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# Comparison of Feature Extraction Techniques for Pattern Classification

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***Abstract: Pattern recognition is a challenging task in research field for the last few decades. Many researchers have worked on areas such as computer vision, speech recognition, document classification, and computational biology to tackle complex research problems. In this article, a pattern recognition problem for handwritten Malayalam character is presented. This system goes through two different stages of HCR namely, feature extraction and classification. Three feature extraction techniques – wavelet transform, zoning, division point – are used in this study. Among these, division is point is able to show best discriminative power using SVM classifier. All the experiments are conducted on size normalized and binarized images of isolated Malayalam characters.***
***Keywords: HCR, Wavelet transform, Zoning, Division point, SVM***

## I. INTRODUCTION

Machine learning is a branch of artificial intelligence, and in many cases, almost becomes the pronoun of artificial intelligence. Different techniques are used to identify objects in images, transcribe speech into text, match news items, posts or products with users' interests, and select relevant results of search. For decades, constructing a pattern recognition or machine learning system required a careful engineering and considerable domain expertise to design a feature extractor that transformed the raw data (such as the pixel values of an image) into a suitable internal representation or feature vector which the learning subsystem, often classifier, could detect or classify patterns in the input [1].

In this paper, a pattern recognition system for handwritten Malayalam character recognition is presented. Handwriting recognition has been one of the most fascinating and challenging research areas in the field of image processing and pattern recognition during the recent years. It has become a popular area of research because of the advances in technology such as the handwriting capturing devices and impressive mobile devices [2]. Automatic handwritten character recognition (HCR) has many academic and commercial interests. The main challenge in this field is to deal with the large variety of handwriting styles by different writers. Furthermore, some complex handwriting scripts comprise different styles for writing words. Depending on the language, characters are written isolated from each other in some cases. In some other cases, they are cursive and sometimes characters are related to each other. This challenge has been already recognized by many researchers in the field of natural language processing (NLP). HCR is more challenging compared with printed characters because (1) handwritten characters of different writers are not only different but also vary in shape and size; (2) numerous variations in writing styles of individual character make the recognition task difficult; (3) the similarities of different character in shapes, overlaps, and interconnections of the neighbouring characters further complicate the character recognition problem. In summary, a large variety of writing styles and the complex features of the handwritten characters make it a challenge to accurately classifying handwritten characters [3].

HCR can be done either offline or online mode. Online character recognition is simpler and easier to implement due to the temporal based information such as velocity, time, number of strokes, and direction for writing. In addition, the trace of the pen is few pixels wide and this does not require thinning techniques for classification. On the other hand, offline character recognition system implementation is even laborious due to high variations in writing and font styles of every user [4]. These systems are very important for the creation of electronic libraries, mail sorting, cheques verification, to mention a few examples.

HCR systems consist of three modules: preprocessing (noise removal, minimum enclosing bounding box, skeletonization, boundary extraction), feature extraction/selection, and classification. Feature selection technique can be used to select the most relevant features and reduce the dimension of a feature vector. It aims to reduce the dimensionality of the feature space for classification by selecting the most informative features that best separate the different classes. It yields higher speed and reduces computational cost for the classification process [5].

Many researchers have tried several techniques for breaking the complex problems of HCR. Rabi et al. performed a survey on different OCR systems for handwritten cursive Arabic and Latin script recognition where it was concluded that the results of contextual sub character of Hidden Markov Models were proven with high accuracy [6].

Sahlol et al. inspected different classifiers such as Genetic algorithms, Particle swam optimization, Grey wolf optimization, and BAT algorithms for Arabic character recognition [7]. Veershetty et al. suggested the concept of an OCR system for handwritten script recognition based on K-nearest neighbor (KNN), support vector machine (SVM) and Linear Discriminant Analysis (LDA) classifiers [8]. Zhang et al. presented the use of recurrent neural network for drawing and recognition purposes of Chinese language [9]. Abandah et al. used classifiers such as quadratic discriminate analysis (QDA), LDA, Diagonal QDA, Diagonal LDA, and KNN for handwritten Arabic character (HAC) recognition [10]. The performance of a classifier can rely as much on the quality of the features as on the classifier itself.

## II. REVIEW ON FEATURE EXTRACTION

Choosing the most discriminant features might be the most important step for achieving a high recognition rate. In general, there are two categories of features: statistical features and structural features. Statistical features include number of connected components, closed loop and concavities, and structural features are zoning, accumulated chain code representation, area to perimeter ratio and transition features. To detect loops in an image, connected component labeling technique can be used.

Accumulated chain code representation: Chain code representation of an input character image is obtained by using Freeman codes while tracing its contour. Accumulate representation consists of browsing the contour of the image, pixel by pixel, and accumulate the number of pixels in the same direction given by 8-Freeman code. As we use 8-connectivity, we will have a feature vector composed of eight components representing the accumulated numbers.

Transition features: For each row and each column in the binary image, compute the number of transitions between foreground pixels and background pixels (1 to 0 or 0 to 1). Then, the largest values in the two directions constitute the transition feature vector [11].

A good set of features should represent characteristics that are particular for one class and be invariant as possible to changes within this class. Commonly used features in character recognition are invariant moments [12], projections [13], zoning feature [14], Fourier descriptors [15], gradient features [16] and contour direction histogram [17]. A feature set made to feed a classifier can be a mixture of such features [5]. Liu and Suen introduced directional gradient features for handwritten Bangla digit classification [18]. Surinta et al. proposed a system using a set of features such as the contour of the handwritten character image computed using 8-directional codes, distance calculated between hotspots and black pixels, and the intensity of pixel space of small blocks [19].

Khan et al. designed a framework for the recognition of handwritten Pashto characters using zoning features and KNN and Neural network as classifiers [4]. Boufenar presented the concept of supervised learning technique named artificial immune system based zoning technique for isolated curved Arabic character recognition [11]. Jameel and Kumar suggested the use of B-spline curves as a feature extractor for offline Urdu character recognition [20]. Rouini et al. presented the use of dynamic random forest classifier based on surf descriptor feature extraction technique [21]. The feature technique based on Radon and wavelet transform is proposed in [8]. Hasan [22] presented a KNN based Arabic digit recognition system which used discrete cosine transform and projection methods for feature extraction. KNN generates classification results by storing all the available cases and stratify new classes based on a similarity measure (distance functions). Patel et al. suggested the use of artificial neural network (ANN) for HCR based on discrete wavelet transform (multi resolution technique) as a feature extraction technique [23]. Elleuch et al. suggested a system in which convolutional neural network (CNN) is used for feature extraction and SVM as a recognizer. CNN learns good features at every layer of visual hierarchy. The features extracted from input image are invariant to shape and shift distortions. Additionally, this model is protected against over-fitting due to the powerful performance of dropout [2]. Alijuaid et al. used a genetic approach to recognize handwritten Arabic characters in which structural features are extracted to distinguish the shape of characters [24]. To recognize isolated HAC, Abandah et al. extracted a subset of 40 features from 95 features using principal component analysis [10]. El-glaly and Quck extracted some statistical features depending on the number of vertical and horizontal transitions and the ratio between the height and width of the characters [25].

Feature extraction techniques generating local and global features are proposed in [26] wherein local features are obtained from sub-images of the character including foreground pixel density information and directional information. The global features measured the fraction of the character appearing below word baseline and the characters' width/height ratio. Impedovo et al. introduced genetic algorithm based clustering approach using zoning features [27], whereas an adaptive zoning technique for handwritten digit recognition is presented in [28]. Two types of feature sets based on modified chain code direction frequencies in the contour pixels of input image and modified transition features have been presented in [29]. Two feature extraction techniques are investigated in [5].

The first one is the chain code histogram, which is developed to describe statistically the boundary of each digit's image. The second one builds on the white-black transition information in the vertical and horizontal directions of a digit image. Each transition feature is characterized by the area defined by the corresponding transition and normalized by dividing it with the whole digit's area.

## III. EXTRACTED FEATURES

Feature extraction is defined as the extraction of most relavant information from the raw data for classification purpose, in the sense of minimising within class pattern variability while enhancing between class pattern variability. Different feature extraction methods fulfill this requirement to a varying degree, depending on the specific recognition problem and available data. Three feature extraction methods are discussed in this study: zoning, division point and wavelet transform. Selection of a feature extraction method is an important factor to achieve high recognition performance in character recognition systems [30].

### A. Zoning Technique

Zoning is a partition of the control box of the pattern (smallest rectangle containing the pattern); the elements of such partitions are used to identify the position in which features of the pattern are detected. It extracts local topological information from the given patterns. Let $I$ be an image, a zoning method $Z_M$ can be considered as a partition of $I$ into $M$ subimages, i.e., $Z_M = \{z_1, z_2, \ldots, z_M\}$. The zoning design is done in two different ways:

Fixed or Symmetrical: The bounding box is divided into zones of equal size.

Variable or nonsymmetrical: The bounding box is non-uniformly divided according to pattern density. Partition of variable size zones is done to overcome the non-uniform distribution of stroke density.

The pixels inside the zones of $Z$ are transformed by the feature vector to a representation of the form $F = \{f_1, f_2, \ldots, f_m\}$, where $f_i$ is the feature vector extracted from $z_i$. In the present study, run length feature is extracted using the foreground pixels contained in the image representation. A binary image can be completely specified by a linked list of its runs. This representation is known as run representation or interval coding of a binary image. A path from $P$ to $Q$ is a sequence of runs $P = P_1, P_2, \ldots, P_n = Q$ such that $P_i$ is adjacent to $P_{i+1}$, $1 \le i \le (n-1)$. Here, the character image is divided into different zones using uniform grids. Then, the number of foreground pixels in each zone is taken to form the feature set. This feature vector is extracted from a size normalized image [30].

### B. Wavelet Features

Wavelet transform allows the description and representation of images in multi-frequencies or resolution. In images, the distinction between repeating and non repeating pattern is very important. The repeating waves composed of a discrete series of overtones can be used to represent background in an image and non periodic features represent the object. To recognize the object, different wavelet features are extracted after the decomposition of image. The features are taken from wavelet coefficients of all detail sub-bands. These coefficients are analysed using statistical measures such as wavelet energy, mean, median, standard deviation, minimum and maximum [30].

1) *Wavelet Energy*: Wavelet energy feature can amplify the intensity variation between regions, and at the same time it can represent intensity inhomogeneity within a region. In addition, this feature can also amplify the faint dissimilarities that may be present between two regions. Initially, wavelet transform is applied on the character image, and it is iterated until a predefined number of levels to obtain the multi-resolution representation of the image. For an image with a size of $s \times s$ pixels, the number of levels is $n$, where $2^n = s/2$. Wavelet coefficients of all detail subbands from $n$ levels are used in the formulation of wavelet energy. Wavelet energy in horizontal, vertical and diagonal directions at $i^{th}$ level is defined as

$$E_i^h = \sum_{x=1}^{P} \sum_{y=1}^{Q} (H_i(x,y))^2 \quad (1)$$

$$E_i^v = \sum_{x=1}^{P} \sum_{y=1}^{Q} (V_i(x,y))^2 \quad (2)$$

$$E_i^d = \sum_{x=1}^{P} \sum_{y=1}^{Q} (D_i(x,y))^2 \quad (3)$$

Since the energy values of components obtained from decomposed images varies widely, these values are normalized using total wavelet energy $E_{total}$.

$$E_{total} = \sum_{k=1}^{K} \sum_{i=1}^{R} \left(c_i^k\right)^2 \quad (4)$$

where *R* is the total number of wavelet coefficients of each subband, *K* is the total number of subbabds, and $c_i^k$ is the i^th^ coefficient of the k^th^ subband. This normalized vector is called wavelet energy feature. The total wavelet energy of detail subbands at each level can also be used as a feature.

2) *Wavelet Mean*: Another feature extracted from detail coefficients is the mean of these values. These measures are taken from each level. The wavelet mean of horizontal, vertical, and diagonal detail subbands of size *p x q* at n^th^ level is given as

$$\mathrm{M}_n^H = \frac{1}{pq}\sum_{i=1}^{p}\sum_{j=1}^{q} D_H(i,j) \tag{5}$$

$$\mathrm{M}_n^V = \frac{1}{pq}\sum_{i=1}^{p}\sum_{j=1}^{q} D_V(i,j) \tag{6}$$

$$\mathrm{M}_n^D = \frac{1}{pq}\sum_{i=1}^{p}\sum_{j=1}^{q} D_D(i,j) \tag{7}$$

where $D_H$, $D_V$, and $D_D$ are the wavelet coefficients of horizontal, vertical and diagonal subbands respectively.

3) *Median:* After wavelet decomposition, median is taken from each detail subband in each level. The median is the middle value in a set of numbers arranged in the order of magnitude. If the count of numbers is even, the median will be the mean of two middle values.
4) *Standard Deviation:* This feature extraction method involves determination of standard deviation of wavelet coefficients in each detail subband of size p x q. The standard deviation of horizontal, vertical, and diagonal detail subbands in each level is determined as follows.

$$S_n^H = \sqrt{\frac{\sum_{i=1}^{p}\sum_{j=1}^{q}\left(D_H(i,j) - \mathrm{M}_n^H\right)^2}{pq}} \tag{8}$$

$$S_n^V = \sqrt{\frac{\sum_{i=1}^{p}\sum_{j=1}^{q}\left(D_V(i,j) - \mathrm{M}_n^V\right)^2}{pq}} \tag{9}$$

$$S_n^D = \sqrt{\frac{\sum_{i=1}^{p}\sum_{j=1}^{q}\left(D_D(i,j) - \mathrm{M}_n^D\right)^2}{pq}} \tag{10}$$

5) *Minimum-Maximum*: The minimum and maximum of wavelet coefficients in each detail subband is also taken as a feature. After wavelet decomposition up to level *n*, these two values are taken from each detail subband at each level [7].

### *C. Division Point Feature*

This method relies on iterative subdivision of character image, so that the resulting subimages at each iteration have balanced number of foreground pixels. In the first iteration step (L = 0), the character image is divided into four rectangular subimages using a horizontal and a vertical divider line. Initially, a vertical line is drawn that minimizes the absolute difference of the number of foreground pixels in the two subimages to its left and to its right. Subsequently, a horizontal line is drawn that minimizes absolute difference of the number of foreground pixels in the two subimages above and below it.

The pixel at the intersection of two lines is referred to as division point. In the succeeding steps, each subimage obtained at the previous step is further divided into four subimages using the same procedure. The procedure is repeated till it reaches a particular granularity level with an intention to get a better representation of the character [30].

## IV. SUPPORT VECTOR MACHINE

SVM, which is derived from statistical learning theory, is considered as one of the strongest and robust algorithms in machine learning. It is introduced as learning machines with capacity control for regression and binary classification problems. It has also been proved to be very successful in many other applications such as handwritten character recognition, image classification, face detection, object detection, and text classification. In the case of classification, SVM try to find an optimal hyperplane that correctly classifies data points by separating the points of two classes as much as possible. For the linearly separable case, the support vector algorithm simply looks for the separating hyperplane with largest margin. The support vectors are the training patterns that lie on the margin boundaries [5].

SVM is regarded as the state-of the art tool for resolving linear and non-linear classification problems due to its parsimony, flexibility, prediction capacity and global optimum character. The basis of their formulation is the structural risk minimization, rather than the empirical risk minimization which is traditionally used in ANN. SVM is basically used to determine an optimal separating hyper plane (Equ (11)) or decision surface by embaracing a novel technique based on mapping sample points into a high-dimensional feature space and it is categorized using a nonlinear transformation $\Phi$, even when the data are linearly inseperable. The optimal hyper plane is gained by solving a quadratic programming problem which is reliant on regularization parameters. This transformation was carried out by kernel functions like linear, RBF, sigmoid and polynomial kernel types;

The linear kernel : $K(x, y) = x \times y$

The polynomial kernel : $K(x, y) = [(x \times y) + 1]^d$

The sigmoid kernel : $K(x, y) = \tanh(\beta_0\, x\, y + \beta_1)$

RBF kernel : $K(x, y) = \exp(-\gamma\|x - y\|^2)$

with d, $\beta_0$, $\beta_1$,and $\gamma$ are parameters that will be determinate empirically.

$$f(x) = W^T\Phi(x) + b \qquad (11)$$

where $W \in R^n$, $b \in R$ and $\Phi(x)$ is a feature map.

Because the feature space is linearly inseparable, a transformation is applied by mapping the input data ($x_i$, $y_i$) into a higher dimensional feature space by using a nonlinear operator $\Phi(x)$. As a result, the optimal hyper plane can be defined as

$$f(x) = \mathrm{sgn}(\Sigma y_i \alpha_i K(x_i, x) + b) \qquad (12)$$

where $K(xi, x) = \exp(-\gamma\|x - y\|^2)$) is the kernel function found on an RBF and sgn(.) is the sign function [2].

## V. EXPERIMENTAL RESULTS

In this handwritten character recognition problem, an image database (KUMCD) containing 14,700 samples of 49 Malayalam characters (each character with 300 samples) is used for classification experiments. It is divided into training set and test set in the ration 4:1. All the three feature extraction methods viz division point, wavelet transform and zoning are applied on the binarized images of characters. Each feature set is then evaluated using SVM classifier. The choice of kernel and the regularizing parameter *C* for SVM is determined via performance on a validation set. The generalized accuracy is estimated using different kernel parameters $\gamma$ and cost parameters *C*: $\gamma = [2^4, 2^3, \ldots, 2^{-10}]$ and $C = [2^{12}, 2^{11}, \ldots, 2^{-2}]$. Based on the experiments RBF kernel is selected, and same (C, $\gamma$) is used for all k(k-1)/2 binary classifiers. The classifier is executed five times, each time with a different random dataset, and recoded the average recognition rate [30].

Wavelet features are extracted from character images after applying wavelet transform to a certain level. The discriminating power of these features mainly depends on the choice of wavelet, decomposition level, and further processing of wavelets. Experiments are conducted to the suitable wavelet and decompositional level for this character recognition problem. It is found that coiflet, daubechies and symlet wavelets are giving best features at the fourth decomposition level. The statistical measures such as mean, median, standard deviation, maximum, minimum and wavelet energy are used to get the corresponding information from wavelet coefficients of each detail subband in each level. Table 1 shows the best discriminating power of wavelet mean using SVM classifier. Db9 performed well with 85.03% recognition accuracy.

TABLE I

Recognition Accuracy (%) Of Malayalam Handwritten Characters Using Wavelet Features

| Wavelet | Mean | Median | Minimum | Maximum | Standard deviation | Wavelet energy |
|---|---|---|---|---|---|---|
| Coif4 | 83.31 | 79.57 | 79.81 | 80.12 | 80.83 | 81.87 |
| Coif5 | 82.54 | 78.92 | 77.37 | 79.19 | 78.33 | 80.11 |
| Db6 | 82.43 | 77.29 | 76.82 | 78.85 | 77.41 | 79.73 |
| Db7 | 81.97 | 78.11 | 76.39 | 77.45 | 76.34 | 78.19 |
| Db8 | 82.62 | 76.26 | 77.58 | 79.71 | 79.21 | 80.45 |
| Db9 | 85.03 | 80.35 | 79.93 | 81.49 | 82.62 | 82.87 |
| Sym7 | 80.41 | 73.47 | 74.71 | 75.38 | 73.22 | 77.62 |
| Sym8 | 81.08 | 74.55 | 74.12 | 74.87 | 74.63 | 77.24 |

Zoning is applied on the binarized image to extract the feature from each zone. Here, the image is divided into 8 x 8 zones uniformly and the run length in each zone is used to form the feature vector. The zoning and SVM combination is able to produce a recognition accuracy of 93.54%. Division point is the other feature extracted from binarized image to classify Malayalam characters. The recursive subdivision of image has gone up to level 2, and sixteen division points are identified in the image. This feature extraction method could give the highest recognition accuracy of 93.7% using SVM [30]. From the results, it can be seen that the achieved accuracy is due to the discriminatory power of features and regression capabilities of SVM classifier.

## VI. CONCLUSION

This classification system is based on SVM, which is considered as one of the most powerful classification technique and is now widely used in many pattern recognition applications. The pattern recognition system should be able to give recognition accuracy using the selected feature extraction technique and classification method. It is the expertise that helps the researcher to develop this feature extraction-classifier combination for a given problem. The feature extraction technique used for one script may not give a similar performance for another script. By considering these facts, this research concentrated on three feature extraction techniques and experimentally proved that division point is able to perform better. Even though the system gave more than 90% accuracy, still there is a scope for improvement by using different classification-feature combinations. The future research is planned in that direction.

## REFERENCES

[1] H Liang, X Sun, Y Sun and Y Gao, “Text feature extraction based on deep learning: a review”, EURASIP J. wireless communications and networking”, pp 1-12, 2017.
[2] M Elleuch, R Maalej and M Kherallah, “A new design based SVM of the CNN classifier architecture with dropout for offline Arabic handwritten recognition”, Procedia Computer Science, Vol 80, pp 1712-1723, 2016.
[3] M Z Alom, P Sidike, M Hasan, T M Taha and V K Asari, “Handwritten Bangla character recognition using state-of-the-art deep convolutional neural networks”, Computational intelligence and neuroscience, Vol 2018, pp 1-13.
[4] S Khan, H Ali, Z Ullah, N Minallah, S Maqsood and A Hafeez, “KNN and ANN based recognition of handwritten Pashto letters using zoning features”, Int. J. Advanced computer science and applications, Vol 9(10), 2018.
[5] A Boukharouba and A Bennia, “Novel feature extraction technique for the recognition of handwritten digits”, Applied computing and informatics, 13, pp 19-26, 2017.
[6] S Naz, AI Umar, R Ahmad, S B Ahmed, S H Shirazi and M I Razzak, “Urdu nastaliq text recognition system based on multidimensional recurrent neural network and statistical features”, Neural computing and applications, 28(2), pp 219-231, 2017.
[7] A T Sahlol, M Elhoseny, E Elhariri and A E Hussanien, “ Arabic handwritten character recognition system towards improving its accuracy”, Proc. INCOS 2017, pp 1-7.
[8] C Veershetty, R Pardehi, M Hangargi and C Dhawale, “Randon and wavelet transforms for handwritten script identification”, Springer 2018, pp 755-765.
[9] X Y Zhang, F Yin, Y M Zhang, C L Liu and Y Bengio, “Drawing and recognizing Chinese characters with recurrent neural networks”, IEEE Trans. PAMI, 2017.
[10] G A Abandhah, K S Younis and M H Khedher, “Handwritten Arabic character recognition using multiple characters based on letterform”, Proc. SPPRA08, pp 128-133, 2008.
[11] C Boufenar, M Batouche and M Schoenauer, “An artificial immune system for offline isolated handwritten Arabic character recognition”, 9(1), pp 25-41, 2018.
[12] C.H. The, R.T. Chin “On image analysis by the methods of moments”, IEEE Trans. Pattern Anal. Mach. Intell., 10 (1988), pp. 496-513

[13] A.L. Koerich, "Unconstrained handwritten character recognition using different classification strategies", in: Proceedings of International Workshop on Artificial Neural Networks in Pattern Recognition, 2003.
[14] L.S. Oliveira, R. Sabourin, F. Bortolozzi, C.Y. Suen, "Automatic recognition of handwritten numerical strings: a recognition and verification strategy", IEEE Trans. Pattern Recogn. Mach. Intell., 24 (11) (2002), pp. 1438-1454.
[15] H. Kauppinen, T. Seppanen, M. Pietikamen, "An experimental comparison of autoregressive and Fourier-based descriptors in 2D shape classification", IEEE Trans. Pattern Anal. Mach. Intell., 17 (1995), pp. 207-210.
[16] C.L. Liu, C.Y. Suen, "A new benchmark on the recognition of handwritten Bangla and Farsi numeral characters", Pattern Recogn., 42 (2009), pp. 3287-3295.
[17] K.M. Mohiuddin, J. Mao, "A comprehensive study of different classifiers for handprinted character recognition", Pattern Recogn. (1994), pp. 437-448
[18] C.-L. Liu and C. Y. Suen, "A new benchmark on the recognition of handwritten Bangla and Farsi numeral characters," *Pattern Recognition*, vol. 42, no. 12, pp. 3287–3295, 2009.
[19] O. Surinta, L. Schomaker, and M. Wiering, "A comparison of feature and pixel-based methods for recognizing handwritten Bangla digits," in *Proceedings of 12th International Conference on Document Analysis and Recognition (ICDAR)*, pp. 165–169, IEEE, Buffalo, NY, USA, 2013.
[20] M Jaleel and S Kumar, "Offline recognition of handwritten Urdu characters using b-spline curves: A survey", Int. J. Computer Applications, 157(1), 2017.
[21] K Rouini, K Jayech and M A Mahajoub, "Offline Arabic handwriting recognition using dynamic random forest", 2017.
[22] A K A Hassan, "Arabic handwritten digit recognition using multi feature and KNN classifier", J.university of Babylon, 26(4), pp 10-17, 2018.
[23] D Patel, T Som and M Singh, "Wavelet based recognition of handwritten characters using ANN", IGI Global 2017, pp 1043-1060.
[24] H Aljuaid, D Mohamad and M Sarfraz, "Arabic handwriting recognition using projection profile and genetic approach", Proc. SITIBS 2009, pp 118-125.
[25] E Glaly, and Quek F, "Isolated handwritten Arabic character recognition using multilayer perceptron and KNN classifiers", 2011.
[26] F. Camastra, A. Vinciarelli, "Combining neural gas and learning vector quantization for cursive character recognition", Neurocomputing, 51 (2003), pp. 147-159
[27] S. Impedovo, F.M. Mangini, G. Pirlo, "A genetic algorithm based clustering approach for improving off-line handwritten digit classification", in: International Conference on Information Science, Signal Processing and their Applications (ISSPA), 2012.
[28] S. Impedovo, F.M. Mangini, G. Pirlo, "A new adaptive zoning technique for handwritten digit recognition", in: ICIAP, 2013.
[29] A. Alaei, P. Nagabhushan, U. Pal, "Fine classification of unconstrained handwritten Persian/Arabic numerals by removing confusion amongst similar classes", in: 10th Int. Conf. on Document Analysis and Recognition, 2009 'b'.
[30] Binu P Chacko, "ICR: A study and analysis of extreme learning machine and support vector machine using division point and wavelet features", Ph.D thesis, 2011.