Printed digits recognition using multiple multi Layer perceptron classifiers and Hu moments

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Abstract— **This paper presents the combination of Multi-Layer Perceptron (MLP) artificial neural network classifier for printed Arabic digits recognition. Different types of feature are used, cavity, zoning, pixel feature and Hu moment invariants which are invariant under change of size, translation, and orientation (rotation). On experimentation with a database of 6240 samples in multi-font and multi-size. We propose an approach based on a combination of Multi-Layer Perceptron using different feature types. The technique yields an average recognition rate of 94.33% evaluated after three methods of learning Kfold cross validation holdout and resubstitution method. The proposed printed digit recognition system can be used within applications related to post office (postal address, postal sorting), car plates, barcode and can also be extended to recognize handwritten Arabic digit.**

Keywords— ***combination of classifiers , Hu moments, multi layer perceptron, artifical neural networks, printed digit recognition, feature extraction.,***

I. INTRODUCTION

Handwritten and printed character or digit recognition is an important research domain. It has wide importance for its applications in OCR systems, post office (postal address, postal sorting), car plates, barcode, street view imagery in [25] etc….. In many literatures recognition of printed and handwritten digits have been presented. In [1] authors proposed a new scheme of fuzzification function for recognition of multi-font numerals based on box method for obtaining the distance feature. Another work in [2] used a quantitative and qualitative methods based on fractal geometry and invariants moment to recognize the printed or handwritten digits. The fractal features are computed for the area of image segment within the frame. The analysis of the results showed that the fractal dimension can be recognized different digits printed at same font size, but it cannot distinguish the printed digits or handwritten at different font sizes.

Mamatha Hosalli Ramappa et *al* [4] used 8 different features computed from zonal extraction, image fusion, radon transform, fan beam projections, directional chain code, discrete Fourier transform, run length count and curvelet transform along with ten different classifiers like Euclidean distance, Chebyshev distance, Manhattan distance, Cosine distance, KNN, K-means, K-medoids, linear classifier, artificial Immune system and classifier fusion are considered, for recognition of handwritten Kannada numerals. In [3] author calculate the correlation coefficient between certain reference images and the image under consideration, the implement algorithm show that very high recognition rates can be achieved.

A new approach is proposed in [6] for preprocessing of handwritten, printed and isolated numeral characters. The new approach reduces the size of the input image of each numeral by discarding the redundant information. This method reduces also the number of features of the attribute vector provided by the extraction features method. Numeral recognition is done k nearest neighbors and multilayer perceptron techniques. Another new system for recognizing Arabic handwritten and printed numerals, using the characteristics loci (CL) is presented in [5] for extracting the numeral features, Numeral recognition is carried out through k nearest neighbors and multilayer perceptron classifiers.

Many researchers usedartificial neural networksfor printed and handwritten digits recognition [20, 21, 22, 23, 24, 25, 26]. During the two last decades, there is an increasing interest to performance improvement by the combination of multiple classier [7, 8, 9, 10, 11, 12, 13]. Classifiers combination represent one of the most widely studied topics in the fields of machine learning and pattern recognition, it has shown their effectiveness to combine results provided by different classifier and to compensate their individual weakness and to preserve their individual strength.

In this paper we present a model for invariant pattern recognition by combining Hu moments and other features using MLP classifier. The considered model will efficiently recognize digits without taking in consideration the possible variations of position, rotation and scale.

The paper is organizes as follows: section II illustrates the proposed recognition system.Section III presents the different used features while section IV describes the MLP classifiers and the combination method. In section V, we discuss the experimental results and conclusions are drawn in section VI.

II. PROPOSED METHOD

A pattern recognition system usually comprises three main steps: preprocessing, feature extraction and classification. In the preprocessing stage we segmented and isolated digits from the input image after binarization, the image is converted into binary image with the help of thresholding (using a

thresholding technique. Black pixel "1"represents the foreground and white "0" pixel represents the background). Feature extraction aims to represent the image by different measurements that may be easily utilized in the classification stage. We used variety of feature extractors like cavity, zoning, retina (pixel representation) and invariant Hu moments. In the classification stage the MLP Artificial neural network is trained individually using different feature characteristics.

The recognition stage is the stage that classifies and recognizes the digits. By comparing the feature of a new digit with all features which are stored in the databases to determine the recognized digit.

In this work, we propose our method shows in "fig. 1.", the classification is done using six feature types vector, which is presented in the following section, for representing the image of the Arabic digits. Each feature type vector will constitute the input to a Multi-Layer Perceptron (MLP) Artificial Neural Network (ANN). The recognition rate is obtained using combination of the several MLP by voting rule.
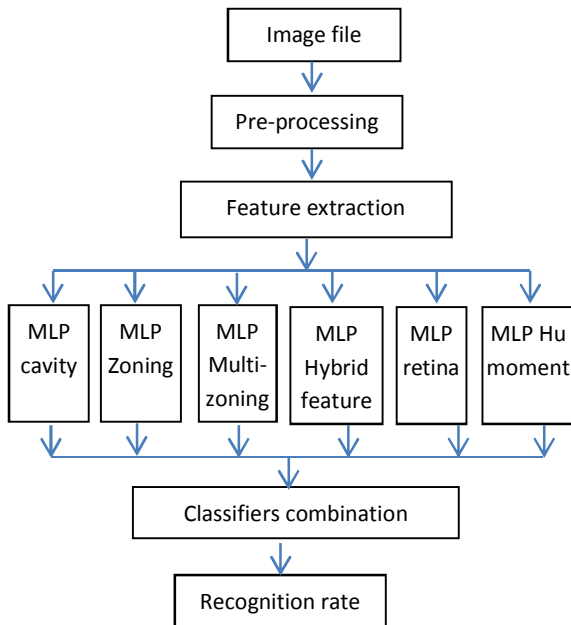

Fig. 1. The proposed digit recognition method.

III. THE FEATURE SETS

Feature extraction is the process to represent the image by a suitable set of features. So many approaches have been proposed for feature extraction in [14] features like statistical features, structural features, contour features. In this paper we present a model for invariant pattern recognition by combining Hu moments and other features using MLP presented in the following

- Ratio: Some letters have an important ratio "height/width", while others have a rather low. To minimize complexity and optimize the recognition rate, this parameter is combined with cavities [15].

- Cavities: Almost all digits include cavities; the number and position vary depending on the digit and font. We define 5 types of cavities: East, West, North, South, and Central. This requires the definition of four cardinal directions in the image: West left, North up, etc… [17]. In our work, we will use as characteristic parameters, the relative surface of different types of cavities (The cavities should be normalized by dividing by the total surface of the cavities), and the number of cavity.

- Natural or retinal representation (pixel features): We take the pixels of the matrix (image) as input (in our case size image is 8x5). This method is widely used in some neural approaches. But does not tolerate geometric transformations (rotation, translation, scaling) or deformation in exception of some noise [16].

- Zoning: .consists of dividing The image into "n" vertical and "m" horizontal small and equalsized zones or blocks (or windows) of n*m pixels to obtain the features. A feature vector is the number of on pixels in each zone (The zoning vector should be normalized by dividing by the total surface of the zone)[14, 4]. This operation reduces widely the size of the image and preserves the useful information for recognition of every input image [6].

- Multi-zoning : initially, statistical feature extraction technique was applied to each segmented character image by calculating the percentage of black pixels in one zone of a character image. The character image was divided into zones, taking data from each zone as a feature for the image. The character image was divided k times into zones (having multiple dimension). These zones have been chosen to cover most of the region in an image which contains information, however can be optimized on the basis of experimental results.[18].

- Hybridization between cavity and zoning: it is difficult to differentiate between similar digits using some features, for example "1" and "7" , "0" and "4", "0" and "8" using cavities features. For this reason we propose to extract cavities features from different blocks resulting from the zoning feature and used together with the main cavities (cavities of digits without zoning). In our case we used a zoning 2x2, 2x1, and 1x2.

- Hu moment [19, 28]: In the field of pattern recognition there exist a significant problem, it is the recognition of objects regardless of their position, size and orientation. For this using of the invariant moments used have been proposed, there are seven Hu moments are well-known to be invariant to position, size and orientation of digit.They are the following:

$$\emptyset_1 = \eta_{20} + \eta_{02} \tag{1}$$

$$\emptyset_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}{}^2 \tag{2}$$

$$\emptyset_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \tag{3}$$

$$\emptyset_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} - \eta_{03})^2 \qquad (4)$$

$$\emptyset_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03}) + (\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \qquad (5)$$

$$\emptyset_6 = (\eta_{20} + \eta_{02})((\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2) + 4\eta_{11}(\eta_{03} + \eta_{12})(\eta_{21} + \eta_{03}) \qquad (6)$$

$$\emptyset_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] - (\eta_{30} + 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \qquad (7)$$

Where η_{ij} are the normalized Geometrical central moments which are invariant to scaling (scale normalized),

$$\eta_{ij} = \frac{\mu_{ij}}{\mu_{00}^{(i+j+2)/2}} \qquad (8)$$

$$\mu_{ij} = \sum_{k=1}^{K} \sum_{l=1}^{L} (k - x_g)^i (l - y_g)^j g(k, l) \qquad (9)$$

Where *g(k,l)* is image function and K, M are image dimensions, and μ_{ij} are Geometrical central moments of order *(i+j)* computed using centroid (gravity center of image) which calculated by (10). μ_{ij} are invariants to translation (with image translation to coordinate origin while computing central moments

$$x_g = \frac{M_{10}}{M_{00}}, \quad y_g = \frac{M_{01}}{M_{00}} \qquad (10)$$

Where M_{ij} are geometrical moments of order *(I + j)* for binary image defined as:

$$M_{ij} = \sum_{k=1}^{K} \sum_{l=1}^{L} (k)^i (l)^j g(k, l) \qquad (11)$$

"Table I" lists moment invariants for different status of digits "2"

IV. CLASSIFIATION

The classification stage is the main stage of a digits recognition system. This stage uses the features to identify the digits. In this work, we propose to use MLP one of many different types of existing neural networks for classification of digits.

The multilayer perceptron (MLP) is the most widely known and used type of neural network is a feed-forward artificial neural network model. It consists of one input layer, multiple

TABLE I. HU MOMENT INVARIANT OF DIGIT "2"

	$\emptyset_1$	$\emptyset_2$	$\emptyset_3$	$\emptyset_4$	$\emptyset_5$	$\emptyset_6$	$\emptyset_7$
2	0.2300	0.0085	0.0002	0.0001	0.0000	0.0000	0.0000
2	0.2655	0.0032	0.0007	0.0006	0.0001	-0.0000	-0.0000
2	0.2655	0.0032	0.0007	0.0002	-0.0000	-0.0000	0.0000
2	0.2582	0.0016	0.0007	0.0002	-0.0000	-0.0000	-0.0000
2	0.2655	0.0032	0.0007	0.0001	-0.0000	-0.0000	0.0000
2	0.3292	0.0447	0.0007	0.0002	-0.0000	-0.0000	0.0000
2	0.2655	0.0032	0.0005	0.0001	-0.0000	-0.0000	0.0000
2	0.2773	0.0177	0.0007	0.0002	-0.0000	-0.0000	0.0000
2	0.2655	0.0032	0.0007	0.0002	-0.0000	-0.0000	-0.0000
2	0.2080	0.0016	0.0000	0.0000	0.0000	-0.0000	-0.0000
2	0.3057	0.0292	0.0005	0.0000	0.0000	0.0000	0.0000

(one or more in our case one layer) hidden layers of neurons and one output layer, with each layer fully connected to the next one. Numberof neurons in the input layer is equal to the length of the features vector, in the hidden layers is decided experimentally (20 neurons in our case) and the number of neurons in the output layer is equal to the number of classes.In our case 10 classes are required.

Learning algorithms for multilayer neural network the most widely used is the retro-propagation algorithm or back-propagation algorithm which is the most widely known and used supervised learning algorithm. It has two phases, first, a training input digit is presented to the input layer of network, and it then propagates the input digits through the network to the output layer. If the result generated by the output layer is different from the desired output, an error is calculated and then propagated backwards through the network from the output layer to the input layer. The weights are modified as the error is propagated. The goal is to minimize the error between the obtained result (obtained by the neural network) and the desired results (result of the output).

During the last decade, combination of classifiers is widely used in many different applications. There are different types of combination. One such type is parallel combination. In this approach, many classifiers are trained separately and independently. The results of these classifiers are combined to obtain a more accurate classification.Voting is the simplest way to combine multiple classifiers. This is also known as committees, ensembles, or linear opinion pools. It corresponds to taking a linear combination of the learners.

In this paper, we haveused6 MLP classifiers.The features obtained from cavity, zoning, multi-zoning, hybridization between cavity zoning, pixels and Hu moments areappliedto MLP separately. The prediction of these classifiers is merged using majority-voting technique to correctly classify the sample. Where the decision is based on the majority of class values which obtained by the several classifiers.

V.   RESULTS AND DISCUSSION

In this work, there are ten images of digits (0-9) used to test our proposed system. Each of images contains 624 instances in different sizes and fonts of Microsoft Word (converted to images by graphic software "Paintbrush"). The image preprocessing is realized using Matlab (Toolbox Image Processing), then a step for localization and limited of digits by rectangles (bounding each digit).

For evaluating our system we exploited for training three techniques of cross validation involves partitioning a sample of data into complementary subsets. Performing the analysis on one subset (called the training set), and validating the analysis on the other subset (called the validation set or testing set). In fact, we used "K-fold cross-validation", "test set validation" (called holdout method), and "Resubstitution method".

In the first method (k-foldcv, k=10 is commonly used), the dataset is randomly partitioned into k equal size subsamples. Of the k subsamples, a single subsample is retained as the validation data for testing the model, and the remaining (k−1) subsamples are used as training data. The cross-validation process is then repeated k times. The k results can then be averaged. The second method is the simplest variation of k-fold cross-validation (2-fold cross-validation) simply divides the database of size n in training sample (superior 60% of the original base) and test sample. We then train on training sample and test on the test sample. The third, Resubstitution method use the all dataset as training and testing data.

For the combination we use a combination of class type, it has the advantage that it can be used for any type of classifier (class, rank or measure), regardless of its structure. In this combination, each classifier outputs is a response on the membership of the unknown form to a class or to a set of classes (with the same degree of preference). However, this is the only information that may be used. The combining of multiple classifiers class type is often based on the principle of the vote [15, 27]. In pattern recognition, voting methods have been used primarily in recognition of writing and for the verification of signatures [27].

As part of the combination, the voting methods consist to interpret each output of a classifier as a vote for one of the possible classes. The class with number of votes greater to a

present threshold is chosen as the final decision. These methods are simple to implement: the classifier votes are not weighted and each class receives as many votes as there are classifiers to combine. Most of these methods require only one decision level.

We present here the principle of voting as a method of combining multiple classifiers. We consider the problem of combining m classifiers S_j to determine one of the n classes C_i possible [15].

The voting rule is the simplest method of combination to implement. Note $S_j(x) = i$ that the classifier S_j assigns the class C_i to the observation x. We assume here that the classes C_i are exclusive. For Each classifier we associate the indicator function:

$$M_i^j(x) = \begin{cases} 1 & \text{if } S_j(x) = i, \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

The combination of sources written by:

$$M_k^E(x) = \sum_{j=1}^{m} M_k^j(x), \quad (13)$$

In the first experiment, each MLP classifier is separately and independently trained with the corresponding feature type. Experimental results shown in "Table II" give the different recognition rates obtained for each MLP classifier. The best recognition rate "94.44%" is obtained by MLP classifier basedon hybrid features (cavity+zoning).

TABLE II.   PERFORMANCE OF 6 SINGLE MLP CLASSIFIERS

Classifiers	10-fold CV	Holdout	Resubstitution
MLP cavitie	66.38	68.27	67.52
MLP Hu moment	53.46	54.06	58.45
MLP Retine	88.83	88.14	92.85
MLP Zoning	29.65	28.10	32.18
MLP Multizoning	82.90	82.08	84.10
MLP Hybride (Zoning+cavity)	93.75	93.38	94.44

By combination of MLP classifiers the recognition rate has been presented in "Table III" which shows the results of classifier combination using majority voting. By considering less number of features and tolerance to the geometric transformations, the good result obtained is (79.74%) by the combination of MLP classifier based on Hu moments and MLP classifier based on hybrid feature. But according to these results using all or subset combination of MLP classifiers has not increased recognition rate compared to recognition rate of separately classifier.

TABLE III. PERFORMANCE OF SEVERAL SUBSET OF MLP CLASSIFIERS

	10-fold CV	Holdout	Resubstitution
6MLP (hybrid+ cav+Hu+mutizoni ng+retine+zoning)	87.02	84.08	88.06
3 MLP (Cav+hybrid+Hu)	77.88	77.14	79.60
2 MLP (Cav+hybrid)	70.35	70.51	71.60
2 MLP (Cav+Hu)	57.21	60.79	63.33
2 MLP (Hybrid+Hu)	77.40	74.68	79.74

Results of another try to increase the rate recognition shownin "Table IV". This try present an attempt to train a larger MLP by concatenating feature vectors (obtain a combined feature vector). The best recognition rate obtained is (98.88%) by concatenation of features "Cavity+ hybrid features (cavity, zoning) +Humoment.+ multi-zoning+ retine + zoning" where the input vector size is equal to 6+12+7+6+40+8=79 with 50 hidden neurons. But by considering less number of features and tolerance to the geometric transformations, we can say the good result obtained is "93.16%" with MLP classifier based on Cavity, Humoment, hybrid features, and "94.33%" with MLP classifier based on Cavity, Humoment, hybrid, multi-zoning features.

TABLE IV. PERFORMANCE OF SINGLE MLP CLASSIFIER BY FEATURES CONCATINATION

Features	10-fold CV	Holdout	Resubstitution
Cavity+Hu moment	86.30	79.81	80.93
Cavity+ hybrid	79.62	87.50	87.79
Hybrid+Hu moment	87.37	85.68	89.10
Cavity+hybrid+Hu moment	90.34	91.24	93.16
Cavity+hybrid+Hu moment+multizon ning	91.73	90.71	94.33
Cavity+hybrid+Hu moment+multizoni ng+retine+zoning	93.70	93.48	98.88

Comparing individual classifiers, combination classifiers method and combination (concatenation) different feature type we note that the last has the better performance.

VI. CONCLUSION

MLP have been widely applied to pattern recognition problems. In this study, a printed digits recognition system has been implemented using 6 features extraction method like cavity, zoning, multi-zoning, hybridization between cavity zoning, pixels and Hu moments. The implemented system is constructed using an MLP neural network classifier with back-propagation. A dataset of multi-font and multi-size printed digits is used. Initially, MLP classifiersareused for the classification. Further, the recognition rate was calculated using classifier combination method and concatenation of features method. With this approach, Set of different experiments was done and various results were achieved. Finally, the best result was "94.33%" correct classification that showed by single MLP based on concatenation of feature vectors by considering less number of features and tolerance to the geometric transformations with Hu moment feature.

To improve the recognition rate, possible future works are as follows. (1) Increasing number of data set. (2) Using other feature type tolerates to the geometric transformations (3) exploiting the combining of classifier mechanisms

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