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Reliable Devanagri Handwritten Numeral Recognition using Multiple Classifier and Flexible Zoning Approach

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Abstract—A reliability evaluation system for the recognition of Devanagri Numerals is proposed in this paper. Reliability of classification is very important in applications of optical character recognition. As we know that the outliers and ambiguity may affect the performance of recognition system, a rejection measure must be there for the reliable recognition of the pattern. For each character image pre-processing steps like normalization, binarization, noise removal and boundary extraction is performed. After calculating the bounding box features are extracted for each partition of the numeral image. Features are calculated on three different zoning methods. Directional feature is considered which is obtained using chain code and gradient direction quantization of the orientations. The Zoning firstly, is considered made up of uniform partitions and secondly of non-uniform compartments based on the density of the pixels. For classification 1-nearest neighbor based classifier, quadratic bayes classifier and linear bayes classifier are chosen as base classifier. The base classifiers are combined using four decision combination rules namely maximum, Median, Average and Majority Voting. The framework is used to test the reliability of recognition system against ambiguity.

Index Terms—Devanagri Numeral Recognition, KNN, Chain Code, Classifier combination, Features

I. INTRODUCTION

Handwriting Recognition is a process of understanding of handwritten information by a machine such as computer. Handwriting recognition is classified as online and offline. Offline Handwriting recognition problem is belonging to a domain of pattern classification. Pattern Classification is a task of mapping a group of testing data T to specific classes using a labeled training dataset P. Classification involves errors due to misclassifications which is costly in many situations like in bank cheque legal amount recognition, signature recognition etc. Classification with low score can also be harmful in Optical Character Recognition (OCR) applications, current research methods have achieved recognition rates higher than 99% on some Latin numeral databases such as MNIST [1] and CENPARMI Database [2]. It is the general expectation that OCR machines should achieve a high recognition rate as well as high reliability.

Offline handwritten character recognition of languages such as Chinese, Arabic and English have extensively been investigated for over twenty years. However, Hindi handwriting recognition research has started only in recent years, even though Hindi is one of the most widely spoken languages in the world. Experiments reported in this paper are conducted on the isolated numerals database. Detecting samples recognized with low confidence as a cause for rejection and thus achieving a high reliability in handwritten numeral recognition is our objective in this research.

Some of the previous research related to Devanagri isolated characters are described in this section. Sethi and Chatterjee in the year 1977 [3] proposed a decision tree based classifier for isolated character recognition. Bajaj et al. [4] proposed multi-classifier connectionist combination approach for their own dataset and used density and moment based feature and obtained 89.6% accuracy. Hanmandlu et al. [5] used fuzzy model approach for their own numeral dataset and obtained 92.67% accuracy for normalized distance based feature. Bhattacharya et al. used direction based feature and MLP based classifier combination scheme and obtained 98.86% accuracy for 64 dimensional feature vector for CVPR, ISI dataset. Agnihotri et al [6] implemented a system for Devanagri handwritten recognition using diagonal features and genetic algorithm for a dataset of 1000 samples and obtained 85.78 % match score. Govindarajan [7] applied classifier Ensemble approach for handwritten Numeral recognition for NIST dataset. They used the combination of RBF and SVM and shown an improve result of 99.3% when the combination is used over the single classifier. The Performance comparison of all the previous research is not completely justified because the dataset benchmark used are their own, also before the year 2009 the standard benchmark dataset for research community was not available. This research makes use of dataset developed by CVPR unit of ISI Kolkata. In this paper an Ensemble of classifier is created using K-nearest neighbor classifier, Linear classifier and Quadratic classifier as base classifier. Features generated using direction of the connected components and experiments are performed for various values of rejection threshold.

For finding optimal error reject characteristic it is necessary to know posterior probabilities of candidate list classes and define relative costs of errors and rejections [8]. By taking different costs, one can get different solutions, each still being optimal in the sense of minimizing overall errors. The set of these solutions defines the optimal error-reject characteristic of a decision maker

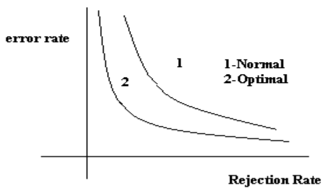

Fig 1. ROC Curve for classification

Thus, to find the optimal error-reject characteristic, it is necessary to recognize candidate list classes under Bayesian paradigm [8], i.e.:

1. To define a set of features describing a candidate list;
2. To estimate in this feature space posterior probabilities
3. To apply Bayes decision rule with different error.

The rest of the paper is organized as follows: Section 2 describes the gathering of input data, section 3 describes the proposed feature extraction method for recognition of Devanagri numeral, section 4 gives the description of the classifier used. Experimental results are presented in section 5 and final summery is concluded in section 6.

II. Input data acquisition and proposed methology

The proposed method for this study includes the steps like preprocessing, feature extraction and classification. The details about the method used in steps are explained in the following sub sections.

A. Devanagri numeral Dataset

Devanagri numeral dataset is developed by CVPR unit ISI Kolkata. The unit has developed the dataset for handwritten Devanagri numerals which is divided into training set and test set [9]. Training set consists of 18,793 grayscale images stored in 'tif' format. Test set consists of 3,773 grayscale images stored in 'tif' format. The figure 2 shows the samples of Devanagri numerals collected.

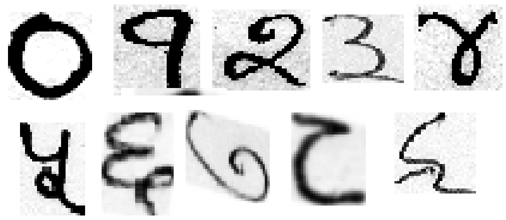

Fig 2. Data samples collected of Devanagri Numerals

B. Pre-processing

In the scanning process, some distortion in images may be introduced due to variability writing of different peoples and intensity variations. Some preprocessing steps are required for rectification of distorted images, such as improving the quality of images using filtering and size normalization. The Fig. 3 shows the output of various preprocessing steps. The main steps of pre-processing are:

- Noise removal: Noise removal refers to removal to any unwanted or insignificant bit pattern in the image which is simply acting like a noise. To remove noise from the image median filtering is applied.
- Normalization: Handwriting produces variability in size of written digits. This leads to the need of scaling the digits size within the image to a standard size, as this may lead to better recognition accuracy. We normalized the size of digit within the image and also translate it to a specific position by the centralization on 72x54size.
- Boundary Extraction: The images are converted to constant width images so as to counterpart the thickness of the writing tool used. Then the outer boundary of the images is obtained as shown in Fig. 3.

Fig 3. (a) Gray-scale image of number '5' (b) Black & white image(c) boundary of the image

III. Feature extraction

Selection of appropriate features is very important for good performance of recognizer. Because we know that human reasoning is somewhat fuzzy in nature which enables us to recognize even degraded patterns. In this paper, a zoning based feature extractor is proposed whose boundary is not sharply defined but is flexible. The different zoning designs used in the study are shown in Fig. 4.

A. Zoning alternatives:

Zoning is basically a division of an image into sub images. Here the features are accumulated zone wise and therefore two alternatives of zoning are used.

Standard zoning: The entire bounding box of the image is divided into 3x3 zones. The chain-code histogram and gradient direction coding is done zone wise.

Elastic Zoning: The concept of elastic zoning is based on equalizing the density of each zone and accordingly referred as global or local. In global zoning the zone separating line is decided on the basis of equal density division, horizontally and vertically in three equal parts. Where as in local method the image is divided horizontally based on density equalization in each zone and then the vertical boundary is decided on the local division of density.

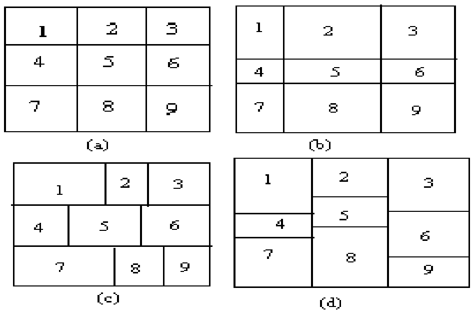

Fig 3. Zoning Methods (a) standard equal Partition (b)Global Histogram based Partition(c),(d)Local Histogram based Partition

The first set of feature (a) is obtained by placing a 3x3 grid on the numeral image and defining the zone from 1 to 9. The second method (b) globally divides the bounding box into nine zones such that the density is equally divided horizontally and vertically in three equal parts on the basis of histograms The third method (c) or (d) divides the zones locally such that the density is divided approximately in nine equal parts. The Gradient features and chain code features were extracted.

B. Gradient features

The gradient feature decomposition originally proposed for online character recognition by Kawamura et al. [10] shows high recognition efficiency for Japanese characters. This method is applicable to machine printed/handwritten, binary grayscale as well as low resolution images. The calculated gradient of the image is decomposed into four, eight or sixteen directional planes. For our analysis we have taken eight directional planes, the Fig. 4 shows the gradient vector decomposition into their nearest vector plane. The magnitude of gradient in sampled eight directions for each of the subsection of original image is accumulated.

Conventionally the gradient is calculated on each pixel of the image. In this study 'Sobel' edge detection algorithm is used to calculate gradient vector at each image pixel of preprocessed grayscale image. The gradient vector can be quantized into eight directions using angle vector quantization or vector decomposition using parallelogram rule. In the first method the magnitude of gradient in each image pixel is assigned to directional plane nearest to it and in the second method the gradient vector is decomposed into two nearest directional planes using parallelogram vector division rule. The parallelogram quantization method gives less quantization error so this method for quantizing gradient vector is used in the present study. Gradient is calculated as per the following equations:

$$gy(x,y) = f(x-1,y+1) + 2f(x,y+1)f(x+1,y+1) - f(x-1,y-1) - 2f(x,y-1) + f(x+1,y-1) \quad (1)$$

$$gx(x,y) = f(x+1,y-1) + 2f(x+1,y) + f(x+1,y+1) - f(x-1,y-1) - 2f(x-1,y) + f(x-1,y+1) \quad (2)$$

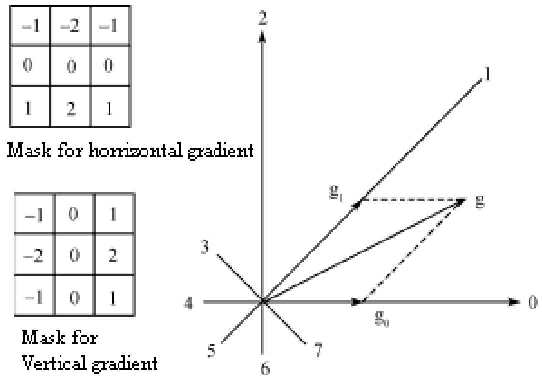

Fig 4. Edge based directional Feature quantized in 8 directions

C. Chain code based features

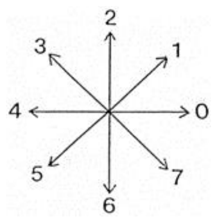

Fig 5. 8 Connectivity of a Pixel

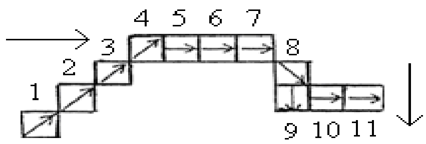

Fig 6. Direction Changes in a Part of image

Chain-code is based on the direction of the connecting pixels. Each pixel is observed for next connected pixel and their direction changes mapped by giving a numerical value to every possible direction. Generally eight connectivity is taken into consideration as shown in the Fig. 6. To obtain chain-code top left corner is considered as origin and scanning is done left to right, top to bottom. Each pixel has observed separately and direction vector for that pixel is noted down. This process is carried out until the last pixel has scanned. Now, the frequency of occurrence in a particular direction is calculated for each segment and the histogram for each segment is used and accumulated as feature vector.

IV. CLASSIFICATION AND REJECTION PERFORMING

A classifier is a mapping algorithm which undergoes training phase. After training it maps the testing objects from feature space to the output space. The mapping may be in the form of distance for nearest neighbor classifier or the density for the density based classifier. The classifiers used in the study are (1) The quadratic discriminant classifier (2) The Linear discriminant classifier and (3) k-nearest neighbor with the value of k equal to 1. The linear classifier and quadratic classifier are both based on the assumption of normally distributed classes. The first assumes equal class covariance matrices. *K-Nearest Neighbor* (kNN) classifier is based on the principle that the instances within a dataset will generally exist in close proximity to other instances that have similar properties. If the instances are tagged with a classification label, then the value of the label of an unclassified instance can be determined by observing the class of its nearest neighbors. The kNN locates the *k* nearest instances to the query instance and determines its class by identifying the single most frequent class label. In general, instances can be considered as points within an *n*-dimensional instance space where each of the *n*-dimensions corresponds to one of the *n*-features that are used to describe an instance. The absolute position of the instances within this space is not as significant as the relative distance between instances. This relative distance is determined by using a distance metric. Ideally, the distance metric must minimize the distance between two similarly classified instances, while maximizing the distance between instances of different classes. Many different metrics have been presented [11,12].

Consider a pattern recognition problem where pattern Z is to be assigned to one of the m possible classes $\{\omega_1, \omega_2\ \omega_3 \ldots\ \omega_m)$. Let us assume that we have R classifiers each representing the given pattern by a distinct measurement vector. Denote the measurement vector used by the ith classifier by $\mathbf{x}i$. In the measurement space each class ω_k is modeled by the probability density function $p(xi \mid \omega_K)$ and it's a priori probability of occurrence is denoted by $P(\omega_K)$. We shall consider the models to be mutually exclusive which means that only one model can be associated with each pattern. Now, according to the Bayesian theory, given measurements xi, $i = 1, \ldots, R$, the pattern, Z, should be assigned to class ω_j provided the a posteriori probability of that interpretation is maximum, i.e.

$$assign\ Z \rightarrow \omega_j \text{ If}$$

$$P(\omega_j | x_1, x_2, x_3 \cdots. x_R) = \max P(\omega_j | x_1, x_2, x_3 \cdots. x_R) \quad (3)$$

K

And the posterior probability using Bayes theorem is given by

$$p(\omega j | x1, x2, x3 \ldots . xR) = \frac{p(x1,x2,x3 \ldots xR \mid \omega j)P(\omega j)}{P(x1,x2,x3 \ldots xR)} \quad (4)$$

A. Rejection Measurements

A n-class classifier is one which divide the feature space into n-sub regions, which may overlap. If the pattern falls in the overlapping region of the classes then it is said to be an ambiguity. For a two class problem the idea of classification with reject option is shown in Fig.

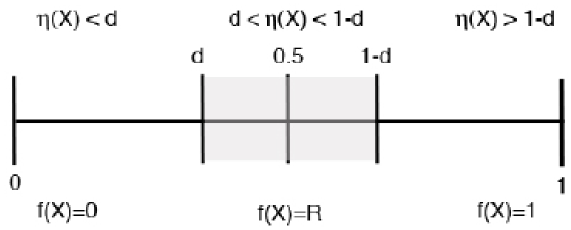

Fig 7. Rejection Strategy for binary classification

For rejecting a character pattern single threshold is obtained. There is various methods for deciding threshold. Rejection of pattern can be of two different types: outlier and ambiguity. In this study rejection of ambiguity in taken into account. It is a mean to limit excessive misclassifications, at the expense either of a manual post-processing of rejections, or of their automatic handling by a more accurate but also com- computationally more costly classifier, and requires therefore a trade-off between the accuracy attainable on non-rejected samples and the amount (cost) of rejections. Analogously, in multi-label problems a classifier with a reject option could automatically take decisions on category assignments deemed reliable for a given sample, and could withheld and leave to a manual annotator only the ones deemed unreliable. This could allow a classifier to attain a high classification performance on non-withheld decisions, which should be traded for the cost of manual annotation of withheld decisions.

B. Classifier combination :

Before considering the combination of classifier we consider the type of decision given by the classifier. The decision can be abstract level where the output is just providing the class label information. Measurement level classifier output gives each pattern a degree of belongingness to every class label. Ranked level output is a special case of measurement level where the output is a ranking of class labels generated according to degree of belongingness. The Measurement level output is most effective as far as the combination is concerned. The classifiers can be combined in three different ways:

Parallel combination: The classifiers can be connected in parallel when they are having different feature sets, when they are described in different physical domains or when the undergone through different type of analysis [13].

Stacked combining: This method is utilizing the same feature space but by different classifiers.

For this experiment a set of off-the-shelf classifiers taken from our Matlab toolbox PRTools [13] and the parameters are not optimized for the particular application. In this way they illustrate well the differences between these classifiers, and, moreover, it serves better the aim to study the effects of combining classifiers of various performances. As argued in the introduction, it is important to make the outputs of the classifiers comparable. We use estimates for the posterior probabilities or confidences. This is a number pj(x), bounded between 0 and 1 computed for test objects x for each of the c classes the classifiers are trained on. These numbers are normalized such that: The combining rules Posterior probabilities $\{pij(x), i = 1, m; j = 1, c\}$ for m classifiers and c classes is computed for test object x, they have to be combined into a new set qj(x) that can be used, by maximum selection, for the final classification. The combining rules can be either fixed combiners or trained combiners [13]. The method of fixed combination is used in this paper

Fixed combiners are heavily studied in the literature on combining classifiers, [14]and [15]. The new confidence qj(x) for class j is now computed by:

$$qj'(x) = rule(pij(x)) \qquad (5)$$

$$qj(x) = qj'(x)/\sum qj'(x) \qquad (6)$$

The following combiners are used for rule in equation (5): Maximum, Median, Majority Voting, and Average. The Maximum rule selects the classifier producing the highest estimated confidence, which seems to be noise sensitive. Median and Mean, averages the posterior probability estimates thereby reducing estimation errors. This is good, of course, if the individual classifiers are estimating the same quantity. Another popular way of combining classifiers is Majority vote: which count the votes for each class over the input classifiers and select the majority class.

V. Experimental Results

An *N*-class classifier is aimed to subdivide the feature space into *N* decision regions *Di*, *i* = 1,…, *N*, so that the patterns of the class ωi belong to the region *Di*. According to the statistical pattern recognition theory, such decision regions are defined to maximize the probability of correct recognition, commonly named Classifier's accuracy:

$$\text{Accuracy}= \text{P(correct)}=\sum_{i=1}^{N} \int_{Di} p(x|\omega i)\, p(\omega i)dx \qquad (7)$$

$$\text{Error} = \text{P(error)}= \sum_{i=1}^{N} \int_{Di} \sum_{\substack{j=1\\ j\neq i}}^{N} p(x|\omega j)\, p(\omega j)\, dx \qquad (8)$$

$$\%\ Reliability = \frac{Recognition\ rate}{1-rejection\ rate} \times 100$$

The experiments are conducted for different rejection percentage. In the standard zoning method, chain code feature and gradient direction quantization features were calculated. Then the Local Zone and Global Zone based features are calculated. The classifiers are combined using Max, Mean, Median and majority vote technique. The experiments are conducted by various rejection percentages starting from 1% to 20% with an interval of 1%. The method of rejection is based on defining a global threshold for all the classes and results obtained for chain code with three alternates of zoning are shown in Fig. 8-10. The results for edge based directional feature are shown in Fig. 11-13.

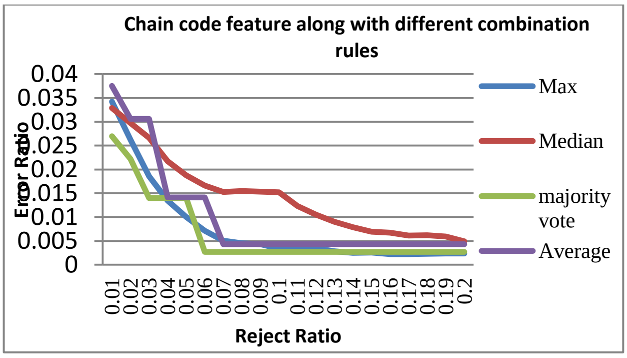

Fig 8. ROC for different combination rules with chain code feature

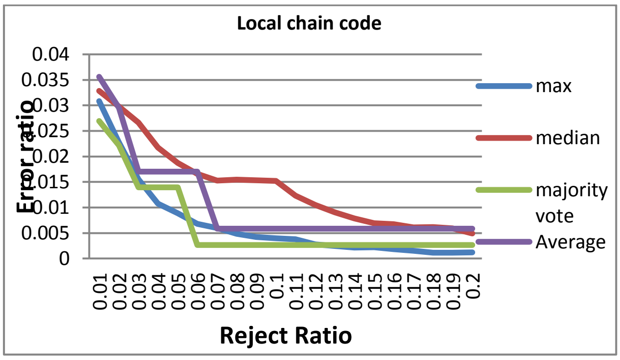

Fig 9. ROC for different combination rules with local zone based chain code feature

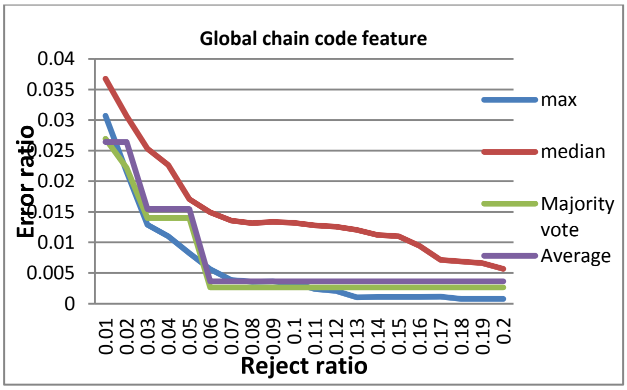

Fig 10. ROC for different combination rules with global zone based chain code feature

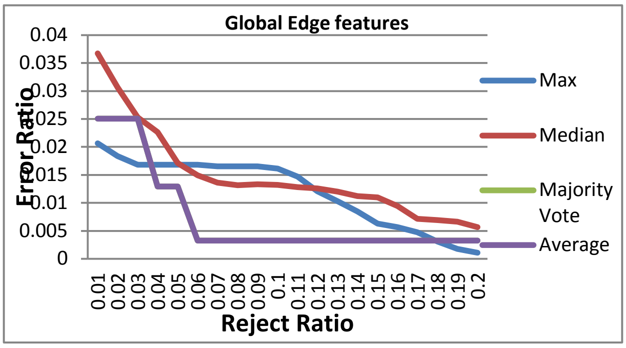

Fig 11. ROC for different combination rules with global zone based gradient edge feature

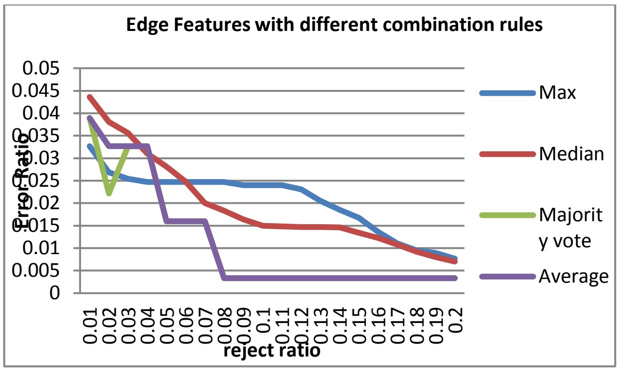

Fig 12. ROC for different combination rules with gradient edge feature

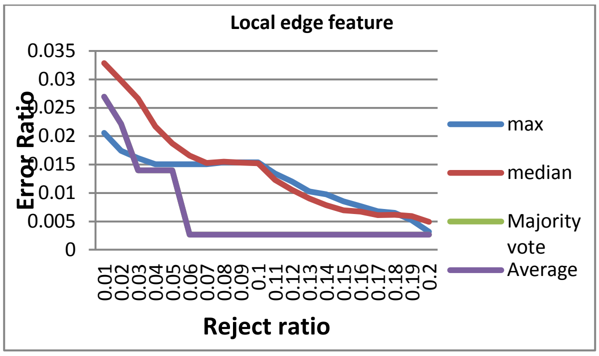

Fig 13. ROC for different combination rules with local zone based gradient edge feature

Table 1 Relative comparison of Results

S . No	Proposed By	Datasize	Accuracy
1	Hanmandlu and Ramana Murthy [5]	Own database	92.67
2	Ramteke et al. [14]	Own database	87
3	Bajaj et al. [4]	Own database	89.6
5	Sharma et el. [16]	22,556 [9]	98.86
6	Agnihotri et al. [6]	Own database	85.78
7	Our Method	22,556 [9]	99.73

Table 2 Performance of various classifier combination rules for Chain code based features

Type of feature	Combination method	% of Rejection	% of Recognition	Reliability	% of Recognition	Reliability	% of Recognition	Reliability
Zoning Method			Standard		Global		Local	
Chain code	Max	1	96.58	97.55	96.92	97.9	96.91	97.8
		6	99.28	100	99.43	100	98.31	100
	Median	1	96.58	97.55	96.32	97.7	96.71	97.6
		6	98.34	100	98.5	100	98.50	100
	Majority Vote	1	97.30	98.28	97.3	98.28	97.30	98.2
		6	99.73	100	99.73	100	99.67	100
	Average	1	96.24	97.21	97.35	98.34	96.44	97.4
		6	98.58	100	99.63	100	99.67	100

Table 3 Performance of various classifier combination rules for Edge based gradient features

Type of feature	Combination method	% of Rejection	% of Recognition	Reliability	% of Recognition	Reliability	% of Recognition	Reliability
Zoning Method			**Standard**		**Global**		**Local**	
Gradient Direction	Max	1	96.73	97.71	97.93	98.24	97.94424	98.93358
		6	97.5	100	98.31	100	98.4945	100
	Median	1	96.1	97.1	96.32	97.29	96.71441	97.69132
		6	98.4	100	98.5	100	98.34123	100
	Majority Vote	1	97.78	98.76	97.49	98.47	97.30406	98.28693
		6	98.4	100	99.6	100	99.7327	100
	Average	1	96.10	97.1	97.49	98.47	97.30406	98.28693
		6	98.4	100	99.6	100	99.7327	100

VI. CONCLUSION

The rejection framework for the Devanagri Numeral recognition is presented for Ensemble of classifier where decision combinations using different rules namely MAX, MEDIAN, MAJORITY VOTING and AVERAGE. The **Maximum** combination with chain code feature is giving an optimal error- reject trade off in all the three zoning alternatives. However the **Average** combiner gives better result for Edge based gradient feature. An improved efficiency of **99.73**% is observed in most of the cases with very low reject rate as low as 6% and still higher accuracy of **99.89**% is observed at a rejection of 13%. Also the Edge based feature when used in standard zoning gives poor optimized response but when the zoning method is changed a better optimized result is observed.

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