An Online Numeral Recognition System Using Improved Structural Features – A Unified Method for Handwritten Arabic and Persian Numerals

Jaafar M. Alghazo[1], Ghazanfar Latif[1], Ammar Elhassan[1], Loay Alzubaidi[1], Ahmad Al-Hmouz[2], Rami Al-Hmouz[3]
[1]*College of Computer Engineering and Sciences, Prince Mohammad bin Fahd University, Khobar, Saudi Arabia.*
[2]*Department of Electrical and Computer Engineering, King Saud University, Riyadh Saudi Arabia.*
[3]*Faculty Of Information Technology, Middle East University, Amman, Jordan.*
glatif@pmu.edu.sa

***Abstract*— With the advances in machine learning techniques, handwritten recognition systems also gained importance. Though digit recognition techniques have been established for online handwritten numerals, an optimized technique that is writer independent is still an open area of research. In this paper, we propose an enhanced unified method for the recognition of handwritten Arabic and Persian numerals using improved structural features. A total of 37 structural based features are extracted and Random Forest classifier is used to classify the numerals based on the extracted features. The results of the proposed approach are compared with other classifiers including Support Vector Machine (SVM), Multilayer Perceptron (MLP) and K-Nearest Neighbors (KNN). Four different well-known Arabic and Persian databases are used to validate the proposed method. The obtained average 96.15% accuracy in recognition of handwritten digits shows that the proposed method is more efficient and produces better results as compared to other techniques.**

***Index Terms*—Arabic Numerals; Persian Numerals; Structural Features; Random Forest; Numerals Recognition; Digit Recognition; Arabic Digits; Persian Digits.**

I. INTRODUCTION

Numeral recognition has been extensively researched in previous literature. The complexity of numeral recognition algorithms is even more significant with online numeral recognition systems. Online recognition of Arabic and Persian numerals refers to handwritten numerals on touch screen or tablet type devices. Online recognition deals with the coordinates of the handwriting while offline method is a fairly simpler process since the complete image of the handwritten numeral is available from the outset. In essence, online recognition deals with the spatio-temporal representation of the writing, while offline recognition deals with the spatio-luminance representation of the digits. Online numeral recognition is a challenging problem due to many reasons some of which could be attributed to the lack of comprehensive benchmark for Arabic and Persian digits, writing on a digital platform which is not as accurate as writing on paper, and the larger set of possible handwriting samples per digit [1]. There are many applications that require real-time automatic recognition of handwritten digits. With the growth in popularity of handheld devices, the number applications that require automatic text and digit recognition is also increasing. Though keyboard applications exist in these devices, there are many application areas that require users to write on the screen or tablet of the device (handwriting) either through a stylus pen or using the tip of their fingers. Therefore, handwriting recognition is an important field and is needed for handheld devices or even touch screen devices such as the vehicle navigation/multimedia systems and SMARTboards used in school and university classrooms. One of the most important features of the SMARTboards is the ability of the lecturer to write using a stylus or fingertip directly on the board. In addition, some financial transactions require this functionality in banks and for form filling. The main motivation of this research paper is to design a methodology and implement an application for real-time Arabic and Persian numeral recognition.

Other areas of application include assistive technology for the support of students with disabilities to empower their learning and effective communication. Students with visual impairment lack the visual sense to see what is written in front of them, however, they supplement that with other features like audio feedback which they depend on heavily. On the other hand, students with hearing impairments are unable to communicate orally and often use sign language or written communication. A dilemma exists when a student who is visually impaired wishes to communicate with a student who is hearing impaired. The only means can be through a human interpreter. The interpreter can see what a hearing impaired student is saying through sign language or written communication and convey this message orally to the visually impaired student. The interpreter also hears what a visually impaired student is saying and communicates that to the hearing impaired student through sign language or written/braille medium.

Our motivation and objective is to design and build a digital interpreter able to recognize text and digits in real-time and convert that to speech so that visually impaired students can hear it and also speech to text conversion in real-time so that the hearing impaired student can read it. A lot of research on smart learning technology and assistive technology has concentrated on English and very little research has been conducted for the Arabic and Persian languages. This paper will concentrate on only one functionality of this interpreter which is online automatic digit recognition. Future research will concentrate on online Arabic and Persian text recognition, Text-to-Speech and Speech-to-Text features.

In this paper, we present a novel method for unified automatic recognition of Arabic and Persian digits in real-time. The technique is based on enhanced structural features and an efficient classifier. The system is tested on four different well-known databases consisting of more than 180,000 handwritten Arabic and Persian numeral samples. An average 96.15% accuracy is achieved by the proposed method. For real-time, handwritten recognition, we used a relatively smaller dataset of 11,900 samples written by 238 different participants and built a training model. It is a relatively small training set which is continuously increasing with user oriented training set as the interpreter device is used by specific users which results in progressive, incremental accuracy improvement. Since the device is used by one person (a student with a hearing impairment), the accuracy will eventually approach a high score close to 100% accuracy for Arabic and Persian numeral recognition. The individual devices are connected such that each sample written on any individual device is uploaded to the cloud thus enhancing the training set for all connected devices using the application. This will enable us to utilize Internet of Things (IOT) systems to apply on the fly stream analytics for handwritten text and digit recognition. The novel feature extraction method developed in this paper was specifically for numerals taking into account the geometric properties of each individual digit. The interpreter device which will be the eventual outcome of such work would need to be able work on numeral, characters, symbols and other items needed for proper verbal and written communication for students with disabilities.

The rest of this paper is organized as follows: Section 2 contains the literature review related to this work, Section 3 introduces the methodology used for the Arabic and Persian digit recognition, Section 4 describes the structure of the experimental databases, Section 5 shows the results of numeral recognition system, Section 6 is the conclusion and future work.

II. Literature Review

The recognition of numeral digits is split into two main streams; offline numeral recognition and automatic real-time numeral recognition; commonly referred to as Online Numeral Recognition. Offline Arabic and Persian numeral recognition has received a lot of attention from the research community while online numeral recognition is still in its early stage of development and only a little research addresses this concept. This is due to many reasons some of which could be that the lack of comprehensive benchmarks for Arabic and Persian digits, writing on a digital platform which is not as accurate as writing on paper and the larger set of possible handwriting samples per digit. In offline recognition, the image of the complete sample is available from the outset while in online recognition the two-dimensional coordinates of the consecutive points of writing are stored based on their order. This implies that offline recognition uses spatio-luminance of an image for analysis and recognition, whereas, online recognition uses spatio-temporal representation of the input for analysis and recognition [1]. The authors in [1] proposed a method for online handwritten Arabic numeral recognition based on fuzzy modeling. This method automatically generated the fuzzy models of the Arabic digits using the segments' directions of Arabic online digits from the training set. Furthermore, they generate weights for the different segments automatically using the training sets. They used a two-phase approach for classification thus leveraging the Support Vector Machine (SVM) in the first phase and a fuzzy based approach using the automatically generated models in the second phase. They achieved an overall accuracy of 99.55% in the first phase and 98.01% in the second phase. In [2], the authors proposed a method to recognize online Arabic digits that was divided into two parts: One to recognize the zero digit and another to recognize the digits from 1-9. They integrated both temporal and spatial information in their recognition technique and were able to achieve 98.73% recognition rate, in addition, they introduced a training set of 30,000 samples in their work.

In [3], the authors proposes a basic technique for online Arabic digit recognition based on four phases: Digit Acquisition, Preprocessing, Feature Extraction and Recognition. The method was tested using 100 samples from 100 users and was able to achieve recognition accuracy rates of 98%. In [4], the authors focused on a key step in the online recognition process which is Feature Extraction in relation to *global* features derived from Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT), and Wavelet Transform (WT) as well as *local* features such as the Two-dimensional coordinates, nth Derivative, Curvature and Angular features. The authors then compared the use of the global features alone, the local features alone and the combination of both global and local. Using the combination approach, the authors were able to obtain more than 95% accuracy on the test dataset and 98% accuracy for recognition of Indo-Arabic numerals from a public dataset.

In [5], the authors proposed a method for Arabic handwriting recognition using Concavity Features and Classifier Fusion. Their method labels the white pixels in a digits image into constructed nine different concavity categories. These labelled concavities are then reduced to four extracted feature vectors with each feature vector ultimately introduced to a linear SVM classifier and Classifier Fusion Methods are used for final decision thus achieving a 99.36% recognition rate accuracy. In [6], the authors analyzed Google's online handwritten recognition system that supports 96 scripts and 97 languages; they presented some novel ideas such as time and position combination based interpretation of the input in a single lattice to allow for joint decoding and using minimal amount of preprocessing to allow handwriting inputs from a variety of inputs, other novel ideas are also presented. Their system is very successful and is currently available in several implemented applications/products. In [7], the authors described the development of online handwritten isolated Bengali numerals using Deep Autoencoder (DA) based on Multilayer Perceptron (MLP). This DA based on MLP uses the MLP training method. The authors explored different DA configuration to achieve an optimal DA classifier and used optimization techniques to reduce overall weight space for the DA based on MLP. In testing, their hybrid approach achieved a 99.18% accuracy performance rate. In [8], the authors introduced a method to recognize online Farsi (Persian) characters written separately. They divided letters into 18 groups based on the shape and structure of the main body. Hidden Markov Model (HMM) was used to recognize main body aspects and final recognition is based on delayed strokes and their HMM. This approach achieved a recognition accuracy rate of 94.2%-95.9% for different groups.

In [9], the authors proposed a method for recognition of online handwritten Urdu characters. Their proposed systems used Geometric Feature Extraction through different means such as Cosine Angles of trajectory, DFT of trajectory, Inflection Points, Self-Intersections, Convex Hull, Radial Features as well as Grid and Retina features. Their proposed system is font, rotation, scale and shift invariant because of the geometric invariant features. Low pass filters are used prior to feature extraction to remove noise caused by input device and hand movement. SVM is used post feature extraction for training and testing. This approach achieved a 97% classification accuracy on test data with very low false rejection rates. In [10], the authors proposed a new method for online recognition of Joint Two-Digit numerals. The method is a hybrid combination of SVM and HMM. SVM and HMM were used for classification and segmentation respectively with the main core of recognition relying on a SVM classifier. HMM was used to detect the location of the boundary for two-digit numbers resulting in 98.75% recognition rate accuracy.

In [11], the authors proposed a hybrid method composed of HMM and Harmony Search Algorithms for writer independent Kurdish character recognition. HMM is integrated as an intermediate group classifier and harmony search is then used in the second phase for recognition using dominant and common movement patterns as a fitness function. The objective function is used to minimize the matching score based on the fitness function and based on the least score of each segmented group of characters. The system subsequently displays the generated word that has the lowest score from the combinations thus achieving a 93.53% recognition rate accuracy at an average of 500 ms processing time.

Offline digit recognition is a fairly simpler process as compared to the online automatic digit recognition as previously stated because complete image is available from the outset and the recognition process deals with the spatio-luminance representation of the image. In [12], the authors proposed a simple method composed of preprocessing the images, segmentation of each individual digit, and finally a set of if-else rules for recognizing characters. Preprocessing steps included conversion to binary, noise removal, morphological filtering, and segmentation. Experimental results yielded 97% accuracy rates. In [13], the authors performed a comparison between HMM and SVM and both methods were used for the recognition of Arabic digits. Results indicated that the SVM method outperformed the HMM method for Arabic digit recognition. In [14], the authors performed a comparative study between the K-Nearest Neighbors (KNN) method and the Multi-Layer Perceptron (MLP) method for cursive handwritten Arabic digit recognition and then the Morphological mathematical method was used for feature extraction. The results indicated that the MLP method outperformed the KNN method for Arabic digit recognition.

In [15], the authors proposed a Windowing method for the segmentation of the numerical amount figure on bank checks. Moment Invariant approach was used for feature extraction. The method then grouped each digit according to feature vectors and used Artificial Neural Network (ANN) for classification and recognition. Results indicated a 99.5% recognition rate. In [16], the authors presented a method for Persian/Arabic numeral recognition based on Robust Feature set and KNN classifiers. Their method converted each digit to the contour form and using block base techniques extracted three features from each these blocks; KNN classifier was then used for digit recognition. Experimental results yielded 99.82%-99.90% recognition rate.

In [17], the author presented a novel Active Learning strategy for the classification of handwritten digits that is based on KNN graph attained with an Image Deformation model. This active and interactive learning procedure consists of asking the user to *label* the vertices with the highest number of neighbors. A Label Propagation function is then performed for automatic labelling of the examples, the procedure is repeated until all images are labeled. The method resulted in 98.54% accuracy rate. In [18], the authors proposed a Feature Learning framework for Arabic handwritten text and digit recognition based on the Bag-of-Features (BoF) paradigm. Using the characteristics of handwritten text and digits, the authors developed two new versions of the Scale-Invariant Feature Transform (SIFT) that are discriminative and computationally efficient with half the size of the original SIFT descriptors. The authors used the Harris Detector, Harris-Laplace Detector and Dense Sampling methods. SVM was then used in the classification technique for this work. Experimental results indicated 99.34% recognition accuracy on the non-touching Arabic/Indian digit dataset. In [19], the authors proposed a new technique for Arabic/Farsi handwritten numeral recognition. The created an invariant and efficient feature set by combination of four directional Chain Code Histogram (CCH) and Histogram of Oriented Gradient (HOG). They extracted local features at two levels with grids of size 2×2 which achieved higher recognition rates. Their feature set has 164 dimensions. SVM with radial basis function kernel was used for classification phase and experimental results indicated 99.31% recognition rate on test datasets.

In [20], the authors performed a comparative study of the available digit recognition methods for digits in Urdu, Arabic and Farsi. A comprehensive list of the methods based on published work from 2003-2013 was presented with different methodologies for digit recognition. In [21], the authors proposed a method to solve the straight line problem in triangle geometry features for digit recognition, their method was tested on digits in different languages including Arabic digits. After presenting the solution to the straight line problem, SVM and MLP were used for digit recognition and experimental results indicated an increased accuracy rate as a result of applying their method to the straight line problem in triangle geometry for feature extraction. In [22], the authors presented a technique for handwritten Arabic digit recognition using Convolutional Neural Networks (CNN) and they also presented a new dataset consisting of 45,000 patterns. Using their technique and tested on their own dataset, they achieved 95.7% recognition rate. In [23], the authors proposed a system to recognize digits in four different scripts: Bangla, Devanagari, Arabic, and Telugu using Mojette Transform. Principal Component Analysis (PCA) was applied for the dimensionality reduction of the feature vector thereby reducing training time. MLP classifier was then applied and experimental results indicated 98.17% recognition rate. In [24], the authors conducted a comparative study for recognition of Hindu and Arabic digits, Three different algorithms were used in the study in order to ensure different inductive biases: Naïve Bayesian, KNN, and Resilient PROPagation (RPROP) algorithm. Experimental results indicated that Hindu digits are easier to recognize and the result was supported in both cases, when the algorithm was trained on raw data images with no feature extraction and when features where extracted using Fourier Transform and Histograms.

In [25], the authors proposed a novel feature extraction method for the recognition of handwritten numerals. The feature set is based on the horizontal and vertical directions of the image combined with Freeman chain code histogram (CCH), this gives the benefit that it does not require any normalization of the digit, the classification systems used in this paper was based on SVM. Experimental results showed an advantage of using this technique that increases the recognition rate. In [26], the authors proposed a method for the recognition of handwritten Persian digits; in the feature extraction phase, the authors set a complementary set of features that consist of 115 features extracted from Persian handwritten digits. In the classification phase, the proposed system used the Ensemble Classifier algorithm to separate sample classes. Experimental results yielded 95.28% recognition rate. In [27], the authors proposed a handwritten Arabic numeral recognition system based on LeNet-5, a Convolutional Neural Network (CNN) trained and tested on MADBase databases. The system showed significant improvement across different machine-learning classification algorithms. In [28], the authors explored the concepts of digital communication and digital image processing for the recognition of handwritten Arabic digits. Analytical features based on distance and slope were calculated to find the curvature rates and Delta Distance Coding was used for distance based treatment while slope analysis was done using Delta Slope Coding and Centroidal Moment of Inertia and Zonal Moment of Inertia were calculated for the Pixel Moment of Inertia. The system achieved an overall recognition accuracy of 99.26% for Arabic digit.

III. Proposed Method

The architecture of the proposed system is illustrated in Figure 1 and consists of three main phases: In the first phase, preprocessing is done for handwritten numerals. The Preprocessing phase includes important steps such as segmentation, binarization, noise removal, size and slope normalization and finally placing the image in the center. In the second phase, local structural features are extracted based on our proposed measurement technique. In this phase we proposed a novel method for extracting 37 Local features that provide a basis for a unified approach to the recognition of the Arabic and Persian numerals. In the final phase, different classifiers are used to recognize the numeral and verify the accuracy of the proposed method. The steps taken for the classification in general include feature reduction, training and testing the classification method. The 3 phases are described in detail below.

A. Preprocessing

Arabic and Persian language text writing is done from right to left while numerals are written from left to right. Arabic and Persian digits are almost similar in writing for all digits except for digits four (4) , five (5) and six (6). Table 1 shows the representation of Arabic and Persian numerals.

People have differing handwriting styles which makes the numeral recognition process more difficult. Arabic and Persian digits have more than 52 writing classes with small variations as compared to other language numerals [15]. The similarity between digit six and two as well as digit eight and seven makes the automatic recognition process even more difficult. Figure 2 shows some samples of different handwritten numerals by different participants, the first four columns represents Arabic numerals writing while the fifth column has Persian handwritten numerals.

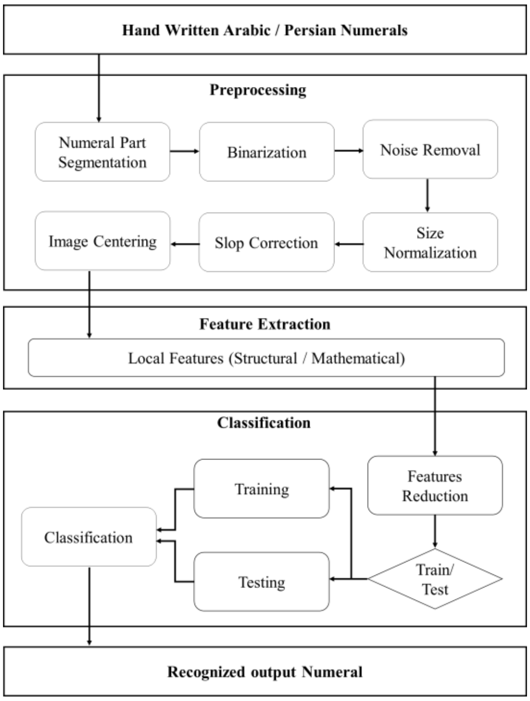

Figure 1: Architecture of the Proposed System for Numeral Recognition

Table 1
Representation of Arabic and Persian Numerals

English	Arabic	Persian
0	٠	۰
1	١	۱
2	٢	۲
3	٣	۳
4	٤	۴
5	٥	۵
6	٦	۶
7	٧	۷
8	٨	۸
9	٩	۹

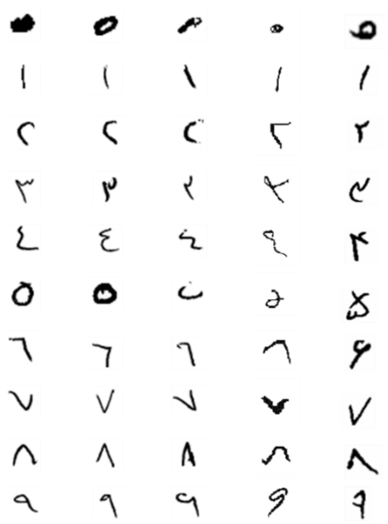

Figure 2: Samples of Handwritten Arabic and Persian Digits. First four columns are Arabic digits while fifth column is a Persian digits sample.

Due to diverse shape, size, location, angle and noise in handwritten numerals as shown figure 2, preprocessing is an important step for automatic online recognition. In the proposed methods preprocessing stage, the following steps are performed:

i. The handwritten numerals are binarized from grayscale by using Octu's thresholding method [29].
ii. Morphological operations; dilation and erosion are applied to remove the noise from the binarized image. A 3×3 window of disk shaped structure is used to remove the noise from the numerals.
iii. Numerals are segmented to separate each digit based on the boundary box of each digit.
iv. Each segmented digit is centered based on the handwritten image region centroids.
v. Furthermore, each digit size is normalized and converted to 36×36.

B. Feature Extraction

Feature extraction is an important and vital part for digit recognition. Due to similarity structure of some digits like two (2) and six (6) as well as seven (7) and eight (8), local structural features gain importance as compared to the global features like DCT, DFT and Histogram based features. In this paper's proposed method, a total of 37 local structural features are extracted based on the proposed criteria shown below. The details of the extracted local structural features are as follows:

1. The preprocessed numeral is divided horizontally from left to right. Three starting and three ending x-axis values based on black pixels are calculated as shown in Figure 3 (a). Similarly, three starting and three ending y-axis values are calculated and divided vertically as shown in Figure 3(b). Both horizontal and vertical distributions give a total of 12 features.
2. The handwritten numeral is then divided into 4×4 segments, total 16 blocks and the number of black pixels in each block is then calculated. Figure 3 (c) shows another16 features based on the black pixels in 16 blocks.

$$BS_m = \sum_{i-1,j=1}^{i=BH,j=BW} B_m[i,j] = 1$$

where BS_m is the black pixels sum of block m. BH and BW are block height and width respectively and B_m is the particular block pixel value.

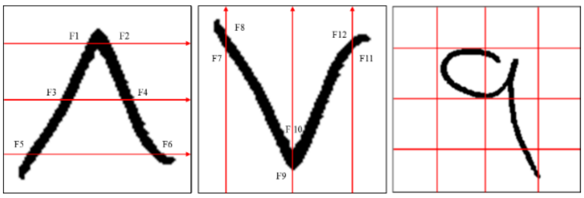

Figure 3: Proposed Structural Features Extraction. From left to right: (a). Three starting and three ending x-axis values based on black pixels, (b). three starting and three ending y-axis values, (c). features based on the black pixels in 16 blocks.

3. The distance between the starting point of a black pixel and the end point of black pixel are measured horizontally and vertically as shown in Figure 4(a), 4(b) respectively. This gives another 3 horizontal features and 3 vertical features totaling 6 features of handwritten numeral:

$$Hdistance_i = VertiS_i - VertiE_i$$

$$Wdistance_i = HoriS_i - HoriE_i$$

where $HDistance_i$ and $WDistance_i$ are the vertical distance and horizontal distance center of each defined axis vector i respectively. $VertiS$ and $VertiE$ are vertical start point and vertical end point respectively, and $HoriS$ and $HoriE$ are horizontal start point and horizontal end point respectively.

4. Height Distance to Width Distance aspect ratio (HWDaspect) is measured based on the calculated distances horizontally and vertically as shown in figure 4(c). This gives another 3 features.

$$HWDaspect_i = \frac{Hdistance_i}{Wdistance_i}$$

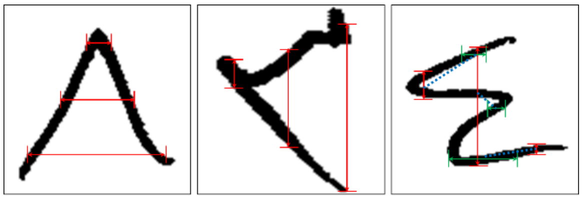

Figure 4: Proposed Structural Features Extraction. From left to right: (a). Horizontal distance between the starting point of a black pixel and the end point of black pixel, (b) Vertical distance between the starting point of a black pixel and the end point of black pixel, (c). Height Distance to Width Distance aspect ratio (HWDaspect).

C. Classification

The proposed extracted features set is used as input to the Random Forest (RF) tree classifier to recognize the Arabic and Persian numerals, here, the RF algorithm plays the role of a grouping function for several decision trees [30]. Initially in the training phase, each tree in the ensemble trains the system based on randomly sampled data with replacement from training vectors. A model-averaging scheme, known as Bootstrap Aggregating (Bagging), is used for averaging to increase the correlation and avoid the issue of overfitting [31]. The important information about individual features can be gathered after model creation. For testing purposes, unknown data is presented to the individual trees for classification and votes are then collected from each individual tree, finally the RF classifies desired output based on majority votes.

The results are compared with other classifiers including MLP, KNN and SVM. Table 2 shows all the different databases used in this study. The experimental results of using different databases is shown in Table 3 which indicates that the Random Forest approach yields better accuracy as compared to the other classifiers.

IV. Handwritten Experimental Data

As discussed earlier, handwriting varies from person to person which makes the recognition process complex and the results can be biased depending on type and size of the reference database. The proposed method is validated with three well known large databases including two Arabic and one Persian database totaling more than 180,000 numeral pattern samples. We also developed our own Arabic numerals database with more complex handwriting styles while using relatively smaller number of samples, 10,900 samples as compared to existing databases so as to facilitate real-time recognition. The first database used is Arabic Online Digits

Dataset (AOD) which is assembled by 300 participants of age group 11 to 70 years [2], this database consists of more than 25,000 digits and is suitable for online Arabic numeral recognition. The second database used for experimental results is Modified Arabic Handwritten Digits Databases (MADBase) which is collected from 700 participants [32], this database contains 70,000 handwritten Arabic numerals with 300 dpi resolution at 28×28 pixels. Another database named HODA for Persian numerals was also used in our experiments [33] and consists of a total of 80,000 Persian digits which are collected from 12,000 different registration forms from university entrance exams. A database locally developed at Prince Mohammad Bin Fahd University (PMU) for the purposes of this study and thus called PMU database. The PMU database was developed through 238 student and employees each writing the numerals from 0-9 five times. The data was written ranging in age from 19-45 years of age. Though databases exist for Arabic Numerals, yet it is the intention of the authors to establish a database for Arabic Numeral and Character recognition for future work. The first building stone of numerals was collected in time to be tested in this study along with the widely used MADBase and AOD datasets.Table 2 shows the summary of the databases used to test our proposed system.

Table 2
Description of dataset used for testing the proposed system

Numeral Language	Database	Data Source	Training Dataset	Testing Dataset	Total Patterns
Arabic	MADBase	700 Participants	60,000	10,000	70,000
	AOD	300 Participants	20,480	5,120	25,600
	PMU	238 Participants	8,880	3,020	11,900
Persian	HODA	12000 Registration Forms	60,000	20,000	80,000

V. EXPERIMENTAL RESULTS

The proposed method was systematically tested on several prominent datasets described in the previous section. After the digits were preprocessed as described above and the 37 local features were carefully extracted in addition to the global features, the digit classification techniques were used to test the accuracy and precision of the digit recognition process. As shown in Table 3, using MADBase, the Random Forest yielded the highest average of 97.1% accuracy and precision of digit recognition among all the different classification techniques used in this study. Using the Arabic Online Digits Dataset (AOD), Random Forest method achieved 94.8% accuracy and 96.3% precision. The PMU dataset, developed specifically for this study and consisting of varying writing styles put all the classification methods to the test and showed unbiased results for the practical performance of the classification methods for real-time digit recognition. SVM achieved an accuracy of 80.9% and precision of 83.4%, while MLP achieved 84.0% accuracy and 84.2 precision. The best performing classification technique proved to be the Random Forest yielding 95.2% accuracy and 95.3% precision as shown in Table 3. Random Forest also outperformed the other classification methods in Persian Numeral recognition. When tested using the HODA dataset, Random Forest achieved a remarkable 97.5% for both accuracy and precision. The MLP achieved 96.8% for both accuracy and precision while SVM achieved 83.4% accuracy and 92% precision.

The results clearly indicate that our proposed method of feature extraction combined with the Random Forest classification Method is an excellent technique for a Unified Arabic and Persian handwritten digit online recognition.

The time complexity of the proposed method is also an important result to show since the proposed method is designed for real-time digit recognition. The time complexity of the proposed feature extraction method is shown in Table 4 and indicates that this method is well suited for online automatic digit recognition.

Table 5 shows the confusion matrix for the Random Forest combined with the proposed feature extraction method. The confusion matrix indicates what digits are confused with each other and the false classification rates of some digits. The MADBase dataset shows some confusion in certain digits; for example, the digit 0 and digit 5. The rest of the datasets are also shown in Table 5. Overall it can be seen that the proposed method has drastically reduced the confusion between digits and has led to the correct classification and correct recognition of the Arabic numerals. The confusion matrix also shows that the confusion for the Persian Numerals has also been reduced leading to greater accuracy and precision in correctly classifying and identifying the Persian digits.

Table 3
Comparison of proposed classifier with other classifiers for all 4 databases in terms of Accuracy and Precisian

Numeral Language	Database	Classifier	Accuracy	Precision
Arabic	MADBase	RF	97.10%	97.10%
		MLP	93.80%	93.80%
		SVM	92.1%	92.5%
		KNN	96.7%	96.7%
	AOD	RF	94.8%	96.3%
		MLP	90.0%	94.2%
		SVM	91.4%	92.6%
		KNN	92.9%	94.7%
	PMU (Own Constructed Database)	RF	95.2%	95.3%
		MLP	84.0%	84.2%
		SVM	80.9%	83.4%
		KNN	86.0%	86.2%
Persian	HODA	RF	97.5%	97.5%
		MLP	96.8%	96.8%
		SVM	83.4%	92.0%
		KNN	94.9%	95.0%

Table 4
Time Complexity comparison of Classifier techniques used

Recognition Method	Time Complexity
Random Forest (RF)	O(mn log n)
Multilayer Perceptron (MLP)	$O(n^3)$
Support Vector Machine (SVM)	$O(n^3)$
K-nearest Neighbor (KNN)	O(mn log n)
Proposed Feature Extraction	$O(n^2)$

VI. CONCLUSION

The complexity of online handwritten numeral recognition is high compared with the offline handwritten numeral recognition. Therefore, fewer studies and methods have been developed for online handwritten numeral recognition compared with offline recognition. In this paper, we proposed a novel Local Feature Extraction method that is used to design a unified Arabic and Persian handwritten numeral recognition system. Previous works have concentrated on SVM, MLP and KNN algorithms for classification and classification method comparison. However, in this paper we proposed and showed that combining the Random Forest (RF) classification method in conjunction with our proposed Local Feature Extraction method yields optimum results for a unified handwritten Arabic and Numeral Recognition system.

Results indicated that we have achieved an average of 96.15% accuracy and 96.55% precision in recognition of handwritten Arabic and Persian Numerals. These rates exceed other methods rates and establish a good Launchpad for future work for the development of a unified system for the recognition of other handwritten numerals in other languages that are close in shape to the numeral sets used in this study. Future work will also concentrate on the study of the relation of number of local features extracted to the average recognition rate. With only 37 local features extracted in this paper, the average recognition rate has exceeded previous proposed methods that worked on 115 or more extracted features. Future work will also continue to develop the digital interpreter for students with disabilities particularly students with visual impairments and students with hearing impairments.

ACKNOWLEDGEMENT

This work is supported by Prince Mohammad Bin Fahd University (PMU) Phase 2 Research Grant. The authors would like to thank Prince Mohammad Bin Fahd University for supporting this research project that is expected to result in more publications in this field.

Table 5
The confusion matrix based each digits recognition by using Random Forest (RF) for all four databases

		Num0	*Num1*	*Num2*	*Num3*	*Num4*	*Num5*	*Num6*	*Num7*	*Num8*	*Num9*
Arabic AOD Database	*Num0*	594	0	0	0	0	0	0	0	0	0
	Num1	0	592	0	0	0	0	0	0	0	0
	Num2	0	0	519	0	0	0	0	0	0	0
	Num3	0	0	0	491	0	0	0	0	0	0
	Num4	0	0	0	0	540	0	0	0	0	0
	Num5	0	0	0	0	0	469	0	0	0	0
	Num6	0	0	0	0	0	0	477	0	0	0
	Num7	0	0	0	0	0	0	0	488	0	0
	Num8	0	0	0	0	0	0	0	0	445	0
	Num9	0	0	0	0	0	0	0	0	0	505
Arabic MADBase	*Num0*	1073	6	3	11	9	15	0	2	3	6
	Num1	7	1248	1	1	1	0	5	0	0	3
	Num2	0	5	1147	22	7	1	0	0	2	1
	Num3	3	11	17	1176	4	0	3	6	1	2
	Num4	6	9	18	6	1141	2	0	2	0	5
	Num5	34	0	4	0	1	1163	1	3	1	0
	Num6	0	4	0	1	3	0	1239	0	0	4
	Num7	6	0	0	6	1	1	0	1171	1	0
	Num8	4	1	2	5	3	1	0	0	1118	19
	Num9	4	3	4	4	1	2	14	3	7	1170
Persian HODA Database	*Num0*	1212	0	0	0	1	5	0	0	0	2
	Num1	0	1214	0	0	6	0	0	0	0	2
	Num2	0	6	1085	13	16	0	12	2	0	3
	Num3	0	0	36	1121	34	0	6	2	0	1
	Num4	2	8	24	20	1114	3	3	3	1	1
	Num5	6	0	0	1	1	1165	1	2	7	1
	Num6	0	2	6	0	3	0	1164	3	0	8
	Num7	0	0	4	0	0	1	0	1218	0	0
	Num8	4	1	0	1	2	4	0	0	1214	6
	Num9	2	0	1	0	7	4	14	0	0	1189
Arabic PMU Database	*Num0*	198	0	0	0	0	0	0	0	0	0
	Num1	1	178	0	0	0	0	0	0	0	0
	Num2	0	5	155	4	4	0	0	0	4	0
	Num3	0	0	6	165	0	0	1	4	0	1
	Num4	0	0	3	0	186	4	0	0	0	3
	Num5	0	0	0	0	1	171	0	0	1	5
	Num6	0	2	1	0	4	0	174	2	2	0
	Num7	0	0	0	2	1	0	0	180	0	1
	Num8	2	0	0	4	1	0	1	1	182	3
	Num9	3	0	0	0	2	3	4	0	0	166

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