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A Novel Weighted SVM Classifier Based on SCA for Handwritten Marathi Character Recognition

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ABSTRACT
The research on handwritten optical character recognition (OCR) of Marathi script is very challenging due to the complex structural properties of the script that are not observed in most other scripts. This paper gives an OCR framework for handwritten Marathi document classification and recognition system. Due to the large variety of symbols the Marathi characters recognition poses great challenge and their proximity in appearance. The weighted one-against-rest support vector machines (WOAR-SVM) assume a noteworthy part to deal with vast feature measures which are utilized for the classification. Here, a new sine cosine algorithm is proposed for the identification of handwritten Marathi text. By utilizing different morphological operations the preprocessing is finished and the Marathi text is flexibly segmented in three levels; line segmentation, word segmentation and character segmentation with Modified Pihu method. Various features like statistical, global transformation, geometrical and topological features are extracted from the preprocessed image by extraction techniques. Result obtained show that various features with WOAR-SVM classifier perform the best by yielding high accuracy as 95.14%.

KEYWORDS
Optical character recognition; WOAR-SVM; Sine cosine algorithm; Modified Pihu method; Global transformation

1. INTRODUCTION

In digital computer machine the serious research topic is simulation of human perusing. Not only the main advantages of such exertion were difficult for simulating human reading but also the probability of efficient application in which printed and handwritten character present on document has to be transferred into machine justifiable format [1]. The automatic character recognition of printed and handwritten written record information has an assortment of practical and commercial applications in libraries, banks and post offices [2,3]. In the field of image processing, pattern recognition, machine learning and artificial inelegancy the optical character recognition (OCR) is an examination. OCR is a procedure of converting scanned images of machine printed or handwritten text into a computer processable format [4]. All the OCR particularly of records in English language has been comprehensively studied and actualized effectively over years [5].

The OCR comprises two classifications based on data acquisition process: off-line character recognition and online character recognition [6–8]. The off-line character recognition is additionally separated into two sections: machine printed and handwritten character recognition. There are heaps of issues in handwritten character recognition when contrasted with documents of machine printed. Since various peoples have distinctive styles in composing, pen-tip estimate and in their writing some peoples have skewness. To overcome this issue every one of the difficulties makes the researchers to work. In India Devanagari script is an older most one, which is utilized to write numerous languages like Nepali, Hindi, Marathi, Sindhi and Sanskrit for documentation [9]. Be that as it may, the generally preferred language is Marathi; a very less measure of work has been finished.

In these areas most of the present work is restricted to English and a few oriental languages. For Indic scripts the absence of efficient solutions in Marathi language has hampered extraction of information from a historical importance and social archives. For text character segmentation different techniques have elaborated; they are wavelet transforms [10,11], curvelet transform [12,13], and Gradient feature [14,15]. Consequently, for the OCR these techniques are not demonstrated dependable [16,17].

In this paper, we exhibit a modified approach for handwritten Marathi text document classification and recognition process. To begin with, the Marathi text documents are changed into the image samples. In the wake of preprocessing the noise is expelled and script was segmented adaptable in three levels utilizing 'Modified Pihu Method'. After that, various feature extraction techniques are applied to segmented image to extract relevant features from character to form feature vectors. These feature vectors are then utilized by a novel approach named weighted one-against-rest support vector machines (WOAR-SVM) classifier for the classification and to recognize the Marathi word image the sine cosine algorithm (SCA) optimization algorithm is used. WOAR-SVM is a binary classification algorithm; nonetheless, it is utilized to classify the feature database of the document. Our approach would add to decrease the error, so our proposed strategy achieves high accuracy and furthermore, this approach accurately recognizes the substantial volume of characters. The rest of the paper is structured as follows: In section 2, the brief review of handwritten character identification is provided. Section 3 expounds the proposed method in detail. Section 4 illustrates experimental analysis and finally, section 5 concludes the paper.

2. LITERATURE SURVEY: A BRIEF REVIEW

Many of the frameworks have clarified about a variety of different strategies for text character segmentation. A portion of the works is assessed here.

Y Zhang *et al.* [18] have presented a novel adversarial feature learning (AFL) model to enhance the HCR execution on restricted data training that incorporates the prior knowledge of printed data and writer-independent semantic features. From accessible handcrafted feature methods, the introduced AFL method is distinctive which automatically exploits writer-independent semantic features and standard printed data as prior knowledge is learnt objectively. To solve the issues of speed and storage capacity, X Xiao *et al.* [19] have introduced a global supervised low-rank expansion technique and an adaptive drop-weight method. A nine-layer CNN intended for HCCR comprises 3,755 classes and devises an algorithm that decreases the computational cost of networks by nine times and in baseline model the network is compressed to 1/18 of the original size with 0.21% accuracy drop. Contrasted with CNN strategy for HCCR, the introduced model is around 30 times speedier and 10 times costlier.

The author [20] assesses the impacts of two sorts of character-level NNLMs as FNNLMs (feed forward neural network LMs) and RNNLMs (recurrent neural network LMs) for enhancing Chinese handwriting recognition. The hybrid LMs are built by joining both neural networks (FNNLMs and RNNLMs) with BLMs. For reasonable correlation with state-of-the-art system and BLMs, assessed in a system with the similar character over-segmentation and classification models as previously, different LMs are analyzed utilizing a little text corpus used previously. In their work the execution of both ICDAR-2013 and CASIA-HWDB competition dataset is enhanced essentially. The character level accurate rate and correct rate accomplish 95.88% and 95.95% in CASIA-HWDB, respectively. R Pramanik *et al.* [21] have introduced a novel shape decomposition-based segmentation technique to disintegrate the compound characters into prominent shape components. The less number of classes to recognize the shape decomposition lessens the classification complexity also enhances the recognition accuracy at the same time. At the segmentation area the decomposition is done where the two fundamental shapes are joined to form a compound character.

A system for offline recognition cursive Arabic handwritten text based on hidden Markov models (HMMs) is presented by R. Mouhcine *et al.* [22]. Without explicit segmentation the system is analytical to perform embedded training. By baseline estimation the statistical features are extricated and in the word image geometric to integrate both peculiarities of the text and pixel distribution characteristics. Using HMMs these features are modeled and trained by embedded training. The popular deep convolutional neural networks (DCNNs) have been introduced by C Boufenar *et al.* [23]. The DCNNs have adequately replaced the hand-crafted descriptors with network features and appeared to provide preferable outcomes than other traditional methods. In machine learning, it is one of the quickest developing areas and promise to reshape the future of artificial intelligence. In three different ways the CNN model can be used: training the CNN from scratch, from a pretrained model utilizing transfer learning strategy to leverage features, keeping the transfer learning strategy and fine-tune the CNN architecture weights.

S Roy *et al.* [24] have exhibited a novel deep learning strategy for the recognition of handwritten Bangla isolated compound character. On the CMATERdb 3.1.3.3 dataset a new benchmark of recognition accuracy is reported. In different pattern recognition issues the greedy layer-wise training of deep neural network has helped to made critical steps. The authors utilize layer-wise training to DCNN in a supervised fashion and to accomplish faster convergence the training process is augmented with the RM-SProp algorithm. To solve the problem of recognizing isolated handwritten words the authors [25] have introduced the use of a new neural network architecture that combines a deep convolutional neural network with an encoder–decoder called sequence to sequence. The presented architecture distinguishes the contextual and characters with their neighbors to recognize any given word. Under several experiments the author's models are tested on two handwritten databases like IAM and RIMES to determine the optimal parameterization of the model.

3. PROPOSED METHOD FOR MARATHI CHARACTER RECOGNITION AND CLASSIFICATION

The design of the proposed OCR system is shown in Figure 1. For this character classification and recognition the preprocessing, segmentation, feature extraction and optimization techniques are proposed in our method. At first, the text documents are changed over into the image samples in the preprocessing stage. Then, the Marathi script was segmented flexibly in three levels as line segmentation, word segmentation and character segmentation with 'Modified Pihu Method' being proposed to enhance the segmentation accuracy. After segmentation various features are extracted from the character image. A typical feature of the handwritten text is the presentation of text created by the author. Feature extraction stage is to expel the data redundancy. These feature vectors are then utilized by a novel approach based on weighted one-against-rest support vector machine classifier and the SCA optimization algorithm. To optimize the WOAR-SVM, the SCA algorithm is utilized to select the Marathi text from the handwritten document.

3.1 Image Acquisition Phase

Image acquisition is an initial phase of character recognition system. In this phase the input handwritten or paper document image is scanned and converted into electronic form in bitmap images such as JPEG, BMT, TIF and TNG. The acquired image is fed to the pre-processing phase Figure 2.

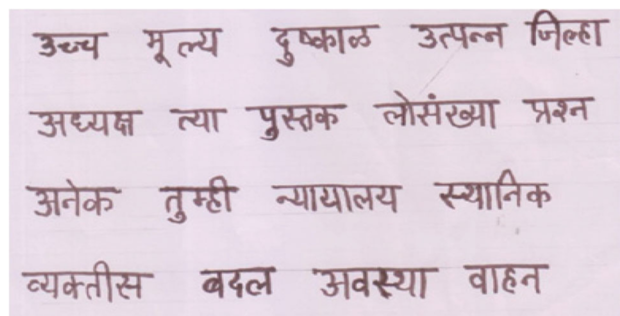

Figure 2: Sample document image

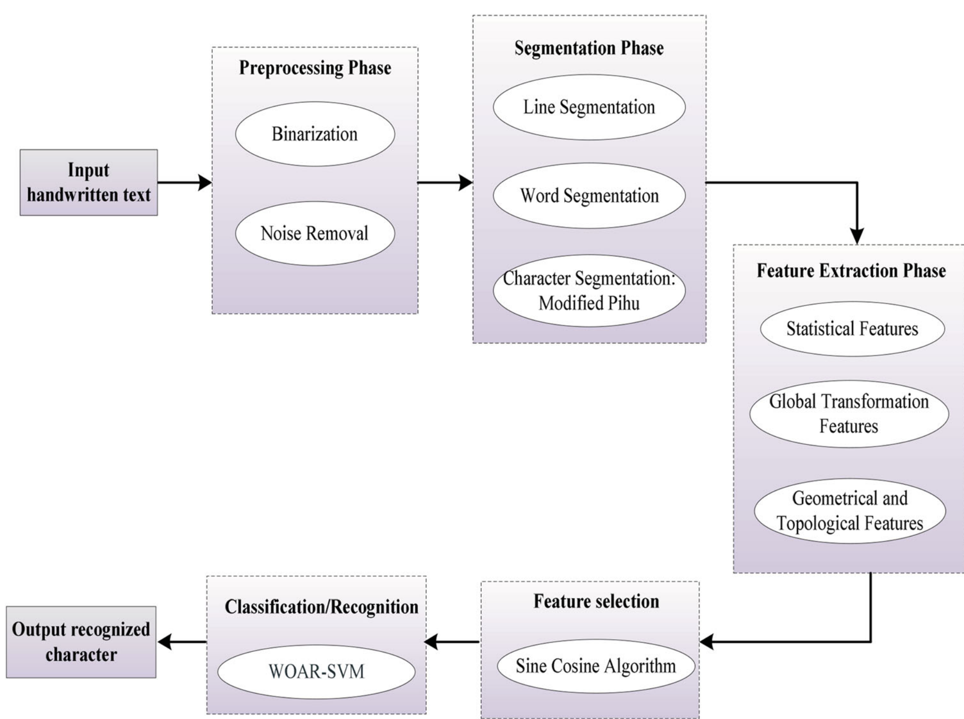

Figure 1: Architecture of the Proposed OCR

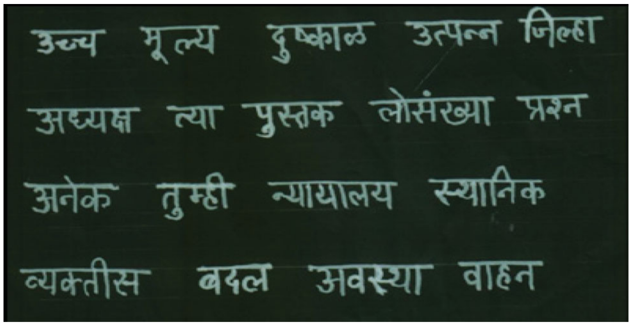

Figure 3: Image after Binarization

3.2 Preprocessing Phase

The next phase is preprocessing, it manages enhancing image quality for better recognition by the system. Preprocessing of handwritten document is required to identify and evacuate all undesirable bit patterns which prompt to lessen the recognition accuracy. The main objectives of preprocessing are Binarization, noise reduction and line removal. After text preprocessing the various feature extraction techniques have been utilized to extract features for recognition process.

(a) ***Grayscale conversion:*** In grayscale conversion, the stored bitmap images (JPEG, BMT, TIF and TNG) are changed over to grayscale image format. Here, in the matrix form the images are available where all the values of every element are identical to how bright or dark the pixel at the fitting position should be colored.
(b) ***Binarization:*** The binarization process utilizes a global threshold approach to convert a grayscale image into a binary image. Based on the threshold value these procedures increment the processing rate and diminished the required storage space Figure 3.
(c) ***Image Noise Removal:*** In scanning devices the generated noises in image are line segment separated, bumps in lines and gaps. The main distortions are local variations, dilation and erosion, etc., and furthermore it is exceptionally essential to supplant the restrictions. The median filtering is utilized to perform noise removal. From the image this strategy decreases the salt and pepper noise.

3.3 Segmentation Phase

In the segmentation phase the continuous character of preprocessed image is broken down into sub-images of individual character. The segmentation plays a noteworthy part in character recognition process. Segmentation process can be sorted as global and local segmentation. The entire image is managed utilizing the global segmentation process and local segmentation dealt with only sub-images. In the global threshold process, based on the image intensity values the threshold level is considered. Here, the global threshold of the image (IM) is $f(x, y)$ represented as T if the intensity value is less than the threshold level, then it is set as 0 (black); the rest are set as 1 (white). The threshold image $g\,(m,\,n)$ is given as follows.

$$g(x, y) = \begin{cases} 1, & \textit{if } f(x, y) \geq T \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

For the segmentation technique the projection profile method is utilized in our method. The segmentation technique incorporates the three vital strategies: Line segmentation, Word segmentation and Character segmentation.

a) ***Line Segmentation:*** In this segmentation method, initially on every line or row utilizing the horizontal projection profile method the sum of all white pixels is estimated and also the appropriate histogram of the image is generated as takes after.
   - The horizontal histogram of the image is constructed.
   - The distance between proper two histograms is recognized, based on the threshold value every histogram is separated and saved.
   - Finally, from the image the segmented line is produced.
b) ***Word Segmentation:*** In word segmentation strategy, to estimate the entirety of every single white pixel the vertical projection profile approach is used. The segmentation of the word is delineated as takes after.
   - At first, the vertical histogram for the image is developed.
   - In every column, discover the number of white pixels and by using the histogram the columns with no white pixel are detected.
   - Replace every such column by 1 and change over the unfilled rows as 0 and content words will have unique pixels and save it.
   - From the line the words are segmented based on the threshold value and the procedure is rehashed for each line Figure 4.
c) ***Character Segmentation using Modified Pihu Method:*** The Modified Pihu method is proposed to overcome the existing method limitations [26,27]. Figure 5 demonstrates the Marathi word and its different components. Amid segmentation the Pihu method [27] does not evacuate the word header line and focuses only on the shape of the characters. So,

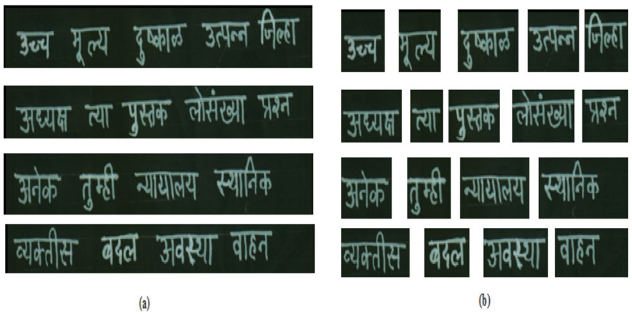

Figure 4: (a) Segmented Line Image (b) Segmented Word Image

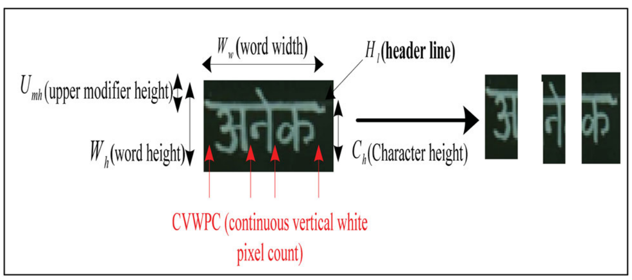

Figure 5: Character image segmentation using Modified Pihu method

the Modified Pihu method is proposed to segment the word header line which is delineated in following advances:

Step 1: Calculate the height (W_h) and width (W_w) of the segmented word image IMas,

$$W_h = \sum_{j=1}^{n} Y(j); \quad \text{for} \quad 1 \le j \le n \tag{2}$$

$$W_w = \sum_{i=1}^{m} X(i); \quad \text{for} \quad 1 \le i \le m \tag{3}$$

where, $Y(j)$ and $X(i)$ are the number of pixels along the y-axis and the x-axis, respectively, m is the m^{th} pixel along x-axis and n is the n^{th} pixel along y-axis.

Step 2: The row with maximum white pixels in the image top 30% area is evaluated as

$$P_w(H_l) = \max\left(H_{l1}, H_{l2}, \ldots H_{lk}\right) \tag{4}$$

Here, $H_{lk} = \sum_{i=1}^{W} P_w(k,i)$ represents the header line rows in the top area of image containing white pixels and the header line is denoted as $P_w(H_l)$.

Step 3: Calculate the $CVWPC$ area, from the bottom left corner up to $P_w(H_l)$of the word as shown by red color arrows in Figure 5.

$$\text{CVWPC} = \sum_{r_{n,0}}^{P_w(H_l)} P_W(j); \quad for\ j \ne 0, 1 \le m \le W_h \tag{5}$$

where, the m^{th} row of the first column is $r_{n,0}$ and $P_w(j)$ denotes the black pixels and the same procedure is repeated for the whole word Figure 5.

Step 4: The IM is segmented using Equation (6)

$$f(ch\_cut) = \begin{cases} \text{true}, \ CVWPC - 95\% \\ \sum_{j=r_{n,0}}^{P_w(H_l)} \sum_{i=1}^{W} IM_{j,i}, \\ \text{true}, \ if(mid(CVWPC - 95\%) \\ \cup\, (5\% P_w \in lmh - 15\%)) \\ \text{Otherwise; false} \end{cases} \tag{6}$$

where, lmh is the lower modifier (LM) height, $f(ch\_cut)$ represents the segmented character and the total character count is L.

$$C_{h_w} = f(ch\_cut)_j; \quad 1 \le j \le L \tag{7}$$

$$C_{h_{avg\_w}} = \frac{C_{h_w}(1) + C_{h_w}(2) + \cdots + C_{h_w}(L)}{L} \tag{8}$$

During the segmentation of image into subunits, there may exist a character (CC) due to the presence of LM. The character width is calculated to check the possibility of said cases and compared with $C_{h_{avg\_w}}$ (average character width).

Case (i): if $C_{h_w} > C_{h_{avg\_w}}$, then the sub-image from CC is segmented using the following function

$$f(CC) = \begin{cases} \sum_{j=1}^{P_w(H_l)} \sum_{i=1}^{W} IM_{j,i}, \text{true}, \ if(P_B \in \text{mid\_} \\ \text{area} \cup C_{h_w} > C_{h_{avg\_w}}) \\ \text{Otherwise; false} \end{cases} \tag{9}$$

Case (ii): if $C_{h_w} > C_{h_{avg\_w}}$,$mid(CVWPC) \ge 95\%$ then images are segmented using Equation (6).

Step 5: Segmentation of modifiers, the upper modifier (UM) is segmented using Equation (10).

$$f(UM) = \begin{cases} \sum_{j=P_{B(H_l)}}^{w_h} \sum_{i=1}^{W} IM_{j,i}, \ \text{true}, \ if(P_w \ge 1) \\ \text{Otherwise;} \quad \text{false}, \ iff(P_w = 0) \end{cases} \tag{10}$$

The LM is segmented using Equation (11).

$$f(lmh) = \begin{cases} \sum_{j=1}^{(H_l)} \sum_{i=1}^{W} IM_{j,i}, \text{true}, \\ if(C_{h_h} \geq (C_{h_{avg\_h}} + lmh)) \\ \text{Otherwise; false}, \\ if(C_{h_h} < (C_{h_{avg\_h}} + lmh) \end{cases} \quad (11)$$

where the height and characters of the LM are lmh and C_{h_h}, respectively. Amid the character recognition process, the advantage is that the modifier optimizes the character class count independently by storing and helps in diminishing the processing time. The separated modifiers are extracted utilizing feature extraction techniques in the following section.

3.4 Feature Extraction

The most vital part of the recognition system is feature extraction technique. This phase is utilized to evacuate data redundancy. The feature extraction can be characterized as extracting the most illustrative data from raw information that limit inside class design variability while improving. Various feature extraction methods are characterized in three groups: statistical features, global transformation features and geometrical and topological features.

3.4.1 Statistical Features

The statistical features are derived from the statistical points of distribution. They provide low complexity and high speed of variation to some extent, also used for reducing the feature set dimension. The following are the statistical features:

a) ***Zoning:*** The character frame is divided into several overlapping or non-overlapping zones. The densities of some features in different regions are analyzed utilizing zoning approach [28].
b) ***Crossings and Distances:*** The number of crossing of a contour by a line segment in a specified direction is the popular statistical feature. The frame containing the character is parceled into an arrangement of regions in different ways and afterward features of each region are extracted.

3.4.2 Global Transformation Features

These features are invariant to global deformations like rotations and translation. For the purpose of classification the continuous signal generally contains more data that need to be represented. By linear combination the signal is represented by series of simple well-characterized functions.

a) ***Zernike moments:*** The Zernike moments normalization aims to influence the recognizing procedure of an object in terms size of image translation and rotation independent. The Zernike moment with order n and repetition $r$of a continuous image function$f(x, y)$ is given as

$$Z_{nr} = \frac{n+1}{3.14} \sum_x \sum_y f(x, y)\, [v_{nr}(x, y)]^* \quad (12)$$

b) ***Hough Transform:*** The Hough transform procedure is utilized for baseline document detection. It is likewise applied to characterize the characters' parameter curves. The Hough transform is given by

$$H(a) = \sum_{i=1}^{L} h\,(x_i, y_i, a_{1,\ldots} a_n) \quad (13)$$

c) ***Fourier Descriptor***: For shape analysis the Fourier transformation is broadly utilized. The transformed coefficients are from the shape of the Fourier descriptors to represent the shape in frequency domain. The number of coefficients generated from the transform is vast, to capture the overall features of the shape the subsets of coefficient are enough. The boundary of particular shape has k pixel numbered from 0 to $k-1$. Along the contour, k^{th} pixel has (x_k, y_k)position. The shape of two parametric conditions with (x, y) coordinates as $s(k) = x(k) + i\,y(k)$. The discrete Fourier transform of $s(k)$ is

$$b(v) = \frac{1}{k} \sum_{0}^{k-1} s(k) e^{\frac{-j2\pi vk}{k}}; \; v = 0, 1, \ldots k-1 \quad (14)$$

d) ***Gabor Transform:*** The variation of the windowed Fourier transform is a Gabor transform. The window utilized as a part of this case is certifiably not a discrete size yet defined by a Gaussian function. In both spatial and frequency domains the transform possesses optimal localization properties. The 2D Gabor transform gives an extracted feature and it is represented by

$$G\,(\chi, \phi, \eta, \kappa) = \exp(\frac{x^2 + \chi\, 2\, y^2}{2\,\xi^2}). \cos(\frac{2\, x\pi}{\kappa} + \varphi) \quad (15)$$

where, $x = a \;\cos\; \theta - y \;\sin\; \theta$ by varying the parameters like χ, ϕ, η, κ the transform can be used better.

3.4.3 Geometrical and Topological Features

These features may represent the global and local character properties and have high resistances to distortions

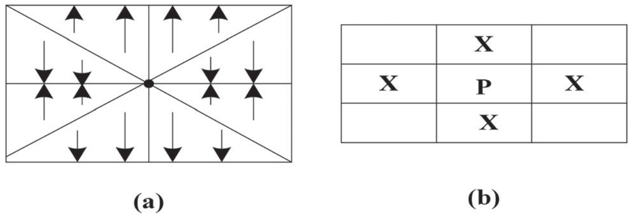

Figure 6: (a) Shadow features of character, (b) Contour point detection

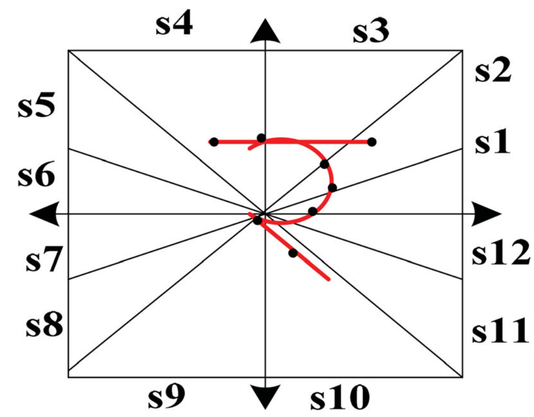

Figure 7: Shape of character using features

and style variations. Some information about the object contour is required to sort components of the object by these topological features.

a) ***Shadow Features:*** The shadow features are computed with rectangular boundary encasing the image of character is separated into eight octants; the character shadow segment is computed on two perpendicular sides in each octant, so a total of 24 features are obtained. Figure 6(a) demonstrates the shadow with projection on side length. On scaled image these features are processed.
b) ***Chain Code Histogram of Character Counter:*** For a scaled binary image the contour points of the character image are identified by considering a window (3×3) encompassed by object points as shown in Figure 6(b). Chain coding is utilized to represent the contour, each pixel is allocated as a various code that shows the following pixel direction. In this approach by utilizing the chain coding neighbor contour pixel associated with the the outline coding and points are captured.
c) ***Finding Junctions/Intersection in Character:*** The junction is suggested as intersection (location) where the chain code goes more direction in a 8-connected neighborhood. Thinned and scaled characters are divided into segments of pixel size. The number of open end points and junctions of each segment is calculated. For a character in different segment the intersection points are unique.
d) ***Extraction of distance and angle features:*** The number of '1' pixel present in k sector is n_k with $k = 1, 2, \ldots, 12$. The normalized vector distance (d_k) for each sector is the sum of distances of all pixel ('1') in a sector partitioned by the number of pixel present in that sector, where the coordinates of sector pixel are (x_i, y_i) and the coordinates of center of character image are (x_m, y_n). This d_k is taken as one set of features and the corresponding angles for each pixel for each sector are computed. Another arrangement of feature is taken as a normalized angle (a_k). Both d_k and a_k constitute 24 features from 12 sectors, as shown in Figure 7.
e) ***Extraction of occupancy and end points:*** The shape profile relies on d_k and a_k, these features were initially proposed with different features such as occupancy and end points of character used in the recognition system. For deciding occupancy only four sectors are utilized by tracing the character the end-points are demarcated. The point is proclaimed as endpoint if no '1' pixel is present otherwise '0'and the sector which is additionally noted as shown in Figure 7.
f) ***Transition feature:*** Another feature is a transition feature approach extracted from calculation and location, from the back ground to foreground pixels in vertical and horizontal directions. Based on gray level sub-images of single characters some extraction methods work, while others work on connected symbol segmented from binary raster image and skeleton symbols.
g) ***View-based features:*** For correct character recognition a human usually needs only partial information about it shape and contour. This feature extraction method views a set of points that plot in one of four projections of object (left, right, bottom and top) comprising pixel belonging to character contour and have extreme values of one of its coordinates. Thus, the characteristics vector is created from the acquired features to portray the given character, which is the base for facilitating optimization and classification.

3.5 SCA for Feature Selection

The SCA is the very best method of optimization in such problems. For developing a new optimization algorithm, SCA is utilized. SCA is based on the population optimization technique; with a set of random solutions it starts the optimization process. By an objective function this random set is evaluated repeatedly and improved by a set of rules that is kernel for optimization. The SCA algorithm looks for the optima of problem in optimization stochastically and there is no guarantee of finding a solution in a single run. In the field of stochastic optimization regardless of the difference between algorithms, the division has two phases: exploration and exploitation [29]. In the former phase, to find a promising region of search space with high rate of randomness the optimization algorithm combines the random solutions. However, in random solution there are gradual changes and random variation is considerably less than those phases. For error character minimization problems the fitness solution can be simply proportional to the objective function value.

Initialization is the first step of the feature extracted solutions of the OCR system. The position updating equation for both phases is proposed as follows.

$$Y_i^{t+1} = Y_i^t + R_1 \times \sin(R_2) \times |R_3 p_i^t - Y_i^t| \tag{16}$$

$$Y_i^{t+1} = Y_i^t + R_1 \times \cos(R_2) \times |R_3 p_i^t - Y_i^t| \tag{17}$$

where, the position of current solution is Y_i^t in $i - th$ dimension and iteration $t - th$, $R_1/R_2/R_3$ are random numbers, the position of destination point is p_t and || this represents the absolute value. The above two equations are combined as follows:

$$Y_i^{t+1} = \begin{cases} Y_i^t + R_1 \times \sin(R_2) \times |R_3 p_i^t - Y_i^t| & , R_4 < 0.5 \\ Y_i^t + R_1 \times \cos(R_2) \times |R_3 p_i^t - Y_i^t|, & R_4 \geq 0.5 \end{cases} \tag{18}$$

The four main parameters in SCA are $R_1, R_2, R_3,$ and R_4. The parameter (R_1) indicates the next regions in space between destination and solution. R_2 defines how far the movement should be towards or outwards the destination. R_3 denotes the random weight for destination and R_4 parameter equally switches between the sine and cosine components. Due to the formation of sine and cosine this algorithm is called SCA. For finding the promising regions of search space the algorithm balances the exploration and exploitation phase also it covers the global optimum level. The range of sine and cosine in Equation (16)-(18) is changed in order to balance the two phases using the following equation.

$$R_1 = A - T\frac{A}{t_{\max}} \tag{19}$$

Step 1: Initialize a set of search agents (solutions Y)
Step 2: Evaluate each of search agents by the objective function
Step 3: Update the following
The obtained best solution so far ()
the parameters ($R_1, R_2, R_3, and\, R_4$)
the search agents position using eq.(18)
while ($T < t_{\max}$)
Step 4: Return the obtained best solution so far as the global optimum

Figure 8: Steps for SCA Algorithm

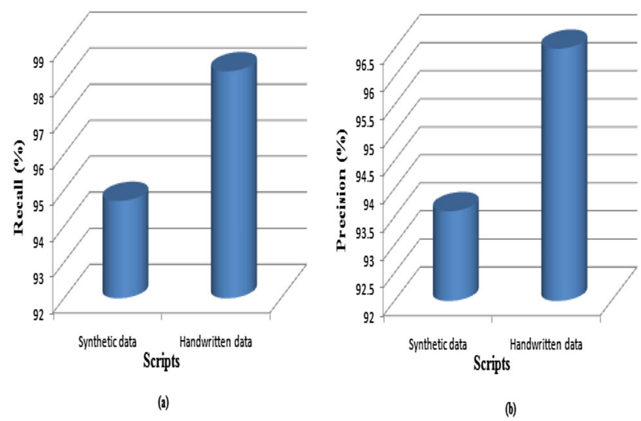

Figure 9: Analysis of (a) Recall (b) Precision using proposed method

where, the current iteration is T, $t_{\max}$ is the maximum number of iteration and the constant is A. The pseudo code of SCA algorithm is presented in Figure 8. Figure 8. Steps for SCA Algorithm

When the iteration counter is higher than $t_{\max}$ the SCA algorithm terminates the optimization process. With the above steps the proposed algorithm is theoretically able to determine the global optimum of problems in optimization due to following reasons:

- For a given problem SCA creates and improves the set of random solutions, so local optima avoidance is compared to other single solution-based algorithms.
- When sine and cosine functions return values (bet ween −1 and 1) different regions of search space are explored.
- Using adaptive range in the functions SCA smoothly transits from exploration to exploitation.

- The best global optimum is stored in variables as destination during optimization and updates their positions.

The next section employs recognition and classification which take the optimized output of the feature extraction techniques to their input and then determine which class it actually belongs to.

3.6 WOAR-SVM-Based Classification and Recognition

The WOAR-SVM is the most extensively used classifier for pattern recognition because of its many promising empirical performance and attractive features. In this paper, for the classification the WOAR-SVM classifier is implemented which takes the optimized output of the feature extraction techniques to their input and determine which class the character image actually belongs to. WOAR-SVM is a powerful supervised classifier based on the utilization of weight coefficients. The main goal of it is error minimization classification and maximization of margin discrimination.

In WOAR-SVM approach the $j-th$ binary prediction of SVM classifier is expressed in Equation (20) for a new observation y_t.

$$d_j(y_t) = \sum_{i=1}^{n} \beta_i y_i K(y_i, y_t) + b \tag{20}$$

Generally, the positive sign of $d_j(y_t)$ indicated that some data points y_t and the value $d_j(y_t)$ represent the certainty measure in that decision. The proposed WOAR-SVM classifier has two assumptions: 1) for test sample the validation set must have sufficient accurate representation, 2) for both training and testing samples the validation must be independent. So the performance of classifier will not verify and results would not be good indicators of the performance of classifiers. The linear coefficients χ_j are introduced for $d_j(y_t)$, the correlation between multiple binary classifiers is reflected in the final decision.

$$d_j(y_t) = \chi_j \sum_{i=1}^{n} \beta_i y_i K(y_i, y_t) + b \tag{21}$$

where, χ_j was a function of sign of $d_j(y_t)$ as shown in Equation (22)

$$\chi_j = \begin{cases} \chi_j^{-} for\ d_j(y_t) < 0 \\ \chi_j^{+} for\ d_j(y_t) > 0 \end{cases} \tag{22}$$

Values of χ_1^{+} scales measure the uncertainty $d_j(y_t)$ in a positive direction, whereas χ_1^{-} denotes the same for negative values of χ_1^{-}. The final decision $d(y_t)$was determined by Equation (23).

$$\begin{cases} d(y_t) = \arg\max_j^c [\chi_j \sum_{i=1}^{n} \beta_i y_i K(y_i, y_t) + b] \\ d(y_t) = \arg\max_j^c [d_j(y_t)] \end{cases} \tag{23}$$

$$\Lambda = \begin{bmatrix} \chi_1^{-} & \chi_2^{-} & \cdots & \chi_j^{-} & \cdots & \chi_c^{-} \\ \chi_1^{+} & \chi_2^{+} & \cdots & \chi_j^{+} & \cdots & \chi_c^{+} \end{bmatrix} \tag{24}$$

Collected weights which are used for the WOAR-SVM approach in matrix Λ as represented in Equation (24). The optimization of Λ is a part of model selection problem for WOAR-SVM approach. Using this way the proposed method is able to identify the texts. It is observed that this identification step helps in improving the OCR performance by getting clear text. This research also considers the handwritten text storage and processing.

4. RESULTS AND DISCUSSION

In this section, the results of the proposed WOAR-SVM classifier with SCA have been discussed with real-time dataset of handwritten and synthetic Marathi characters. From different people the handwritten documentation materials have been composed as proposed databases. Furthermore, from school, home, and office, the real-time datasets are gathered in this section. The evaluation results of the proposed WOAR-SVM classifier are in contrast with those of the current classification, segmentation and feature extraction strategies are portrayed. Additionally, the analysis of the proposed method is performed using the FAR (false acceptance rate), accuracy, precision, recall, F-measure and FRR (false rejection rate) metrics over the existing algorithms.

4.1 Dataset Description

In this research, a self-created database (handwritten and synthetic data) was utilized. Here, for testing and training processes 33 Marathi characters are utilized. All the data samples are divided into two parts after the preprocessing stage: for training purpose 56100 data samples are reserved while for testing purpose 9900 data samples are reserved. In the dataset, for the accuracy and the performance evaluation the training samples are utilized by WOAR-SVM classifier.

4.2 Evaluation Metrics

For the proposed WOAR-SVM classifier with SCA the performance validation metrics are considered for the

Table 1: Performance of evaluation metrics with the proposed method

		Script	
S. No	Metrics	Synthetic data	Handwritten data
1	Accuracy (%)	92.80	95.14
2	Precision (%)	93.6	96.5
3	Recall (%)	94.7	98.3
4	FAR (%)	91.24	95.04
5	FRR (%)	90.41	93.52
6	F-measure (%)	94.68	98.1

recognition of optical character in this section. The quantitative metrics used are accuracy, precision, recall, FAR, FRR and F-measure to evaluate the classification results, as shown in Table 1.

a) ***Analysis based on Recall and Precision:*** In each analysis the data samples consists of following classes true positive (T_p), true negative (T_n), false positive (F_p), false negative (F_n) (Figure 9). By these four classes the handwritten Marathi characters are correctly classified. Here, the positive label T_p is correctly identified by the classifier. The negative labels T_n(correctly rejected) were correctly labeled. The incorrectly classified, negative labels F_p and positive labels $F_n$were incorrectly labeled as negative by the classifier. In the following equations they are delineated,

$$\text{recall} \quad = \frac{T_p}{T_p + F_n} \tag{25}$$

$$\text{Precision} \quad = \frac{T_p}{T_p + F_p} \tag{26}$$

b) ***Analysis based on Accuracy and F-measure:*** The weighted mean of precision and recall is F-measure which is formulated in Equation (27).

$$\text{F - measure} = 2 \times \left[\frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \right] \tag{27}$$

The accuracy comprising of two parameters (FAR and FRR) is given by

$$\text{Accuracy} = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \tag{28}$$

Figure 10 shows the analysis of accuracy and F-measure using the proposed method. While comparing both synthetic and handwritten data the accuracy of the system is heavily dependent on the variation of the writing styles in training datasets. For training the accuracy of the system improves as we increase the test samples.

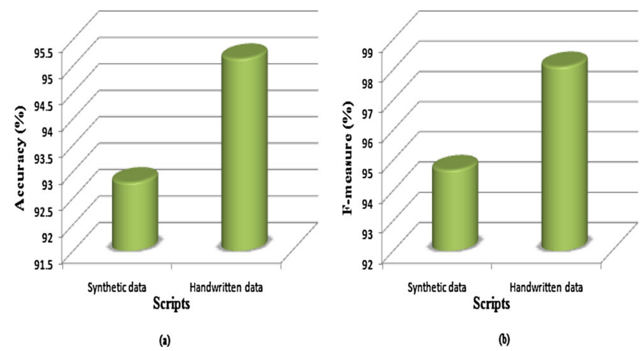

Figure 10: Analysis of (a) Accuracy (b) F-measure using the proposed method

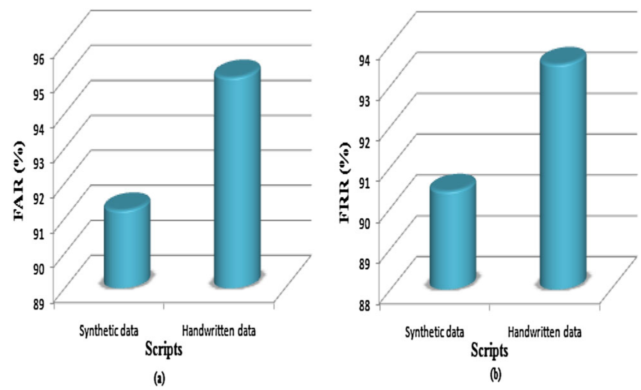

Figure 11: Analysis of (a) FAR (b) FRR using the proposed method

c) ***Analysis based on FAR and FRR:*** The total number of the indelicately identified recognition of characters is FAR. It is given by

$$\text{FAR} = F_p/(F_p + T_n) \tag{29}$$

The FRR is the total number identified the rejected characters recognition is given by

$$\text{FRR} = F_n/(F_n + T_p) \tag{30}$$

The analysis curve based on the FAR is shown in Figure 11(a). The analysis curve based on the FRR is shown in Figure 11(b). For the reliable recognition system the classifier is used normally and the rejection rate is reduced for the optimal performance. The false rejection analysis is based on the synthetic and handwritten data. While comparing both the handwritten data have 93.52% FRR and 95.04% FAR.

4.3 Performance Comparison

In this section, based on classification rate, classification time and error parameters the performance of proposed method is evaluated. Also the proposed method is compared with different classifiers such as K-NN

Table 2: Performance evaluation with different classifiers

S.No	Classifier	Classification rate (%)	Classification time (ms)
1	K-NN	88.6	98.04
2	SVM	73.3	43.59
3	WOAR-SVM (proposed)	94	42.15

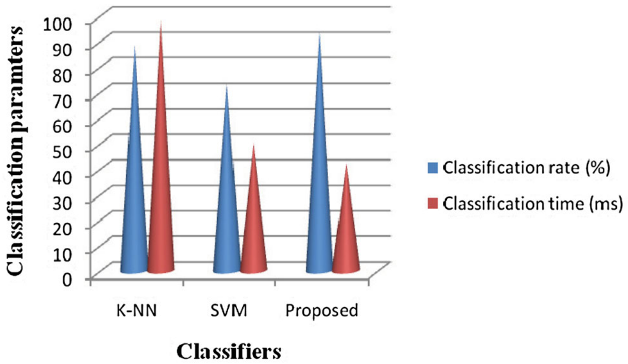

Figure 12: Evaluation of classification parameters using different classifiers

Table 3: Execution time comparison of the existing method with modified Pihu method

Image	Existing method [26]	Modified Pihu method
Size (pixels)	1169 353	1169 353
Execution time for segmentation (s)	4.76	2.72

(K-nearest neighbor), SVM (support vector machine) as shown in Table 2.

Figure 12 illustrates performance comparison of the proposed classifier with other classifiers. It can be seen that the proposed classifier has high classification rate of 94% for handwritten text identification. While comparing with other techniques the classification time is less in the proposed than in K-NN.

The comparative analysis of the segmentation using Modified Pihu method and existing method is shown in Table 3. Additionally the average execution time of the Modified Pihu method as compared with the existing method to segment the natural image was about 2.72s which was 55.16% lesser than existing methods [26]. Table 4 shows the performance of the proposed algorithm in terms of error rates and classification time.

Marathi character. The proposed approach accomplishes high accuracy, precision, recall, F-measure, FAR and FRR and further the error rates are less while comparing with existing techniques for accurately recognizing the substantial characters.

Table 4: Error comparison using the proposed method

S.No	Algorithm	Script	Error (%)	Classification time (ms)
1	Zheng *et al.* [30]	Synthetic data	6.2	85.37
		Handwritten data	6.8	
2	Lin *et al.* [31]	Synthetic data	2.5	52.16
		Handwritten data	7.9	
3	Proposed	Synthetic data	1.7	42.15
		Handwritten data	0.3	

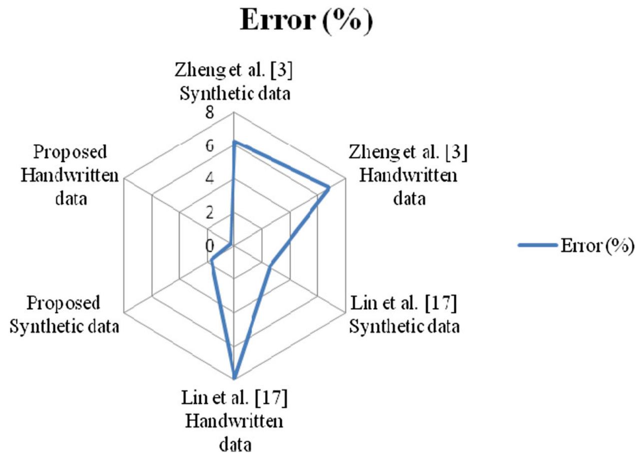

Figure 13: Comparison of error using different algorithm

Figure 13 illustrates the error comparison between the proposed method and the existing approaches. The proposed algorithm has less error rates in the range of 1.7% to 0.3% for Marathi script recognition than Devanagari script, *i.e.* these texts are classified more accurately. Due to small synthetic characters these errors are shown and are similar to some handwritten characters. Thus the proposed method has 42.15 and 0.3% faster than Zheng *et al.* [30] and Lin *et al.* [31], respectively, and highly accurate. Due to the presence of a large number of features Zheng *et al.* [30] consume more time than the proposed method.

5. CONCLUSION

This paper proposes a new SCA algorithm for identification of handwritten Marathi character using WOAR-SVM-based classification. The OCR system performance can be influenced by many factor varieties. The recognition system uses the Modified Pihu method for character segmentation process. From the segmented Marathi character various features are extracted and the accuracy of our proposed method is enhanced by utilizing these features. The SCA algorithm is used to select the best solutions, after the SCA process the optimized feature vectors are given to the input of the WOAR-SVM classifier to classify and recognize the best handwritten.

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