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RECOGNITION OF PERSIAN HANDWRITTEN NUMBERS BASED ON ASSEMBLY OF REINFORCED CLASSIFIERS

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ABSTRACT
According to the economic justification study in field of recognition of handwritten letters and numbers and specially the more sensitiveness of handwritten numbers, in this report has tried to do a deep survey on this field. One of the general weaknesses that in most of research in Persian language and often English language are raised is using simple classifiers that finally lead to recognition with Low accuracy. This especially is raised about recognition of numbers. Hitherto, different methods have introduced for increasing classifier's efficiency that in most of them efficiency of a particular classifier optimize for a particular sets of data. According to this that the number of recognition categories in these issues are a lot, using binary classifiers can efficiently leads to more accurate detection. In this report it will be tried to present new and efficient method compared to the existing methods for recognition of single handwritten digits. Detector classifiers of each category are trained especially. Then by using classifiers combination methods, the final decision has predicted for category of an input digit.

KEYWORDS: detection of Persian handwritten numbers, assembly of binary classifiers, methods base on Consensus, basic classifier of decision tree, artificial neural network, 3 nearest neighbor.

INTRODUCTION
Reading Simulation and text detection by machine divide into 2 general group: 1. Offline detection: includes pictures that are provided from writings; such as photograph by digital camera, scanning of letters and book pages [1]. 2. Online detection: Simultaneous with the writing of that, the written text has detected and change into its character [2]. Such as detection of handwriting in tablet pcs; type of text in text detection systems that has printed by machine is possible in two type of handwritten text or typed text; such as books, magazines and …. [3].

AUTOMATIC DETECTION OF HANDWRITTEN NUMBERS
In topic of detection of Persian handwritten numbers, the purpose is finding of the model or a detection system that by getting a picture including a handwritten number in range of 0 to 9, detect that this picture exactly involve which number. Extracted properties of these numbers a properties vector of n that extraction method of them should also be determined. This practice is called classification of pictures idiomatically. Because hard nature of intelligence problems, these problems are from type of NP-Hard problems.

RELATED WORKS
Pattern detection systems or recognition systems; are systems which in them the purpose is detection of an input sample and predication of that sample to one of the batches of pre-defined. The general format of a pattern recognition system is like following fig [4].

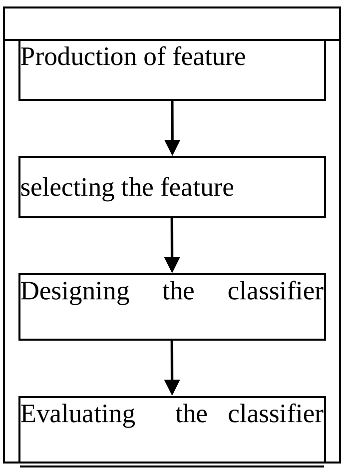

Figure 1. The general format of a pattern recognition system

Classification accurately and scientifically means to determine the discriminant function so that this function map, n dimensions features space to decision areas of categories. One of the most important purposes of artificial intelligence is to achieve high classification or recognition rate. Nowadays pattern detection is used in a wide range of usages [5].

Classifiers multiple combinations can be considered as a general pattern detection problem, which in inputs are results of single classifiers and output is their combination decision. The idea of this subject has originated from where that classifiers with different features or different Methodologies can complete each other or cover each other's weakness. If some different classifiers vote together as an assembly, the general error of them will be decreased significantly [5].

Generally creating combination recognition systems is possible in four levels [5].

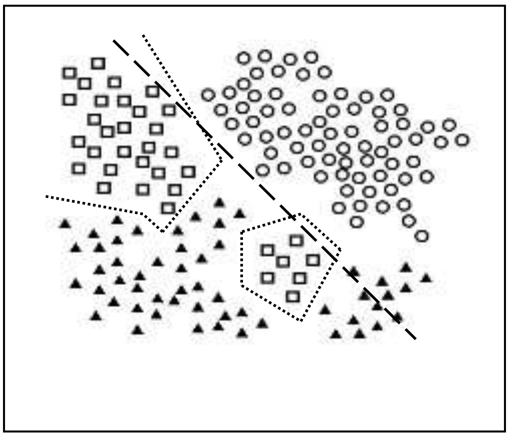

Figure 2. Types of recognition systems in term of the numbers of classifiers

Classifiers considering to the numbers of categories that are to be different to each other, are divided into two types of the periodic classifiers and multiple category [5]. Purpose of a multiple category classifier is distinction of a category from other category [6]. Since that a periodic classifier only is trained for distinction between two categories and ignores other category, decision borders in that compared to decision borders of multiple category classifiers is more simple and more efficient [7].

Pairwise classification, is a combination method which in instead of using a single multiple category classifier, all possible binary classifiers is used. If we consider the numbers of the classifiers as c, this method needs to use $(c\times(c-1))/2$ classifiers [6]-[13]. This method has a good efficiency for problem with less numbers of categories, but with increasing the number of categories the numbers of binary classifiers have a significantly growth. Optical character's detection in Persian language is not possible because of Persian language's special features, whether in appearance or in shape of storing in computer, that is different with usual methods of optical character's detection in Latin languages. Therefor the amount of progressing in methods of optical character's detection in Persian language is not equal to amount progressing of these methods in Latin language. Recognition of handwritten letters and numbers always has been one of the interesting subjects of researchers [26]. Recognition of handwritten characters in pictures has done by using different methods that everyone has significant error percentage [18]. Some of researches is this field in Persian language have been done in recent years [19]. Moshki and torki rahmani in [19] have offered a method for optimization of feature extracting from Persian handwritten numbers. They try to extract feature by using genetic algorithm that maximize the rate of recognition in data of validation. They have benefited from genetic algorithm for searching of features. Azmi and kabir in [20] have used torque features and Bayesian's classifier for recognition of Persian handwritten letters. Nafisi and kabir in [21] have used from features of characteristic places, Bayesian's classifier and also Markov chain for recognition of handwritten numbers. Also Razavi and kabir in [22] have used from triplex method for extracting of features from Persian handwritten numbers. Masrori and Pormohseni Khamene in [23] have used from a method based on dynamic time warping to recognition of numbers. Also methods based on Fuzzy Logic have presented for this work [24]. Darvish et al in [25] also have used from the method based on description of handwritten numbers shape. They have used from pattern matching algorithm for description and comparison of two handwritten numbers. Some of other researches that have done in field of Persian optical character's detection systems are as follow:

Persian recognition handwritten letters based on active training algorithm by using Committee of classifiers [9], Implementation of Persian optical character's detection systems by using the Morphological operators [10]. Online recognition of single Persian letters with Persian network [11]. A system for recognition of Persian printed text that has been presented by combination approach (using of both approaches based on separation of words and based on recognition of word as a unit pattern) [12]. An algorithm for online segmenting of Persian handwritten words, the meaning of segmenting is here is finding of segment which by using that all the words can be created. This means the set of written words are divided to more simple words by different people till will be used for recognition [13]. The methods for recognition of Persian handwritten words have been presented in a limited set without segmenting words. These methods act in level of words or under the level of words. It has used from Fourier transform. Its used classification was been decision tree. Accuracy of its method on a little test data set was about 88% recognition [14]. It then improved its work and by using Hierarchical classification and by using from Amargany's feathers improved the accuracy of its work up to 92%. Moghasemi, namazi, asadi and timsari have presented four single methods [15]-[16]. Detection of Persian handwritten letters by using fuzzy and light hybrid systems [17]

PROPOSED IDEA

A series of existed methods has implemented for improving efficiency of classifiers combination's system and has used in order to recognition of Persian handwritten numbers system. The main idea of these methods is designing classifiers combination's systems.

One of the most important agents of efficiency improvement of combination classifier, is using from more scattered basic classifiers. The more accuracy and more scattering of basic classifiers will have the more accuracy in achieved combination. Although, the accuracy of classifiers assembly will not be better than the best basic classifier, but will not have less accuracy than the average of single basic classifiers.

The new presented combination methods in this paper for improving the rate of recognition of multiple category classifiers will be used the concept of two category classifier. The main idea of these methods is using from two category classifiers. Because of more accuracy in these types of classifiers than multiple category classifiers, using of them in combination leads to decreasing error in flawed areas of feature space. In proposed methods, at first a multiple category classifier is trained and interference matrix relate to that calculate. Then, pair categories that according to the interference matrix and evaluating data have the most error recognize. For increasing accuracy, in detection of them from each other, some two category classifiers add to system. Finally, weighted voting is used for combing of results. In this method, neural networks have been used as primary classifier. Determine of weights in final classifier is used with genetic algorithm. The results of prosed method have been evaluated on a set of data of Persian handwritten numbers.

SETS OF DATA AND FEATURES

The data set used for benchmarking of proposed ideas in this survey is the set of Hoda Persian handwritten numbers. The data sets of Hoda with 60000 training samples and 20000 experienced samples is the biggest sets of data in field of detecting Persian handwritten numbers. These sets of data have extracted from 11942 filled forms by participating diploma people in entrance examination and the power of reparability of these sets of data samples is 200 point on inch. The exact numbers of this set of data is totally 102364 samples of Persian handwritten numbers 0-9. Training, evaluating and exam set in all over the experiments of this survey, respectively includes 60000, 20000 and 20000 numbers, have been considered. As noted earlier, for the representation of numbers from 106 feature has been used that include image scaled of fixed dimensions, Horizontal and vertical cross-sectional images, as well as the profiles of quadruple numbers. It should be noted that the 16 basic gradients instead of 8 basis orientation have been used to for rotations of images.

First purposed model

After determining the pair of flawed classes of interference matrix, at this stage turn reaches to twoclass classifier training. At this stage two-class classifier training, only by using the two class samples is done. Since proposed method is a flexible method, any number of binary classifier can be added to the first classifier. It is expected to, accuracy of this classifiers in distinction of the pair classes, be higher than primary classifier. To select flawed pair classes, it is enough to arrange pair of classes in terms of the number of errors that occurred between them, and Select an arbitrary number of them. This number can be determined by trial and error.

In the first method proposed, combining the output of the first classifier and two class classifier is considered as a new feature space. The output of this classifier is used as new features space and the combiner input. The output of combiner function, determines the final output system there are different methods to combine the classifier results. Here, we do this work using weighted voting method. The problem that arises here is, How to determine optimum of these weights. In this paper, a genetic algorithm is used to find the optimal weights. Due to ability of the genetic algorithm in the transition from local optimums, it is estimated that output of this method is better than primary trained classifier to obtain the interference matrix. Form of the structure of this detection system shows that in it, a series of base classifiers as primary classifiers and the binary classifier, And the weighted voting as a combiner, is used.

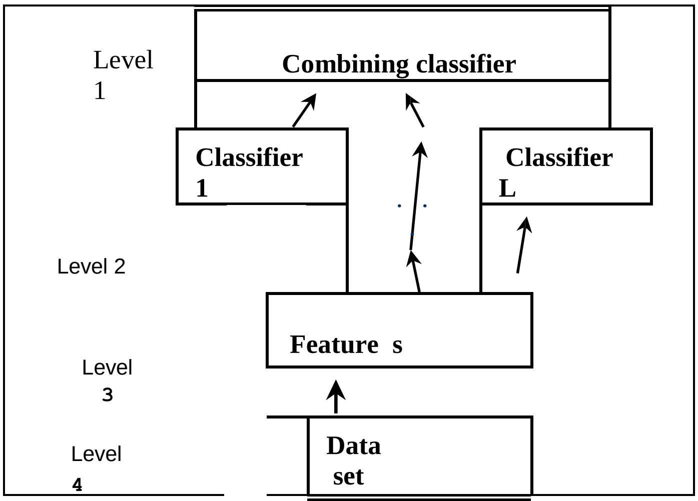

Figure 3 the structure of the proposed method for optical detection system of handwritten numbers

The number of existing classes, Genetic algorithms is used. Each of genetic algorithms, According to the primary classifier and two-class classifier results, gives its vote for recognition of its class. Eventually a class is selected that Genetic algorithm related to that class, more firmly have voted to it. This is simply done by applying a maximum taker function.

Second purposed model

In the first stage, we train a multi-class classifier on training data. Then, by using the results of this classifier on assessment data, interference matrix is formed. This matrix contains important information regarding performance way of classifier. Close together and flawed classes, by using this matrix are identifiable actually interference matrix, specifies the distribution of error on different classes. a_{ij}Element of interference matrix determines that How many instances of c_j have been detected part of c_i class. In this paper, a neural network is used as the primary classifier. To achieve this matrix, neural network with two layers has been used. 10 neurons in the first layer and in second layer 5 neurons have been used Function of activity of neurons in neural networks, in first layer linear and in second layer has been tangent sigmoid. TRAINLM learning method has been used for learning. Criteria have been Efficiency of mean square error on the validation set. Learning rate is considered 0.1.

As we expected, Digits 5 by mistake 14 times zero and zero by mistake have been detected15 times 5; meaning in total, 29 times the error in distinction between the two digits has occurred. Pair classes with highest error in this matrix are (2, 3), (0, 5), (3, 4), (1, 9), (6, 9). We display i- Th flawed pair classes with$EPPC_i$.

The first phase of second proposed model is shown in Figure 5. In the first stage, we train a multiclass classifier on training data. Then, by using the results of this classifier on assessment data, interference matrix is formed. After determining the pair of flawed classes of interference matrix, at this stage turn reaches to two-class classifier training. At this stage two-class classifier training, as pervious only by using the two class samples is done. Then, as Figure 5 shows, first data for each flawed pair classes has been separated. Per two-class classifier in order to achieve a strong classifier, we train a body of two class classifier. Assembly of two class classifier that is going to learn $EPPC_i$ is shown withPWC_i. We show j- Th existing two-class classifier in the assembly of ith two-class classifier with PWC_{ij} .Each of two-class classifiers in an assembly of PWC_itwo-class classifiers on b percent of their data on their own class, meaning$EPPC_i$ Will be built in the training set and calculate accuracy of each of them on the entire data on their own class in the training set (they only b percent of the data of those two in their own class) and are displayed withP_{ij}.

Participation Weight of PWC_{ij}classifier inPWC_i will be calculated from equation (1).

$$w_{ij} = \log\left(\frac{p_{ij}}{1-p_{ij}}\right) \quad 1$$

And PWC_i is calculated from equation (2)

$$WC_i(x|h) = \sum_{j=1}^{m} w_{ij} \times PWC_{ij}(x|h) \quad ٢$$

That $h \in EPPC_i$. Kenchova has shown that the use of weights provided from equation 1 is optimum weights. In fact, in the first proposed method by replacing a set of two-class classifiers instead of simple two-class classifier we reach to the second proposed method. As the first method any number of binary classifier can be added to the first classifier. It is expected to, accuracy of this classifiers, be higher than the first purposed classifier.

After determining the pair of flawed classes of interference matrix and obtaining assembly of twoclass classifier, turn to build a method for combining the output of assembly of two-class classifier and primary classifier comes. As it is seen in Figure 6, for each class, a genetic algorithm is run. the first genetic algorithms, the is responsible for learning first class (class zero) and i-th genetic algorithms is responsible for learning the i-th class. Function of effectiveness of i-th GA is obtained from equation 3.

$$F(W_i, ValSet) = \sum_{x \in ValSet} f(x, W_i) \quad 3$$

That $f(x, W_i)$ function is calculated from equation 4

$$f(x, W_i) = equal(x, i) \times \left(BinaryOutput(x, W_i) + MultiOutput(x, W_i)\right) \quad 4$$

That equal function is calculated from equation 5

$$equal(x, i) = \begin{cases} 1 & label_x = i \\ -1 & label_x \neq i \end{cases} \quad 5$$

And $BinaryOutput$ function is calculated from equation 6

$$BinaryOutput(x, W_i) = \sum_{j=1}^{k} \sum_{h=1}^{2} W_i(s+h) \times PWC_j(h|x) \quad 6$$

That s is calculated from equation 7

$$s = (j-1) \times 2 \quad 7$$

And $MultiOutput$ function is calculated from equation 8

$$MultiOutput(x, W_i) = \sum_{j=1}^{c} W_i\,(2 \times k + j) \times MCC(j|x) \quad 8$$

Figure 7 shows the testing phase for second proposed structure for the detection of optical handwritten numbers. The final decision of Figure 7 classifier is calculated from equation 9.

$$EndVote(x) = \arg(\max_i f(x, W_i)) \quad 9$$

The third proposed model

Phase one of the third model is like the second model. After determining the flawed pair categories of interference matrix and obtaining two class classifications assembly that are shown in in Fig 5, another solution for combining (second phase) is presented that is shown in Fig 8. The final classification decision of Figure 8 is calculated from equation 10.

$$EndVote(x) = \begin{cases} T(x) & G(x) > \beta \\ P(x) & otherwise \end{cases} \quad 11$$

Where β is considered a decision threshold value and two $\mathrm{G(x) = max_{h \in EPPC_{sc}}}\left(\mathrm{MPWC_{sc}(h|x)}\right)$, function and $\mathrm{P(x) = max}_{h \in \{1,\dots,c\}}\left(MCC(h|x)\right)$ function and function T (x) are calculated from equation 11

$$T(x) = \arg\left(\mathbf{max}_{h \in EPPC_{sc}}\left(\boldsymbol{MPWC_{sc}(h|x)}\right)\right) \quad 11$$

And sc is calculated from equation 12.

$$sc(x) = \arg\left(\mathbf{max}_i\left(\mathbf{max}_{h \in EPPC_i}\left(\boldsymbol{MPWC_i(h|x)}\right)\right)\right) \quad 12$$

Basic used classification

Three base classifiers have been used. First classifier used is multi-layer neural network. In the MLP neural network, two hidden layers have been considered. In the first and second layer of MLP neural network, respectively, 5 and 10 neurons have been considered. In all MLP neural network uses, its parameters are considered constant. Function of activity of neurons in neural networks, in the first linear layer and in the second layer tangent is sigmoid. TRAINLM learning method has been used for learning. Performance criteria have been mean square error on the validation set. Learning rate has been considered 1.

The second classifier used is decision tree. In the decision trees, decision criteria, has been considered the Gini measure. In the decision tree pruning has also been used. The pruning threshold parameter has been considered 2. In all uses of, decision trees, such as the uses of multi-layered neural networks, their parameters have been considered constant. We continue decision tree training that Standard error percentage on the validation set is reduced. The third classifier used is k-nearest neighbor. Amount of k in all uses of k- nearest neighbor has been considered equal to the numbers that have the lowest percentage of error on the validation set, it should be noted distance criterion in all of implementations has been the Euclidean distance criterion. In all uses of k-nearest neighbors like uses of decision trees and neural network Multilayer Perceptron, their parameters have been considered constant.

EXPERIMENTAL RESULTS

The results obtained are summarized in Table 1. Notice that to achieve the following results from a constant set of training, validation and test, has been used for various performances. This work is done in order to compare the results.

Table 1: the results of recognition of Persian handwritten digits with various ways

Method	neural network	decision tree	Nearest neighbor
Simple classifier	97.83	96.57	96.66
The first model	98.89	97.93	96.86
The third model	99.04	98.99	97.14
The third model	98.46	99.01	96.89

In this result that is presented as a table, each row is indicator of a used method. In this result each column is indicator of one of the basic methods of classification. Clearly, this methods show that in using third proposed classifier method with base decision tree classifier we will see best performance whereas in using second proposed classifier with base neural network classifier we will see the best performance. In using first proposed classifier also with the base neural network classifier we'll see best performance. Best performance also belongs to the second proposed method classifier, with the base neural network classifier; where accurate classification reaches to 99.04 percent. Now the question is that this accuracy is how much meaningful. Meaning how much our error of accuracy is. According to the formula, model error range will be achieved with 95% confidence.

$$error \pm Z_{\alpha}\sqrt{\frac{error\times(1-error)}{n}} \qquad 13$$

Where α equal to half of a minus of the level of assurance we need. Given that n = 20000 and that we want the 95% confidence level and $Z_{0.975\,\%} = 1.96$ Therefore simple neural network model error range with an accuracy of 97.83 in Table 1 is as follows.

$$0.9783 \pm 1.96\sqrt{\frac{0.9783\times(1-0.9783)}{20000}} \Rightarrow [0.9763,0.9803] \qquad 14$$

By obtaining rate of change of the rest of range models, we will have Table 1 in form of Table 2 that is given in the following,

Table 2: the meaningful range of results of recognition of Persian manuscripts by figures in various ways with the 95% confidence level

Method	**neural network**	**decision tree**	**3Nearest neighbor**
Simple classifier	97.83±0.2	96.57±0.25	96.66±0.25
The first model	98.89±0.15	97.93±0.2	96.86±0.24
The third model	99.04±0.14	98.99±0.14	97.14±0.23
The third model	98.46±0.17	99.01±0.14	96.89±0.24

Lower bound of the accuracy of each model is given in Table 3.

Table 3: lower bound Persian handwritten digits recognition results in various ways, with a confidence level of 95%

Method	**neural network**	**decision tree**	**3Nearest neighbor**
Simple classifier	97.63	96.32	96.41
The first model	98.74	97.73	96.62
The third model	98.90	98.85	96.91
The third model	98.29	98.87	95.65

By obtaining upper bound of the rest of models in Table 1, we will have Table 4, which is given below.

Table 4 upper bound Persian handwritten digits recognition results in various ways, with a confidence level of 95%

Method	**neural network**	**decision tree**	**3Nearest neighbor**
Simple classifier	98.03	96.82	96.91
The first model	99.04	98.13	97.10
The second model	99.18	99.13	97.37
The third model	98.63	99.15	97.13

In the second analysis, we do statistically comparison between the line sections to see if in the desired confidence range (usually 95%), difference between the accuracy of these two classifiers is meaningful or not. Dietrich [8] presented comparison way of accuracy of two classifiers with precision of p_2 and p_1 as the following form. Z must be calculated first in the following.

$$z = \frac{p_1 - p_2}{\sqrt{\frac{2p(1-p)}{N}}} \quad 15$$

Where $p = \frac{p_1+p_2}{2}$ and N equals the number of experimental data. Then by calculating z_α that is α times of half a minus of assurance level we need, we examine that whether $z < |z_\alpha|$ if this condition was true, we accept the assumption that the difference of the accuracy of these models is not meaningful; otherwise, we reject it and accept that the difference is meaningful. In our example we perform analysis of the difference between the third proposed classifier with base neural network classifiers and third proposed classifiers with the base tree decision classifier. In this example we have $p_1 = 98.63$ and $p_2 = 99.13$ precisions, for 95% confidence range, $z_{0.975} = 1.96$ and $z = 5.45$ that condition is not true and we accept the difference is meaningful. Hatched point in Table 5 that has value of 1, is indicator of it that between these two classifiers (paragraphs 8 and 10 classifiers) with 95% confidence, difference is meaningful. In Table 5 we have a 12 in 12 matrix that wherever it is one means between classifiers with number of rows and columns of that element with 95% confidence have meaningful difference. Anywhere in the matrix there is zero means between classifiers with number of rows and columns of that element with 95% confidence doesn't have meaningful difference. As you see, these results indicate that conclusion ways meaningfully are superior to the base classifiers.

CONCLUSION

In this paper, three methods based on consensus were introduced that is based on two classes' classifiers. In this method three classifier decision trees, neural networks and 3 nearest neighbor has been used. It was shown that the use of base 3-near-the neighbor classifier in the proposed methods is not so much appropriate. In proposed classifier by using base 3-nearest neighbor classifier significant improvement hasn't been achieved. Of course, this result was not so unexpected; because the base 3-nearest neighbor classifier is one of the sustainable classifiers. The use of decision tree classifier in the proposed classifiers has created the most improvement. It was also predictable; because the decision tree base classifier is one of the most unstable classifiers. Of course in proposed classifiers by using of each base classifier significant improvement has been created that In general it can be claimed that the third proposed method is more suitable for base decision tree classifier, while the second proposed method is more suitable for base neural network classifier. The best result also in second proposed method by using base neural network classifier is obtained. In future works the effect of types of sampling techniques, on efficiency of proposed models accuracy can be studied.

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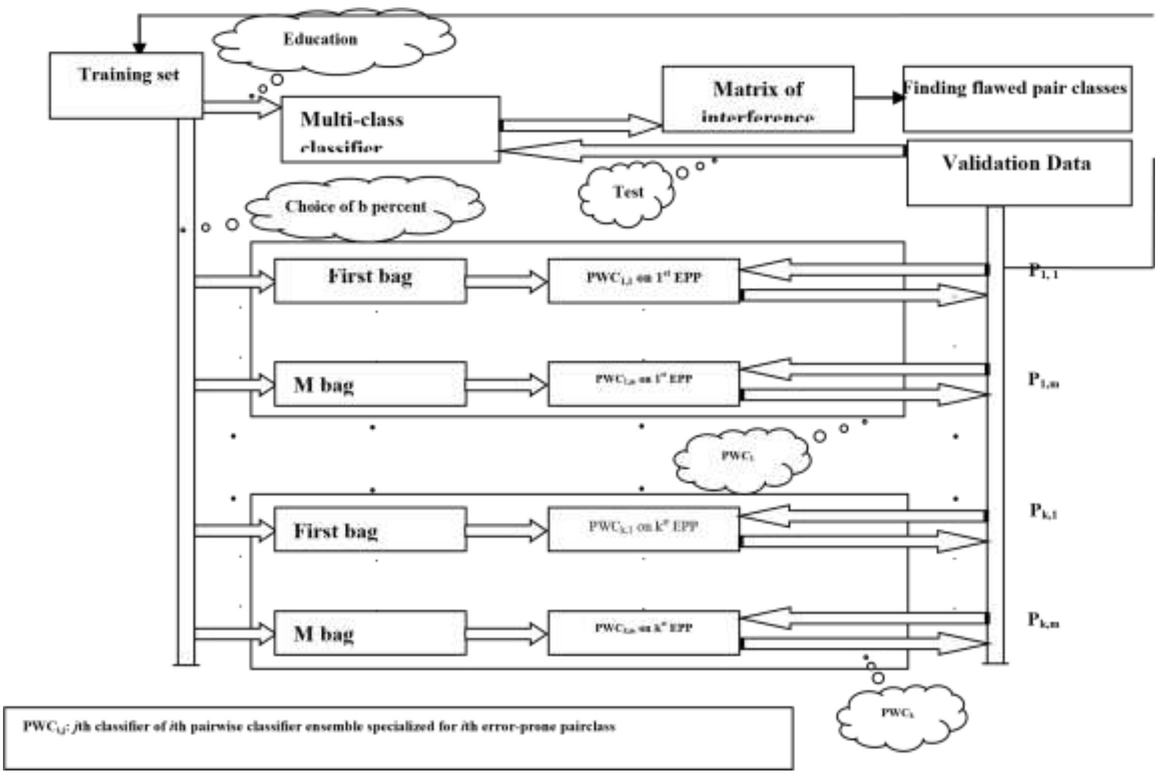

Figure 4: the first phase of the second proposed method for optical detection system of handwritten numbers

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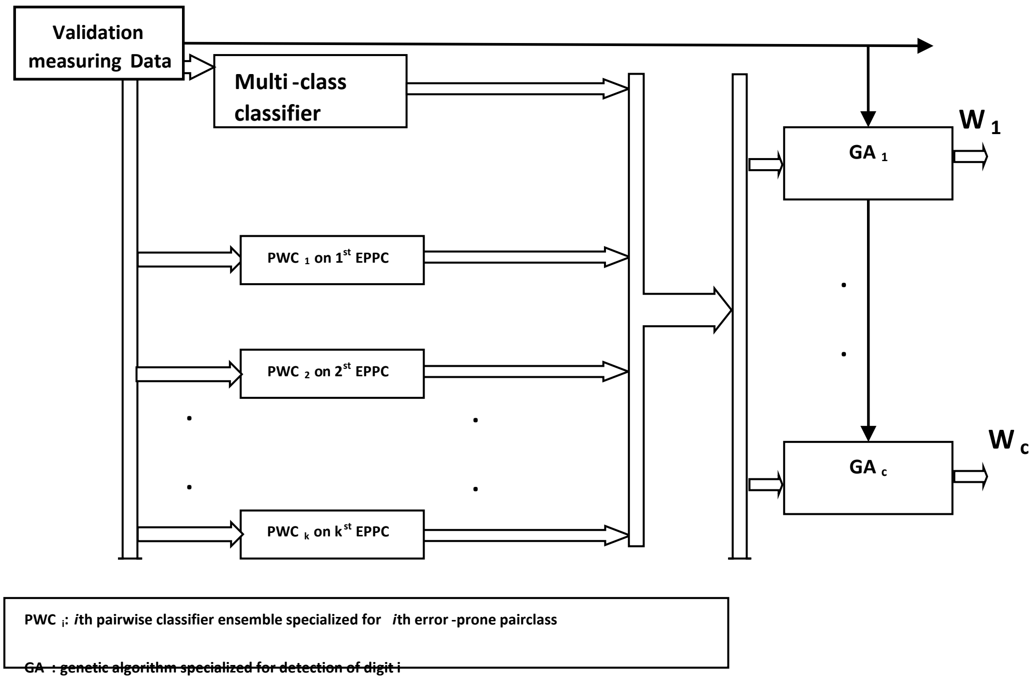

Figure 5: the second phase of structure of second proposed method for optical detection system of handwritten numbers

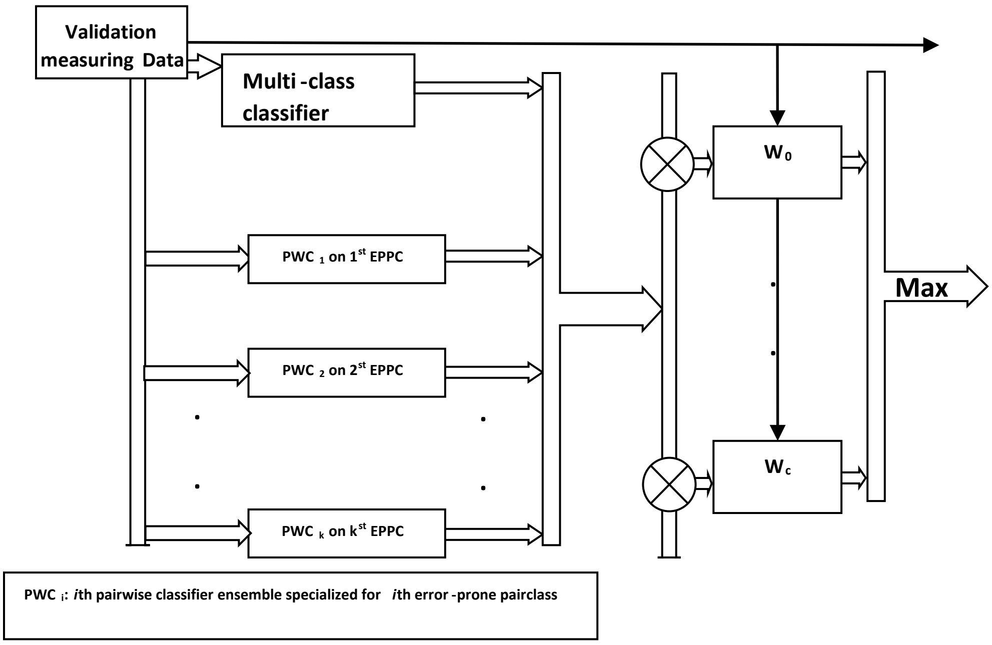

Figure 6: the testing phase of the structure of proposed second method for optical detection system of handwritten numbers

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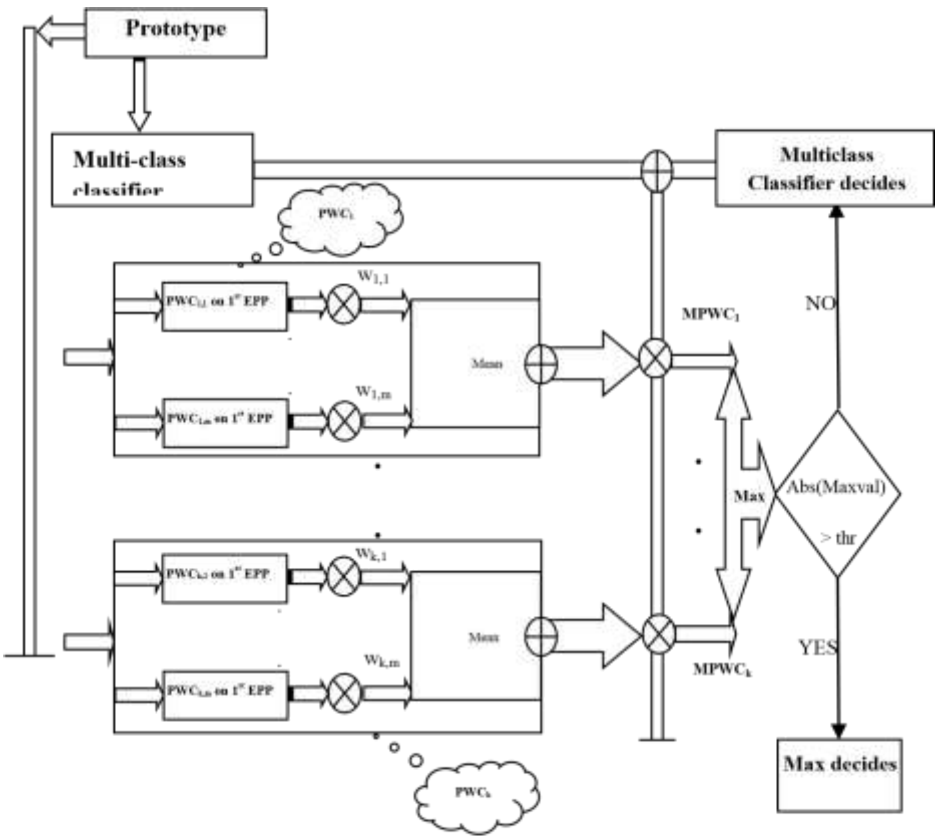

Figure 7: the second phase of the structure of third proposed method for optical detection system of handwritten numbers

No. classifier	**method**	**No. classifier**											
		1	2	3	4	5	6	7	8	9	11	11	12
1	Sh.A	0	1	1	1	0	1	1	1	1	1	1	1
2	D.T	1	0	0	1	1	0	1	1	1	1	1	0
3	3-n.n	1	0	0	1	1	0	1	1	1	1	1	0
4	Fist classifier Sh.A	1	1	1	0	1	1	0	0	1	1	0	1
5	Fist classifier D.T	0	1	1	1	0	1	1	1	1	1	1	1
6	Fist classifier 3.n.n	1	0	0	1	1	0	1	1	0	1	1	0
7	Second classifier Sh.A	1	1	1	0	1	1	0	0	1	1	0	1
8	Second classifier DT	1	1	1	0	1	1	0	0	1	1	0	1
9	Second classifier 3NN	1	1	1	1	1	0	1	1	0	1	1	0
11	Third classifier Sh. A	1	1	1	1	1	1	1	1	1	0	1	1
11	Third classifier D.T	1	1	1	0	1	1	0	0	1	1	0	1
12	Third classifier 3-nn	1	0	0	1	1	0	1	1	0	1	1	0