  Max ← 0;
  for i ← 1 to C
  S ← 0;
       for j ← 1 to L
            S ← S + T[I,j];
       end
       if S > Max then
              Max ← S;
            Class ← I;
     end if
   end for
   Return Class;
End
```

The simplicity and good performance of majority voting has attracted a lot of attention in the literature on the scheme of combining classifiers. A simple analytical justification for majority voting is given by the well-known Condorcet theorem [25]. This technique is one of the easiest ways to combine the predictions of multiple machine learning algorithms. The principle of combination uses the most probable class for each classifier. Indeed, the safest final class is the one supported by the majority of classifiers [26]. If we represent the score of the class noted *i* in the classifier noted *j* by: $S_i^j$, then the safest final class is:

$$\text{Class}= C_{\max_{i=1}^{C}\sum_{j=1}^{L} S_i^j} \tag{3}$$

where C represents the number of classes, and L represents the number of classifiers.

## 4. RESULTS AND DISCUSSION

### 4.1. Experimental setup and algorithms best configuration

The experiment simulations and modeling are developed in the MATLAB R2020b programming environment. The experimental computer is powered by a 2.00 GHz turbo Intel i7-8550U CPU, 16 GB of RAM, and a 512 GB SSD hard drive. In this sub-section, we present the findings of the three classifiers based on the HOG, LBP, and Gabor filter descriptors. We extracted 100 classes with the highest incidence rates from the IFN/ENIT dataset. The resulting dataset was separated into two parts: training data (12,490 images) and test data (3123 images). All images have been standardized to the same size of 40×150 pixels. We adjusted the k-NN classifier's hyperparameters to reduce cross-validation loss. This is done by minimizing the following hyper-parameters: sizes of the nearest neighborhood from 1 to 30, and the distance function. Figures 3 to 5 represent the curves obtained by the optimization function to find the best hyperparameters for the three models studied.

In Table 1, we present the best hyperparameters found for the three studied classifiers. Moreover, we also present the loss and the execution time. From this table, we have suggested more than one better combination for a model. We have noticed that some combination requires more execution time to achieve a minimum loss rate. This is remarkable for both models based on the Gabor filter and LBP descriptors. In this work, the hyper-parameters are chosen according to the minimum loss rate and not according to the execution time.

### 4.2. Criteria for evaluation

In general, the confusion matrix is used to evaluate the performance of created models. We employed the confusion matrix for multi-class prediction since the handwritten character set has numerous classes. The confusion matrix is built by computing the following elements: true positive (TP), true negative (TN), false positive (FP), and false negative (FN). The class predicted by the classifier is the expected output/label, while the class labels supplied in the dataset are the actual outputs. Because our confusion matrices are multi-class, we must calculate the TP, FP, FN, and TN values for each class in the matrix. In this investigation, four score criteria were used: accuracy, precision, sensitivity, and specificity. The equations (4)-(7) provide these metrics:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

$$Sensivity = \frac{TP}{TP+FN} \quad (6)$$

$$Specificity = \frac{TN}{TN+FP} \quad (7)$$

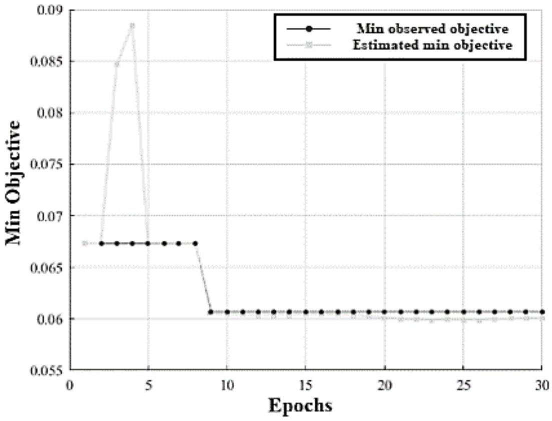


Figure 3. Evaluation function diagram of k-NN model classifier using Gabor filter descriptor

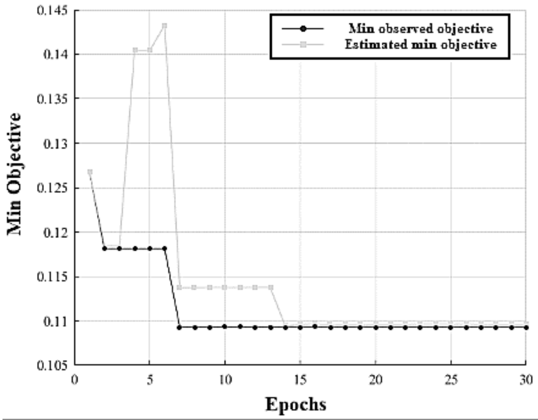


Figure 4. Evaluation function diagram of k-NN model classifier using HOG descriptor

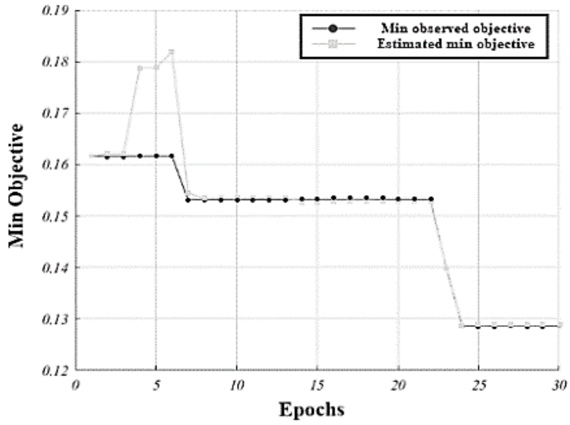


Figure 5. Evaluation function diagram of k-NN model classifier using LBP method

Table 1. The best configurations obtained by the classifiers using objective function

| Models | Loss | Runtime (Second) | Neighbors | Distance |
|---|---|---|---|---|
| HOG Model | 0.1093 | 130.51 | 5 | correlation |
| | 0.1181 | 213.11 | 3 | correlation |
| | 0.1268 | 216.34 | 3 | minkowski |
| GF Model | 0.0607 | 899.37 | 7 | correlation |
| | 0.0673 | 863.75 | 3 | minkowski |
| LBP Model | 0.1286 | 306.84 | 5 | cityblock |
| | 0.1399 | 306.9 | 1 | cityblock |
| | 0.1532 | 307.76 | 5 | minkowski |
| | 0.1616 | 288.82 | 3 | minkowski |

### 4.3. Testing results

In this subsection, we present the testing results of the three features extraction methods exploited to build the final prediction model. The k-NN algorithm was used in the training step to build the three tuned models. Therefore, we tuned the algorithms using the optimal combinations defined in the previous subsection. In addition, each model fits the training data extracted by the studied image descriptor, namely the HOG, LBP, and GF descriptors. The results obtained during the classification process are represented using a confusion matrix. Consequently, the three models provided a particular classification of training images. It was difficult to plot three confusion matrices with a dimension of 100 by 100 elements to present the classification provided by each classifier. For this purpose, we have summarized these matrices in one table, which groups together all the essential elements of a confusion matrix. Based on these matrices, we evaluated the trained models performance by computing the measurement metrics. The performance evaluation consists of calculating five measures, which are accuracy, sensitivity, specificity, precision, and loss value. From the testing results, we can notice that there is a difference in the performances of the generated fourth models. The accuracy and error rate of the three basic models varies between [99.69% to 99.85%] and [6.07% to 12.86%] respectively. Therefore, we observed that the hybrid model achieves an extreme performance. This model achieved a maximum accuracy of 99.88% with a confidence interval (CI) of [98.67 to 100%] at 0.95.

### 4.4. Discussion

In this work, we used three image description methods to build a hybrid system for the recognition of a limited vocabulary. The IFN/ENIT dataset was used to generate this vocabulary. We picked 100 different word classes with occurrences ranging from 64 to 368. The quality of the words to be processed and the absence of noise are both important factors in ensuring the reliability of the recognition. The selected word images were subjected to a range of preprocessing techniques like normalization, smoothing, skeletonization, and binarization. We divided the dataset into two halves, with the training set accounting for 80% of the dataset and the test set accounting for 20%. We used three different description techniques to extract significant features and create a feature vector for each image in the feature extraction step: the oriented gradient histogram, the Gabor filter, and the LBP approach. Each image is given a vector of 2448, 15200, and 3540 values using the three descriptors HOG, GF, and LBP. The k-NN technique was used to train the three models. By comparing an unknown image to forms recorded in a reference class, the k-NN classifier assigns it to the class of its nearest neighbor. To determine the best combination of parameters for each method, we ran a parameter optimization. A decision strategy makes it possible to assign confidence values to each of the competing classes and to assign the most probable class to the unknown image. The generated model is created by combining the three prior models that were trained using the majority voting approach. The models' performance is assessed using score measures such as (loss, precision, specificity sensitivity) experimental results demonstrate that all models achieved extreme accuracy with a reduced loss rate. Moreover, these results affirm that the integration of a hybrid model based on the feature descriptor selection method enhances the prediction performance compared to other models in the literature. In Table 2, we compare the performance of the proposed model with some related work studied in this article.

Despite the fact that the results of this study are good, there are some flaws. The biggest drawback is that all of the findings come from a single data source. Indeed, the results obtained by the model based on the Gabor filter descriptor are the most accurate, despite a significant increase in computational complexity in terms of execution time. This is an anticipated trade-off for increased precision, however using parameter optimization in future work will improve our results not just in terms of precision but also in terms of execution time.

Table 2. Comparisons with some other related work.

| Author | Used model | Accuracy | Sensitivity | Specificity | Loss |
|---|---|---|---|---|---|
| Mouhcine *et al.* [27] | Hidden Markov models | 87.93% | N/A | N/A | N/A |
| Almodfer *et al.* [8] | Multi-column deep neural networks | 91,50% | N/A | N/A | N/A |
| Alalshekmubarak *et al.* [11] | Support vector machines | 92.34% | N/A | N/A | N/A |
| Alyahya *et al.* [10] | Convolutional neural network | 98.30% | N/A | N/A | N/A |
| Balaha *et al.* [28] | Convolutional neural network | 90.7% | N/A | N/A | N/A |
| Present work | k-NN + Majority voting | **99.88%** | 97.90% | 99.86% | **1.18%** |

## 5. CONCLUSION AND PERSPECTIVES

In this study, we provide an architectural system based on a new hybridization approach for identifying a vocabulary of handwritten Arabic words. The primary goal was to increase recognition accuracy and create a more efficient recognition system. A vocabulary of 100 classes has been chosen from the IFN/ENIT dataset. The performance of three models based on the HOG, GF, and LBP is combined in the generated model. The performance of this model reached a recognition rate of 99.88% and a loss rate of 1.18%. By comparing the findings to current research for a publically available dataset, the generated model's performance and reliability for vocabulary recognition of handwritten Arabic words were proven. In future works, we aim to design a hybrid architecture by using the convolutional neural networks for features extraction phase and the hidden Markov model (HMM) for the classification step.

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