Artistic Multi-Character Script Identification

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Artistic multi-character script identification using iterative isotropic dilation algorithm

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Abstract. In this work, a new problem of script identification named artistic multi-character script identification has been addressed. Two types of datasets of artistic documents/images prepared with Bangla, Devanagari and Roman script have been used: one is real life artistic multi-character script image and another is synthetic artistic multi-character script image. After binarization using Otsu's algorithm, some character images found to be broken into components. To overcome this, a novel iterative isotropic dilation algorithm is proposed here to convert the components into a single component object. Then two types of features, namely shape based and texture based features have been considered. Discrete Gabor wavelet has been exploited with 2 scales and 4 orientations for texture feature extraction and PCA is used to reduce the dimensionality of the texture feature space. The performance of the proposed algorithm has been tested with different machine learning classifiers and promising accuracy has been observed considering the inherent complexity of the artistic multi-script documents.

Keywords: Script identification, Multi-character script, Otsu's binarization method, Random forest, Multilayer perceptron.

1 Introduction

Since last decade Script identification [1] - [8] has come up with a very interesting research topic which is the precursor to OCR [9], is one of the promising domain of research in the field of image processing and pattern recognition. Many methods have been proposed for automatic identification of script identification in different phases like block level, word level, line level, etc. and many combinations like bi-script [10], tri-script [11] and multi-script [12] [13] scenario. Different characters in different scripts have attributes which causes difficulty in character recognition of multi-script word and it is not possible to devise a universal approach and technique to get better performance in OCR. The countries

like India, where multilingual with a multi-script written people live, developing a generalized OCR for all Indus Script is not possible due to different graphic symbols in the script. Moreover, script identification, i.e. a particular language belongs to which script is itself a complicated work. So, designing a preprocessor of script identification system first, then script specific OCR can be applied.
Script identification has progressed, but is not the same when we talk about artistic documents. It is one of the interesting problems which yet to get proper attention from the researchers, though the presence of not only mixing of scripts along with wide variation in style, size, color texture etc. but mixing of scripts individual word makes it a more interesting problem. For example, see figure2.
Section 2 describes the review of literature in script identification. Section 3 describes data collection and preprocessing. In section 4 feature extractions has been discussed and in section 5 experimental results have been shown. Contribution in this work includes by collecting the multi-script images from dif-ferent places and broken component within images have been connected by our algorithm iterative isotropic dilation.

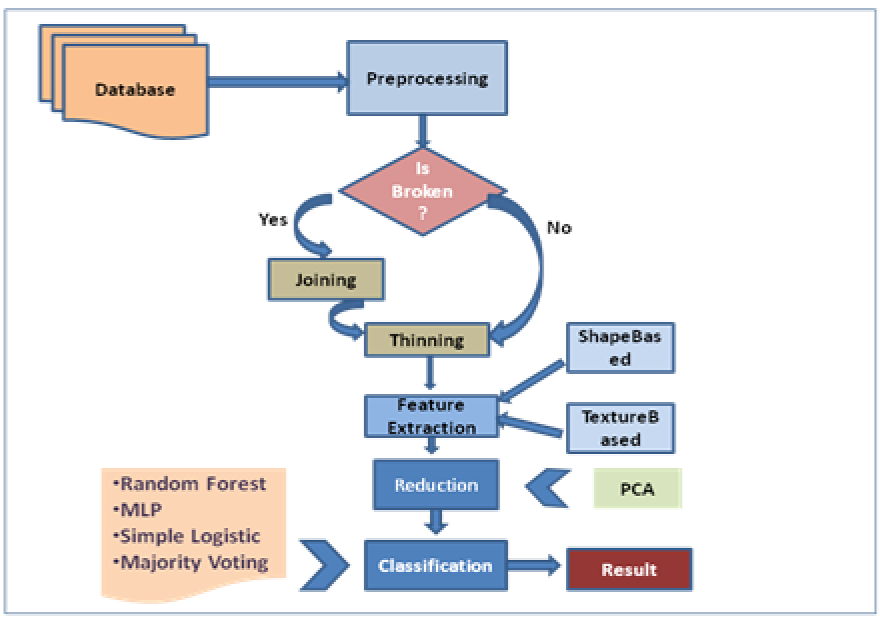


Fig. 1: Flowchart of our proposed work.

2 Literature Review

In [14] D. Dhanya et.al. classify the scripts at the word level, in a bilingual document consisting of Roman and Tamil scripts with various fonts assuming each word contains at least four patterns. Though quite a few English words do not meet this requirement, the probability of getting such words, in a bilingual Tamil document with discrete English words, is quite low. This problem has been treated in two ways. In the first way, distinct spatial zones have been considered for each word. The spatial stretch in upper and lower zones and with the density of a word has been considered and in second way the directional energy distribution of a word using Gabor filters used to identify the script.

In [15] D. Dhanya et.al. proposed a hierarchical feature extraction technique for ac-knowledgment of printed Tamil and Roman text. Features have been computed by extraction of some spatial structural features from the geometric moments, DCT based features and Wavelet transform based features. A linear transformation is used on the subsets for feature space representation by PCA and maximization of Fisher's ratio and maximization of divergence measure. This method obtains good accuracy as a result of the transformations.

Peeta Basa Pati et al. [16], have used a Gabor function based multichannel directional filtering approach for both text area separation and script identification at the word level.

S. Mohanty et.al. [17] proposed a work to distinguish between Roman script and Oriya script. They used dynamic thresholding technique for binarization and histo-gram analysis through horizontal and vertical projection used for segmentation. By chain code method the structural features are extracted and by rule based methods the classification is done.

U.Pal et.al. discussed in [18] the problem of segmenting and recognizing the complex documents of Bangla and Devanagari with text line having curved and with different orientations. They used convex hull and reservoir principle for segmenting characters with the help of candidate envelope points and after dividing the character into different zones, circular and convex hull features are extracted which are fed to SVM classifiers and obtained a very good recognition rate.

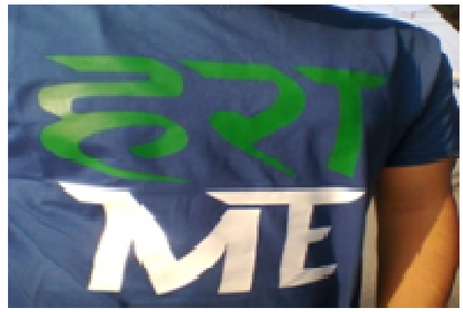
3 Data Collection and Preprocessing

Data collection is very important in any pattern recognition problem as from developing the algorithm to validation of the system all depends on the quality and variety of the data. So, for the current problem we need a database which is not only very good in size, but it contains all possible variations from not only font, size and color variations but their combinations considering texture and scripts considered for the present work. But, the hardcore reality is they are very difficult to collect. To overcome the same in the proposed work we aren't only planning to collect data from all possible sources to cover the above mentioned variations but also generate synthetic data bridge the gap.

In the proposed work, we plan to consider Bangla, Devnagari and Roman scripts under the tri-script formula as described in [1]. English language is an international language. It is a successor of the primordial Proto-Indo-European language family unit. About 340 million people in our country use this language as a communication and education medium. Hindi is the one of the most popular

languages in India. In India about 200 million people, mainly residing in northern and western part use this language as their communication medium. Bangla or Bengali language is one of the most popular languages in India. It is spoken by 190 million of the population of India living mainly in the state of West Bengal. The Hindi and Bengali both languages originate from the Indo-European language family.
Till now a database of 30 real world images are collected and a total of 300 synthetic word images are generated. The images are collected from hoarding, festoon, placard, banner, wall writing, newspaper advertisement, t-shirts graffiti etc. using mobile phones, camera etc. The mobile cameras used for the same varied from 8 MP to 16 MP and DSLR still camera (Nikon D3300) having 24.2 MP resolution and 18-55 mm lens. Around 1033 characters have been extracted from the real and synthetic database where 306 Bangla, 439 Roman and 288 Devanagari scripts.
Some sample images of our dataset are shown in figure 2. Some of the images are simply written with a single script (Roman) as shown in (a). Whereas in (b) image was collected from a T-shirt where two words are written with different scripts (Roman and Devanagari), in another case (c) image was collected from of a movie title where a single word written with two scripts (Devanagari and Roman), in (d) image was taken from a hoarding of library where a upper word written with two scripts (Bangla and Roman) and lower word is written in Roman only, in (e) image was taken from a newspaper cut out where a single word written with two scripts (Bangla and Roman), in (f) image was captured from hoarding of a Biriyani shop where a single word written with two scripts (Bangla an Roman) and other line is written with single script (Bangla) and also with different size, in (g) image was collected from a movie title of a movie where upper part is written with a single script (Bangla) and lower part is written with two different script (Bangla an Roman) and also there is variations in color between the scripts, in (h) the image was captured from logo of company where the image is not only written with different scripts (Devanagari, Roman) but also it is written artistic way.
From these images it has been seen that the images have, not only in variations in color, size, fonts, textures, but also the backgrounds have wide variation like bag, T-shirt, wall etc. In this scenario, detecting region of interest automatically is a very complicated task. So, to make this step simple, we detect the ROI manually.
After collecting the images we have used Otsu [19] based binarization method to convert into a binary image after converting to gray image. Prior to that we have ex-tracted the ROI and segmented the images into characters. In our database, the words are formed by bi-script characters. Considering 3 different scripts Bangla, Devanagari and Roman, the words are formed by Bangla with Devanagari, Devanagri with Roman and Roman with Bangla or in other words, there are $\binom{3}{2}$ combinations of script in word formation. After manual segmentation, we separated each character into its corresponding script class.

(a)



(b)

(c)

(d)

(e)

(f)

(g)

(h)

Fig. 2: Shows some sample images from our database.

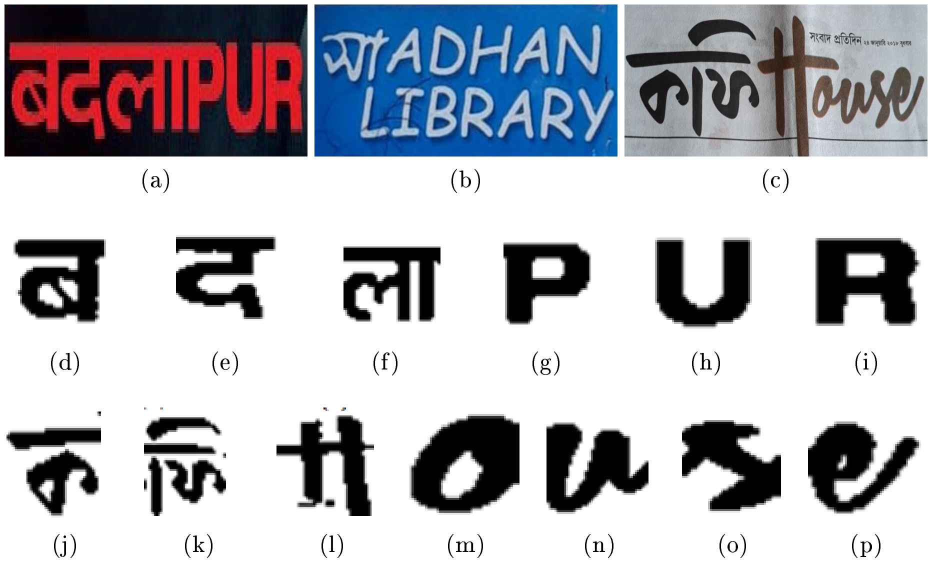


Fig. 3: Figure (a), (b), (c) shows ROI extraction of real images and (d), (e), (f), (g), (h), (i), (j), (k), (l), (m), (n) are the binarized and segmented character images.

During binarization, we found that some of the images are very well binarize or converted to two tone images, but in some cases it is found that the characters are broken into parts which needs to be connected to get proper results. Here we have used novel iterative isotropic dilation algorithm to join the broken parts. Isotropic dilation is the technique of thresholding the distance transform.This algorithm uses connected component labelling [20][21] and flood fill algorithm [22] to find out number connected component object and Euclidean distance transform [23] algorithm to make the components join with changing the threshold value.

Algorithm 1 Iterative Isotropic Dilation

Input: Binary_ Image, Number_of_connected_component
i. N= Number_of_connected_component
ii. Initialize t=0
iii. If (N>1) then go to step (iv)
iv. Repeat Step (v) to (vi) until N= =1
v. Binary_Image = Euclidean distance transform <=t
vi. t=t+0.1
vii. update N
Output: Joined Binary_Image.

(a) (b) (c) (d)

Fig. 4: Figure (a), (b) are the broken binarized character images and figure (c), (d) are the images after the iterative isotropic dilation algorithm has been applied

From figure 4(c) and 4(d), we can see the broken parts of the characters are joined by only a single pixel. In this algorithm, by changing the threshold value t by 0.1, the Euclidean distance transformed value also changed and at some value of the threshold the number of components will be 1 and the iterative isotropic dilation algorithm will stop executing and we get joined images as shown in figure 4(c) and 4 (d).
Next, we have normalized the characters into a predefined size of [32, 32]. This was done to avoid size variation of the images as explained in section 3. Next, the thinning of the character images has been done using Zhang-Suen thinning algorithm [24]. This thinning algorithm consists of 2 phases. First phase to remove south-west pixels and second phase to remove north-west pixels and these phases are iterated if any pixels remain to remove.

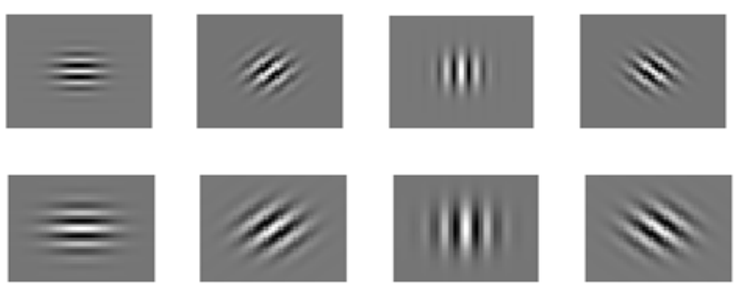
4 Feature Extraction

Feature extraction is an important pattern recognition task. Features should be robust enough to differentiate the scripts and at the same time it should be easily computable. In this paper, we have used feature based on the shape and texture to identify the scripts.

4.1 Shape Based Features

The shape based properties [25] used in shape perceptive along with their details are reviewed. Shape feature is extremely useful in many image databases and pattern matching applications
The simple geometric features can categorize shapes with large differences. The features computed based on shape are area, major axis length, minor axis length etc. which are explained below. These features are selected with the assumption that they will be simple to compute at the same time we will be able to distinguish the inputs. To compute the features we have separated the images into 4 parts from the Center of Mass [26]. The Center of Mass is selected as a segmentation point, so the every quadrant contains sufficient numbers of object pixels, so that we can extract proper feature from the images.
a. Area: This scalar feature measures number of pixels in the region of the whole image.

b. Major Axis Length: Returns a scalar value as the major axis of the ellipse that has the same normalized second central moments as the region, formed around the object.
c. Minor Axis Length: Returns a scalar value as the minor axis of the ellipse that has the same normalized second central moments as the region, formed around the object.
d. Eccentricity: The eccentricity which has the same second-moments as the region is the ratio of the distance between the foci of the ellipse and its major axis length.
e. Orientation: This scalar value represents the angle between the major axis and x axis of the ellipse that has the same second-moments as the region.
f. Convex Area: this scalar quantity denotes the number of pixels in convex image.
g. Euler Number: Euler number is a scalar value calculated as the number of objects in the region minus the number of holes in those objects.
h. Equiv Diameter: Returns a scalar can be represented as the diameter of a circle with the same area as the region.
i. Solidity: Returns a scalar representing the proportion of the pixels in the convex hull that are also in the region.
j. Extent: A scalar value which can be calculated as the Area/ the area of the bound-ing box.
k. Perimeter: A scalar represents the distance between each neighboring pair of pix-els around the border of the region.
l. Circularity ratio: This is the ratio of the area of a shape to the area of the bounding circle.



(a)

Fig. 5: The real part of Gabor wavelet having 2 scales and 4 orientation of 0°,45°, 90°, 145°.

4.2 Texture feature

Texture features describe the contents of an image or a region of an image and give important low level features and mean oriented energy. Discrete Gabor wavelet is a oriented filter and returns mean oriented energy as a texture feature [27][28].
The discrete Gabor wavelet transform on an image I(x, y) having dimension m X n can be represented as

$$G(x,y) = \sum_s \sum_t I(x-s, y-t)\psi_{\mathrm{pq}}{}^*(s,t) \tag{1}$$

Where s, t are the filter mask sizes.ψ^* is the complex conjugate of ψ which is a self similar function generated from dilation and rotation of the mother wavelet ψ, can be represented as

$$\psi(x,y) = (\frac{1}{2\pi\sigma_x\sigma_y})\exp(\frac{-1}{2}(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}))\exp(2\pi jWx) \tag{2}$$

The self-similar Gabor wavelets are obtained through the generating function

$$\psi_{pq}(x,y) = a^{-p}\psi(x', y') \tag{3}$$

Where p denotes scale and q denotes orientations and

$$x' = a^{-p}(x\cos\theta + y\sin\theta) \tag{4}$$

and

$$y' = (-x\sin\theta + y\cos\theta) \tag{5}$$

for a>1 and

$$\theta = \frac{\pi q}{Q} \tag{6}$$

After applying Gabor filters on the image with different orientation at different scale, the energy content is calculated using

$$E(p,q) = \sum_x \sum_y |G_{pq}(x,y)| \tag{7}$$

2-D Gabor filter with modulation frequency W can be represented as

$$G(x,y) = g_\sigma \exp(2\pi jW(x\cos\theta + \sin\theta)) \tag{8}$$

where

$$g_\sigma(x,y) = (\frac{1}{2\pi\sigma_x\sigma_y})\exp(\frac{-1}{2}(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2})) \tag{9}$$

The parameters θ and σ denotes orientation and scale of Gabor filters. For different values of these parameters features can be obtained.
A total of 512 Features has been extracted using Gabor wavelet. But to use

this huge dimension of feature is very challenging an many of the features are redundant. So to minimize the feature dimension and preserve the diversity of feature intake we have reused the feature dimension.
Feature dimensionality reduction is one of the challenging problems in pattern recognition and there are a number of algorithms like PCA [29], kernel PCA [30], LDA [31] , GDA [32] etc. for the same.
Here we have used PCA as it uses eigenvectors of the covariance matrix of the feature set which are easily computable. Here we have retained our Gabor feature set of 40. From shape based feature, 12 features are obtained and as we have divided the characters into 4 parts from the center of mass point as discussed in section 4.1, the features are extracted from the 4 parts of a character and from the character itself, makes 5 X 12 = 60 shape based features. So, in total 40 (Gabor wavelet) + 60 (shape based) = 100 features are extracted.

5 Experiments

5.1 Evaluation protocol

In this work, for evaluating the performance of our method, 10 fold cross validation (CV) has been used. In this 10-fold method, we divide the dataset into 10 equal sized parts. From 10 parts, training and testing sets are chosen. One part is chosen as the testing and remaining 9 parts chosen as the training and this process is repeated for all parts and result is obtained by averaging all results. The performance parameter metrics have been used are Correct Recognition Rate (CRR), kappa static, Root Mean Square error (RMSE) can be defined as follows.

$$CRR = \frac{(\#correctly\ identified\ character\ images)}{(\#total\ character\ images)} * 100\% \tag{10}$$

The Kappa statistic compares an observed accuracy with an expected accuracy. Ex-pected accuracy can be defined as the accuracy that any random classifier would be anticipated to realize based on the confusion matrix.

$$Kappa = \frac{(observed\ accuracy - expected\ accuracy)}{(1 - expected\ accuracy)} \tag{11}$$

Another metric Root mean square error (RMSE) can be defined as

$$RMSE = \sqrt{\frac{\sum_{m=1}^{M} \sum_{n=1}^{N} I(x-s, y-t)}{MN}} \tag{12}$$

Where I (x, y) and T (x, y) stand for reference and target image of size M X N respec-tively.

Table 1: Classifiers with different parameters.

Classifier	CRR	Kappa Statistic	Root Mean Square Error
Random Forest	93.18	0.8959	0.2731
Majority Voting	92.20	0.8815	0.2089
Simple Logistic	90.90	0.862	0.214
MLP	90.90	0.8618	0.2462

5.2 Result & Analysis

During experimentation, performance of different well known classifiers namely random forest [33], majority voting [34], simple logistic [35] and multilayer perceptron (MLP) [36][37] were considered.

From the table, we found that the best result is obtained using random Forest of 93.18% recognition rate followed by Majority Voting, MLP, Simple Logistic and it is observed that MLP and Simple Logistic and gives the same recognition rate. The oth-er parameter values for Random Forest i.e. Kappa Statistic and Root Mean Square Error are 0.8959 and 0.2731 respectively.

From table1 it can be observed that using Random Forest, Majority Voting, MLP and Simple Logistic the mis-classification rates are obtained 6.81,7.79, 9.09, 9.09 respec-tively and RMS errors we get 0.2731, 0.2089,0.214,0.2462 respectively. In table2 we tabulate the confusion matrix of the highest performer classifier on our dataset.

Table 2: Confusion Matrix for the highest accuracy rate of Bi-script identification using Random Forest.

	Bangla	Devanagari	Roman
Bangla	291	3	12
Devanagari	32	252	4
Roman	18	4	417

From table2 it has been seen that 291 characters out of 306 has been correctly classi-fied as Bangla characters, 3 characters as Devanagari and 12 as Roman. In case of devanagari script, 252 characters out of 288 have been correctly identified as Devangari but 32 have been identified as Bangla script and 3 as Roman script. For Roman characters, 417 out of 439 have been correctly classified as Roman but 22 characters have been misclassified and out of 22, 18 characters have been seen in Bangla class and 4 in Devanagari class.

6 Conclusion

A new problem of script identification, from artistic multi-script characters has been addressed in this work. Such problem has inherent complexities in terms of character size, color, texture, pattern, orientation and sometimes heterogeneous background making the problem really challenging. Using some structural and texture based features we found an average accuracy of 93.18% applying random forest classifier. The result is promising observing the inherent complexity of the said problem.

Availability of standard dataset is an issue for this type of work. At present we have considered both synthetic and natural images for the experiment. In future, we would like to extend our dataset by incorporating more natural artistic images. Proposing some novel script dependent features to improve the recognition accuracy is also in our plans.

References

1. Ghosh, D., Dube, T., & Shivaprasad, A. Script recognition-a review. IEEE Transactions on pattern analysis and machine intelligence, 32(12), 2142-2161 (2010).
2. Obaidullah, S. M., Santosh, K. C., Das, N., Halder, C., & Roy, K. Handwritten Indic script identification in multi-script document images: A survey. International Journal of Pattern Recognition and Artificial Intelligence, 1856012 (2018)..
3. Obaidullah, S. M., Bose, A., Mukherjee, H., Santosh, K. C., Das, N., & Roy, K. Extreme learning machine for handwritten Indic script identification in multi-script documents. Journal of Electronic Imaging, 27(5), 051214 (2018)..
4. Obaidullah, S. M., Halder, C., Santosh, K. C., Das, N., & Roy, K. Automatic line-level script identification from handwritten document images-a region-wise classification framework for indian subcontinent. Malaysian Journal of Computer Science, 31(1), 63-84 (2018).
5. Obaidullah, S. M., Santosh, K. C., Halder, C., Das, N., & Roy, K. Automatic Indic script identification from handwritten documents: page, block, line and word-level approach. International Journal of Machine Learning and Cybernetics, 1-20 (2017).
6. Obaidullah, S. K., Santosh, K. C., Halder, C., Das, N.,& Roy, K. Word-level multi-script Indic document image dataset and baseline results on script identifica-tion. International Journal of Computer Vision and Image Processing (IJCVIP), 7(2), 81-94 (2017).
7. Obaidullah, S. M., Halder, C., Santosh, K. C., Das, N., & Roy, K. PHDIndic_11: pagelevel handwritten document image dataset of 11 official Indic scripts for script identification. Multimedia Tools and Applications, 77 (2), 1643-1678 (2018).
8. Obaidullah, S. M., Halder, C., Das, N., & Roy, K. Bangla and oriya script lines identification from handwritten document images in tri-script scenario. International Journal of Service Science, Management, Engineering, and Technology (IJSSMET), 7 (1), 43-60 (2016)..
9. Mori, S., Suen, C. Y., & Yamamoto, K. Historical review of OCR research and development. Proceedings of the IEEE, 80 (7), 1029-1058 (1992).
10. Rajput, G. G., and H. B. Anita. Handwritten script identification from a bi-script document at line level using Gabor filters. Proc. of SCAKD (2011): 94-101.

11. Aithal, P. K., Rajesh, G., Acharya, D. U., Krishnamoorthi, M., & Subbareddy, N. V. Script identification for a Tri-lingual document. In International Con-ference on Advances in Communication, Network, and Computing (pp. 434-439). Springer, Berlin, Heidelberg (2011).
12. Pal, U., Sinha, S., & Chaudhuri, B. B. Multi-script line identification from Indian documents. In null (pp. 880). IEEE (2003).
13. Pati, P. B., & Ramakrishnan, A. G. Word level multi-script identifica-tion. Pattern Recognition Letters, 29 (9), 1218-1229 (2008).
14. Dhanya, D.,& Ramakrishnan, A. G. Script identification in printed bilingual documents. In International Workshop on Document Analysis Systems (pp. 13-24). Springer, Berlin, Heidelberg (2002).
15. Dhanya, D.,& Ramakrishnan, A. G. Optimal feature extraction for bilingual OCR. In International Workshop on Document Analysis Systems (pp. 25-36). Springer, Berlin, Heidelberg (2002).
16. Pati, P. B., Raju, S. S., Pati, N.,& Ramakrishnan, A. G. Gabor filters for document analysis in Indian bilingual documents. In Intelligent Sensing and Information Processing, 2004. Proceedings of International Conference on (pp. 123-126). IEEE (2004).
17. Mohanty, S., Dasbebartta, H. N.,& Behera, T. K. An efficient bi-lingual optical character recognition (English-Oriya) system for printed documents. In Advances in Pattern Recognition, 2009. ICAPR'09. Seventh International Confe-rence on (pp. 398-401). IEEE (2009).
18. Pal, U., Roy, P. P., Tripathy, N., & Lladós, J. Multi-oriented Bangla and Dev-nagari text recognition. Pattern Recognition, 43(12), 4124-4136 (2010).
19. Otsu, N. A threshold selection method from gray-level histograms. IEEE transactions on systems, man, and cybernetics, 9(1), 62-66 (1979).
20. Chang, F., Chen, C. J., & Lu, C. J. A linear-time component-labeling algorithm using contour tracing technique. Computer vision and image understanding, 93(2), 206-220 (2004).
21. Samet, H.; Tamminen, M. Efficient Component Labeling of Images of Arbi-trary Dimension Represented by Linear Bintrees. IEEE Transactions on Pattern Analysis and Machine Intelligence. IEEE. 10 (4): 579 (1988).
22. Silvela, J., & Portillo, J. Breadth-first search and its application to image processing problems. IEEE Transactions on Image Processing, 10 (8), 1194-1199 (2001).
23. Breu, H., Gil, J., Kirkpatrick, D., & Werman, M. Linear time Euclidean distance transform algorithms. IEEE Transactions on Pattern Analysis and Machine Intelligence, 17 (5), 529-533 (1995).
24. Zhang, T. Y., & Suen, C. Y. A fast parallel algorithm for thinning digital pat-terns. Communications of the ACM, 27 (3), 236-239 (1984).
25. Yang, M., Kpalma, K., & Ronsin, J. A survey of shape feature extraction techniques, Peng-Yeng Yin. Pattern Recognition, IN-TECH, pp.43-90 (2008).
26. Harmsen, J. J., & Pearlman, W. A. Steganalysis of additive-noise mod-elable information hiding. In Security and Watermarking of Multimedia Contents V (Vol. 5020, pp. 131-143). International Society for Optics and Photonics (2003).
27. Ma, W. Y., & Manjunath, B. S. Texture features and learning similarity. In Computer Vision and Pattern Recognition, 1996. Proceedings CVPR'96, 1996 IEEE Computer Society Conference on (pp. 425-430) IEEE (1996).
28. Zhang, D., Wong, A., Indrawan, M.,& Lu, G. Content-based image retrieval using Gabor texture features. IEEE Transactions PAMI, 13-15 (2000).
29. Jolliffe I.T. Principal Component Analysis, Series: Springer Series in Statistics, 2nd ed., Springer, NY, XXIX, 487 pp. 28 illus (2002).

30. Schölkopf, B., Smola, A.,& Müller, K. R. Nonlinear component analysis as a kernel eigenvalue problem. Neural computation, 10(5), 1299-1319 (1998).
31. Martinez, A. M.; Kak, A. C. PCA versus LDA (PDF). IEEE Transactions on Pattern Analysis and Machine Intelligence. 23 (=2): 228-233 (2001).
32. Baudat, G., & Anouar, F. Generalized discriminant analysis using a kernel approach. Neural computation, 12(10), 2385-2404 (2000).
33. Rodriguez-Galiano, V. F., Ghimire, B., Rogan, J., Chica-Olmo, M., & Rigol-Sanchez, J. P. An assessment of the effectiveness of a random forest classifier for land-cover classification. ISPRS Journal of Photogrammetry and Remote Sensing, 67, 93-104 (2012).
34. Franke, J.,& Mandler, E. A comparison of two approaches for com-bining the votes of cooperating classifiers. In 11th IAPR International Conference on Pattern Recognition. Vol. II. Conference B: Pattern Recognition Methodology and Systems (pp. 611-614). IEEE (1992).
35. Gardezi, S. J. S., Faye, I., & Eltoukhy, M. M. Analysis of mammo-gram images based on texture features of curvelet Sub-bands. In Fifth International Conference on Graphic and Image Processing (ICGIP 2013) (Vol. 9069, p. 906924). International Society for Optics and Photonics (2014).
36. Alkan, A., Koklukaya, E.,& Subasi, A. Automatic seizure detection in EEG using logistic regression and artificial neural network. Journal of Neuroscience Me-thods, 148 (2), 167-176 (2005).
37. Orhan, U., Hekim, M.,& Ozer, M. EEG signals classification using the K-means clustering and a multilayer perceptron neural network model. Expert Systems with Applications, 38 (10), 13475-13481 (2011).