Research Article

International Journal of Advanced Technology and Engineering Exploration, Vol 10(108)
ISSN (Print): 2394-5443 ISSN (Online): 2394-7454
http://dx.doi.org/10.19101/IJATEE.2023.10101421

Handwritten character recognition using optimization based skewed line segmentation method and multi-class support vector machine

Keerthi Prasad Ganeshaiah[1*] and Vinay Hegde[2]
Research Scholar, Department of Artificial Intelligence and Machine Learning, GM Institute of Technology, Davangere, India[1]
Associate Professor, Department of Computer Science and Engineering, R V College of Engineering, Bengaluru, India[2]

Received: 20-September-2023; Revised: 16-November-2023; Accepted: 17-November-2023

Abstract
Handwritten character recognition (HCR) has become a growing research, owing to its several applications in processing the images, recognizing the patterns, communication technologies, etc. However, HCR is affected because of different styles of writers, or even if one writer has a different type of writing style according to the situation. Therefore, it is a tedious task to efficiently extract and recognize the digits or characters in the document/image. In that, HCR and classification is the toughest task in the field of pattern recognizing due to the various writing instruments and styles obtained from dissimilar widths, orientations, and sizes. In this work, multi-class support vector machine (MSVM) classifier is utilized for character identification. At first, the handwritten images are developed from real-time and Chars74k datasets, and then, pre-processing is executed for character image enhancement using Binarization. Moreover, the discrete lines are segmented by applying the modified whale optimization algorithm (MWOA)-based Otsu thresholding technique. The proposed MWOA-MSVM gained better evaluation outcomes at 99.2% accuracy, 98.43% precision, 98.99% recall and 97.54% F1-score in HCR when compared to the other techniques that were, hybrid feature-based long short-term memory (LSTM) and stacked sparse auto encoder.

Keywords
Handwritten character, Binarization, Adaptive threshold, Fitness function, MWO-OTSU, Steerable pyramid transform, Classifier.

1.Introduction
The rapid growth in use of camera devices has resulted in capturing of a huge amount of images every day on various occasions [1–3]. These images not only obtain visual information but also contain abundant documented material [4]. Nowadays, digitization and handwritten textual recognition play important role in information processing [5]. So extracted text information is the most informative source of information as well as provides a high resource of semantic information [6]. The semantic information helps in various applications like artificial character recognition in text and messages, the detection of cursive characters in natural language, multi-lingual character recognition, etc. [7, 8].

However, the computer visualization, pattern identification, and document analysis research fields continue to face a significant problem in accurately detecting and recognizing text in photographs of natural scenes [9, 10]. Even the traditional optical character recognition (OCR) techniques were not effective enough for recognizing text from scanned documents, even when the text is typically well-arranged and taken in a well-controlled setting [11, 12]. Segmentation performs an important role in textual image recognition as well as in delivering efficient information about the visual framework of the system [13].

On the paper-based information, a simple contextual and constant font style and size represent the presentation of contemporary lucrative OCR algorithms [14–17]. To increase the accuracy, a huge number of datasets are created to train deep learning algorithms, neural networks (NN) as well as the

*Author for correspondence

machine learning algorithm [18, 19]. Furthermore, the high performance of the OCR techniques depends on the detailed analysis of the pre-processing, segmentation, and feature extraction processes used for removing the irrelevant noise present in the natural image as well as extracting the aspects from the input document images [20]. Among them, segmentation plays an important role as it separates the image text into singular characters from lines, words and sentences [21–25]. The handwritten character recognition (HCR) faces problem due to the varying writing styles which creates complexity while recognizing the characters [26]. This problem is considered as the motivation for this research work, which is to help building an effective HCR module [27, 28]. Moreover, this research is mainly based on the feature selection and segmentation of the relevant aspects of the textual information [29].
The main contribution of this research is given as follows:

- In this research, natural character recognition is done using multi-class support vector machine (MSVM) classifier to classify the segmented aspects. In addition to this, high-dimensional data is handled and extracted features help to overcome imbalanced data problems.
- Whale optimization algorithm (WOA) with modified mutualism phase (MMP) modified whale optimization algorithm (MWOA) is used to evaluate every fitness function to get the global optimal solution as well as prevent the WOA low exploration problem of the function. Moreover, the character recognition's accuracy is increased.
- The performance of the proposed method is estimated by performance metrics of accuracy, sensitivity, specificity, precision, and F1-score.

This research work is arranged as follows: the existing work related to handwritten recognition in natural images is detailed in section 2. Explanation of the WOA segmentation with optimization is explained in section 3. The result and discussion of the existing and proposed work are illustrated in section 4. The overall discussion of the obtained results is described in section 5 and conclusion of this work is described in section 6.

2.Literature survey

In Kathigi and Honnamachanahalli [30] a hybrid features-based long short-term memory (LSTM) was created to enhance the efficiency of HCR in Kannada, Arabic, and English languages. This method mainly comprised three stages: extraction of features, character segmentation and categorization. The character segmentation was utilized for segmenting the characters from gathered image, the suggested approach reduced the problems regarding over-fitting, and the classification improved performance regarding to running time and recognition accuracy. According to the results the recognition accuracy was achieved significantly in Kannada, Arabic and English. However, the recognition of handwritten Kannada characters from the documents was a critical task in the suggested method.

Dey et al. [31] implemented a fixed-size sliding window and edit distance-based feature extraction methods for the character recognition. The implemented method appropriately derived and produced the required features from offline text images and numbers, by estimating the inclination of the near-vertical strokes by averaging the angles. The implemented method attained superior performance in many applications. However, the implemented method was unable to achieve a recognition accuracy that existing methods attained.

Arun and Arivazhagan [32] introduced zoning and histogram of gradients (HOG) method for character recognition. The introduced method created a specified handcrafted feature descriptor depending on the above mentioned two-feature extraction methods. The implemented method had considerable cost reduction. However, many misclassifications happened due to confusing characters with same architectures.

Ganeshaiah and Hegde [33] presented a hybrid feature extraction (HFE) with morlet stacked sparse auto-encoder (MSSAE) method for HCR. HCR was integration of various textual and shape features, i.e., HOG, grey-level co-occurrence matrix (GLCM), discrete wavelet transforms (DWT) and skeleton features (SF). The MSSAE method utilized a morlet wavelet activation function for improving dimensionality reduction capacity for efficient reduction. The presented method attained an enhanced reconstruction capacity and reduced sparsity. However, attaining high accuracy by utilizing a huge number of features was challenging.
Elaraby et al. [34] suggested a novel Siamese network for HCR that utilized a transfer learning and pre-trained AlexNet as feature extraction method in Siamese structure. The fine-tuning of pre-trained network was faster and the training of the Siamese structure was done with contrastive loss, instead binary cross-entropy. The suggested method attained

lesser training time. However, the fine-tuning of AlexNet in English and Kannada takes more time for training.

Siddanna et al. [35] developed a hybrid recurrent neural network (RNN) for HCR. The developed method trained efficiently through the dataset, and by developing NN. The last feedback of the image was acquired after the analysis was finished. The implemented method enhanced the data accuracy but, attaining high accuracy by utilizing a huge number of features was challenging.

Lee et al. [36] implemented an improved local binary pattern (LBP) with shallow deep convolution neural network (ILBPSNet) method for character recognition. The implemented method chose an edge with high intensity for minimizing influence of noise points, while letter features were calculated in local binary through scale detection of efficient edge. In network structure design, according to variations in input features, networks of various depths such as LBP and deep convolutional neural network (DCNN) were utilized for learning. The implemented method had a major effect on the application of real-time character recognition. However, the operation of convolution and spatial convolution were still a major problem.

Zanwar et al. [37] introduced an ensemble machine learning method for character recognition. The ensemble method integrated different elements of Naive Bayes propagation algorithm with back propagation and feed forward. The introduced method combined the two method such as hybrid firefly particle swarm optimization (HFPSO) for efficiency in search ability. The hybridization balanced the exploration and exploitation phases, leading to relevance outcomes with limited evaluation functions. Nonetheless, the introduced method had limited available software.

Ali and Mallaiah [38] presented a DCNN method utilizing squeeze and excitation (SE) blocks with ResNeXt (SE-ResNeXt) method for character recognition. The convolutional neural network (CNN) method extracted spatial features in lower layers, while the upper layer extracted the complex features. SE blocks were updated for improving DCNN performance through the fusion of channel wise and spatial data, and dependency of inter channel by SE within local related areas. The benefits of skip connection and batch normalization provided the fast-training capacity in large datasets. But the presented method had overfitting problem due to less training data.

Kavitha and Srimathi [39] suggested a CNN for HCR. The suggested method was trained with Tamil characters in offline mode and attained better recognition outcomes on training and testing datasets. The suggested method attained the less training time. However, attaining high accuracy by utilizing a huge number of features was challenging.

Khan et al. [40] developed a support vector machine (SVM) with CNN for character recognition. The CNN integrated with SVM utilized a dropout layer for efficient recognition of characters. The implemented method attained superior data security. However, attaining high accuracy by utilizing a huge number of features was challenging.

Sonthi et al. [41] developed an intelligent Telugu HCR system using multi-objective Mayfly optimization combined with a Dense Net deep learning model. They achieve this by combining multi-objective Mayfly optimization with a deep learning-based dense net model. This approach aims to enhance the accuracy of Telugu character recognition. The research focuses on the integration of advanced optimization techniques and deep learning to improve the recognition of Telugu handwritten characters.

Abdalla et al. [42] introduces a substantial dataset designed for the recognition of Kurdish handwritten digits and isolated characters. The research likely provides information about the creation, structure, and potential applications of this dataset, which can be valuable for training and testing systems related to Kurdish character recognition.

Dan and Li [43] have introduced particle swarm optimization (PSO)-based CNN for handwritten Chinese character recognition, discusses their work in improving the recognition of handwritten Chinese characters. They utilize a PSO approach to optimize a CNN. This optimization aims to enhance the network's ability to accurately recognize and classify handwritten Chinese characters.

Omayio et al. [44] have designed a system for recognizing handwritten Hindi scripts that performs both word spotting and character recognition. They achieve this by employing the integral histogram of oriented displacement (IHOD) descriptor.

Maray et al. [45] utilized a unique approach for recognizing Arabic handwritten characters by combining the Sailfish Optimizer with deep transfer learning techniques. The details of their methodology, including how the Sailfish Optimizer and transfer learning methods are applied, and it provides valuable insights into the realm of recognizing Arabic handwritten characters, offering potential advancements in this specific area of character recognition

Therefore, the HCR is seen to face problems due to the varying writing styles which create complexity while recognizing the characters. This problem is considered as the motivation for this research work, and helps in building an effective HCR module. Moreover, this research is mainly based on the feature selection and segmentation of relevant aspects of the textual information.

3.Methodology

In this study, a feature selection-based machine learning system is used to recognize handwritten characters in natural language images. In this methodology, the handwritten characters are collected from Chars74k and realtime datasets. Binarization of pre-processing step is carried out to improve the character recognition performance in natural images [46]. To separate the pertinent components of the textual information, a modified WOA optimization technique is used. MSVM classifiers are employed to categorize the character. The block diagram of the MWOA optimization method is shown in *Figure 1.*

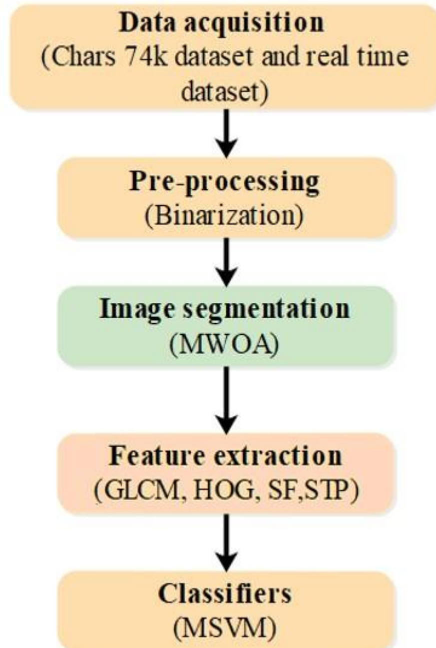

Figure 1 The block diagram of MWOA- MSVM image segmentation

3.1Dataset

In this manuscript, the discovered optimization MWOA model's performance is analyzed based on Chars74K and real time handwritten Kannada dataset.

3.1.1Real time datasets

In the real time datasets, there are 657 handwritten Kannada characters categorized into different classes. To assure a variety of writing styles and sizes of the handwritten characters, the dataset gathers data from various governmental organizations, high schools, a college of engineering and law, Open Universities, etc. The real-time handwritten Kannada dataset contains illustrative handwritten sample images which are presented in *Figure 2.*

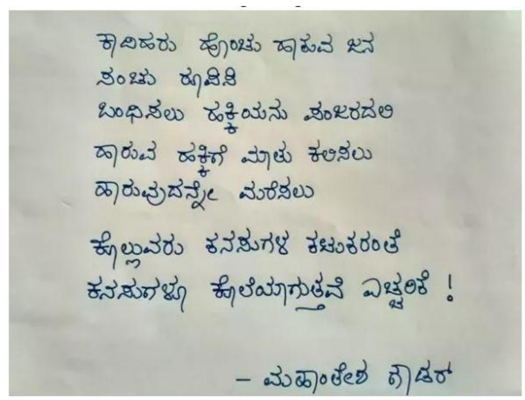

Figure 2 Original image of real time Kannada datasets

3.1.2Char74k datasets

The Char74k [47] dataset used in this experiment includes both the English and Kannada symbols for natural character recognition. The letters of the alphabet from A to Z and the numerals 0 to 9 are all divided into 64 classes in the English language. This method consists of 74,107 English characters, while 7,705 are actual photographs and 3,410 are images of handwritings. A graphical representation of the Chars74K dataset's sample images is shown in *Figure 3.*

Figure 3 Original image of char74k datasets

3.2Binarization pre-processing

During the pre-processing, the quality of the image is greatly improved which is essential for the development of computer vision algorithms. In this function, binarization is performed to convert the 0’s and 1’s of the original image in the system [48]. Moreover, it is the process of converting a document image into a bi-level document image. The binarization method turns grayscale photographs which have 256 different shades to grey binary images. To perform the binarization process, a threshold value for the grayscale photos needs to be denoised and contrast normalization for analysing has to be implemented. The original images of before and after binarization are given in *Figures 4* and *5*, respectively. The mathematical expression of binarization is showed in the Equations 1 and 2.

$$X'_{i,j,k} = s\frac{X_{i,j,k}-X^{-}}{max\left\{\in,\sqrt{\lambda+\frac{1}{3rc}\sum_{i=1}^{r}\sum_{j=1}^{c}\sum_{k=1}^{3}(X_{i,j,k}-X^{-})2}\right\}} \quad (1)$$

$$\sigma_T^2 = \sum_{i=0}^{L-1}(i-\mu T)^2 Pi, \quad (2)$$

Where, P represents probability,
I represents intensity of L number,
T represents the threshold,
$X'_{i,j,k}$ represents binarization output,
μ represents average weight,
L represents light intensity,
σ_T^2 represents the variance
s represents standard deviation

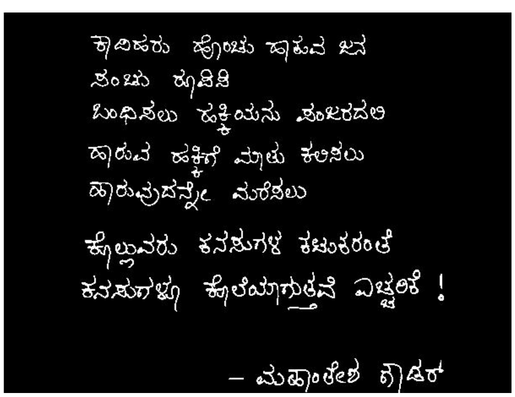

Figure 4 Original image of before Binarization

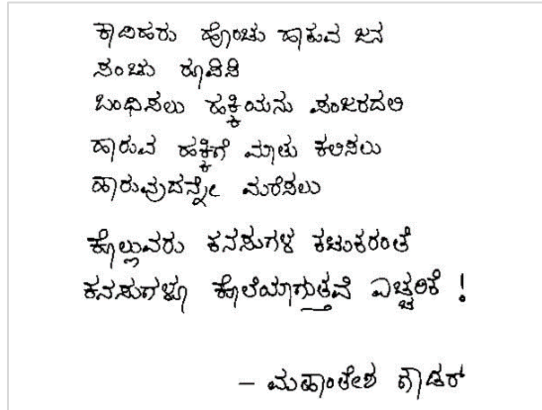

Figure 5 Image of the after Binarization

3.3Image segmentation

An image is segmented into its constituent parts such as its regions or its objects. Using multiple approaches like line, word, and character segmentation, input images are primarily broken down into singular lines, which are separated into words and later segmented into solitary characters. Contours are a useful tool for analysing an image's shape, as well as identifying its objects.

3.3.1Operational test support unit (OTSU)

The OTSU technique is a global adaptive binarization threshold image segmentation algorithm that chooses its threshold based on the interclass variance, which is found the most between the background and the target image. Because OTSU splits the image into foreground and background based on its greyscale characteristics, the difference between the foreground and background is the greatest when the best threshold is chosen [49]. The OTSU approach makes use of the highest inter-class variance, which is a widely used measurement standard as it is a crucial sign of the uniformity in the grey distribution.

The following is a description of the fundamental idea behind OTSU-based threshold segmentation:
If the range of the image's grey scale is I = 0, 1, and the number of pixels with grey scale k is nk, then the total number of pixels in the image is N as shown in Equation 3.

$$N = \sum_{K=0}^{L-1} nk = n0 + n1 + \ldots + nl - 1 \quad (3)$$

When Gray-level k occurs, there is a probability of Equation 4

$$p_k = \frac{n_L}{N} = \frac{n_k}{\sum_{K=0}^{L-1} n_k} \quad (4)$$

Where, p_k represents Probability of gray-level k occurrences,
N represents total number of pixels,
n_k represents number of pixels with grey scale k.

The OTSU is performed based on Equation 4 to select the number for thresholding and analysing the original image with the segmented image. Therefore, the WOA is proposed to segment the original natural image into the gray level image. The widely used TWOA-OTSU segmentation algorithm is unsupervised, adaptive, and parameter-free. But the conventional WOA algorithm uses an exhaustive search strategy which is computationally difficult and time-consuming.

The peak signal noise ratio (PSNR) and structural similarity index (SSIM) fitness functions are executed to segment the original handwritten image into the segmented image. It is the most typical and extensively used image evaluation index. The highest permissible pixel value divided by the mean square error (MSE) to calculate the PSNR is 10 times the ratio's logarithmic value. The image quality improves as the PSNR increases. PSNR measurements are made in decibels (DB) which are given in Equation 5.

$$PSNR = 10 \times lg \frac{225^2}{\frac{1}{MN}\sum_{x,y} v^2(x,y)} 10 \times lg \frac{225^2}{MSE} \quad (5)$$

Where, PSNR represents the peak signal noise ratio,
M represents number of rows in cover image,
N represents number of columns in cover image.
x represents width of image,
y represents height of image.

The predicted value of the square of the difference between the estimated value and the true value is typically described as MSE.

3.3.2Modified WOA optimization (MWOA)

This process after initializing the random population based on the WOA algorithm enables the textual information to have a balanced approach, and to thoroughly investigate the search space while preventing the overuse of computational resources. However, it has some noise and skewed presence information. Therefore, to overcome both the header and baseline section, adaptive thresholding algorithm is used for noise and skew reduction. Initially, the collected image undergoes binarization during the pre-processing for converting the grayscale image into binary based on OTSU thresholding algorithm [50]. Therefore, it will increase the contrast of the natural image for segmentation. The adaptive segmentation function MWOA is introduced to optimize the images. In addition, after initializing the new search process, the individual fitness is evaluated to identify the best global solution for the function. In this case, every iteration MMP is executed individually (P_i). Where, the P_i function divides into two random individuals as (P_m and P_n), along with the selecting interval of $i \neq m \neq n$.

The updating function of the minimum fitness function P_m among the two random individuals are given in Equations (6 to 9).

$$P_i^{K+1} = P_i^K + rnd(0,1) \times (P_m - MV \times BF^1) \quad (6)$$

$$P_n^{K+1} = P_n^K + rnd(0,1) \times (P_m - MV \times BF^2) \quad (7)$$

Otherwise,

$$P_i^{K+1} = P_i^K + rnd(0,1) \times (P_n - MV \times BF^1) \quad (8)$$

$$P_m^{K+1} = P_m^K + rnd(0,1) \times (P_n - MV \times BF^2) \quad (9)$$

Where, P_i represents i^{th} member of population,
P_j represents organism which is selected
Randomly to interact with P_i,
rnd represents random number,
MV represents mutual vector,
BF represents Benefit vector,
K represents generation,
P_{best} represents best individual

Where MV is counted as mean and $Mean\ (P_i, P_n)$ is classified as the first occasion while $Mean\ (P_i, P_m)$ is classified as the second occasion of the system.

Additionally, BF^1 and BF^2 are the benefit factors having either one or two generated values.

The following illustrates specific phases of the MWOA-OTSU picture segmentation algorithm:

1. The random whale population function is selected.
2. Initially, the random population calls every fitness value of each search agent in the network.
3. The best search agent among all the whale population value functions is found.
4. After the search agent, the MMP is executed to select two random search agents, and the fitness function of random is called individually.
5. Then the object evaluation is performed to verify the effectiveness of segmentation using the signal-to-noise ratio (SNR) and PSNR. Additionally, it will associate the evaluated image with the original natural image.
6. After the segmentation update, the position of the agent is updated using the position coordinate function, thereby the new fitness function value gets the maximum value of the system.
7. Then, the WOA is applied to prevent the low exploration problem, as well as the future accuracy of the natural image is improved.
8. The optimization process is repeated until it terminates at the criteria that satisfies the function.

Therefore, the individual whale fitness function is accepted, hence enabling the high diversity solution. In addition, the selection among two random populations based on the MMP along with the symbiotic organism search (SOS) algorithm improves the diversity of the solution. Then the updated global best solution is sent to the WOA method and therefore, WOA has the absence of exploration problems for selecting process. So, the diversity of the solution is increased, helping to reduce the chance of WOA being trapped in the local optima which also increases the convergence speed [45]. So, the MWOA is proposed to make new WOA techniques to find a better fitness function. The pseudocode of MWOA is as follows:

Step1: Initialize the whale
Step2: Calculate fitness of each search agent
$X\{best\}$ = the best search agent
Step3: while (t < maximum number of iterations)
    for each search agent:
        Update
    P_m *and* P_n if (P<0.5)
            Update current agent
    else:
            Select a random agent

            update current agent by eq (8)
    else:
        update search agent by eq (9)
    end-for
Check if any search agent goes beyond the search space and amend it

Calculate fitness of each search agent

Update $X\{best\}$ if there is a better solution

    $t = t + 1$
end-while
Step4: return $X\{best\}$

3.3.3Skew line segmentation

Skew line correction

To find the skew angle, a peak in the gradient orientation histogram of the input grey-level image is selected. By rotating at a particular an angle, the document's skewness is fixed. A similar method is used to identify the characters' slants, and a shear operation is used to rectify them. The skew correction algorithm is necessary for the proposed line segmentation. The suggested skew correction approach uses the image's pixel-level intensity information to produce a performance that is comparable to line segmentation. The fundamental goal of skew correction is to locate the white spaces between the lines instead of the text, and then move from the centre of the first space line to the centre of the following one until the end of the page is reached. Skew correction is considered in this procedure at the page level.

3.3.3.1Text line segmentation

Segmenting text lines from document images presents one of the biggest hurdles in document image analysis. Text block segmentation and text line segmentation give essential information [51] for the tasks of character and text string recognition. Images that are free of noise and skew are submitted to the system to be processed further. To create an image I'HXW with black text on a white backdrop, the input binarized picture is inverted. Next, image strength (I) is determined for the black text in the document. The image strength (P), which varies from image to image, defines the text image threshold as shown in Equation 10.

$$P = \sum_{y=1}^{W} I'(x,y)\ [1, H] \tag{10}$$

Where, P represents pixel strength.
W represents the pixel weight,
H represents the pixel height.
The rows with black pixels that exceed the document's standard deviation value are extracted. The original image of text line segmentation is given in *Figure 6.*

Figure 6 Original image of Text line segmentation

The group of rows that make up the text line are extracted as pixel (P), which is located between the footer and header as shown in the Equation 11.
For header: $Px_i: x_{i-1} < x_i > x_{i+1}$

For baseline: $P\ x_i': x_{i-1}' > x_i' < x_{i+1}'$ (11)

Where, P represents pixel strength.

3.3.3.2Ligature/word segmentation

In ligature segmentation, text lines are divided into words using the vertical profile approach, and text lines are divided into words using the projection profile method. Handwritten or printed text pages in Kannada chars74 are inserted as inputs during pre-processing. The page is first divided into numerous text lines, and then the text lines are put through a word/ligature segmentation algorithm, which separates lines into the smallest ligatures possible. Ligatures are automatically put in order, as words are segmented sequentially by the algorithm. The image of the word segmentation is given in *Figure 7.*

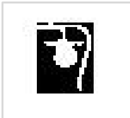

Figure 7 Image of the word segmentation

3.4Feature extraction in image

Feature extraction is a form of dimensionality reduction when a large number of pixels in the image are effectively allowed for the effective capture of interesting areas. In this work, feature extraction is classified into GLCM, HOG, SF, and steerable pyramid transform (SPT) which are mentioned below.

3.4.1GLCM

The GLCM has a row and column count that is equal to the entire number of grey image levels. The correlation between multiple pixels in the same moment, referred to as the reference and two neighbouring pixels, are what are referred to as the GLCM texture. This texture includes properties of correlation, energy, and contrast. When analysing images, the texture is determined by groups of intensities that are detected and statistically estimated at certain points that are connected within the image. There are many ways to achieve dimension reduction which is the process of breaking down a set of data with enormous dimensions to smaller data with more useful and clear information.

3.4.2Histogram of gradient

There are HOG features used in the HOG technique to classify images and identify objects.

Step 1- Divide the image into neighbouring cells, then calculate the gradient in each cell using the pixel's relative magnitude.

Step 2- The gradient is used to construct distinct cells as histogram bins.

Step 3- Every pixel provides a bin to the gradient.

Step 4- Make a collection of cells that are 16 by 16 pixels in size.

Step 5- Blocks that normalize the group are necessary features.

The gradient of HOG features is the immediate image area to determine an image in a window or region of interest (ROI). This illustration in the HOG property in Kannada, composite cells for 5050 characters of 33 pictures. The 900 feature vectors and 9-bin quantized gradient directions are provided by the computed feature vector.

3.4.3Skeleton features

SF points are acquired from a skin region and are a prerequisite for tracking human gestures. A new large-scale hand sign language dataset called real-time dataset which includes Kannada words of state-of-the-art models' SF is showcased. Skeletal features are represented in the model for feeding to three surfaces and provide more detailed features. The SF are represented differently from hand key points by employing estimated key points and the midpoint algorithm.

3.4.4SPT for image

A helpful front-end for image-processing and computer vision applications is the SPT, which is a linear multi-scale, multi-orientation picture decomposition. SPT is a multi-scale wavelet transform that is recursive, and features derivative operations in many directions with varying size requirements. The filters' orientation must adhere to the following requirements in SPT.

- Filter is rotated to create another filter design where all filters are copied in rotating counterparts.
- A filter with coordination is created on the basis of filter’s combination.

3.5Classifiers

Multi class support vector machine (MSVM)

MSVM [52] demonstrates the effectiveness and provides highly accurate classification when compared to existing methods for many classifications such as decision tree (DT), NN, K-nearest neighbor (KNN) and random forest (RF), by supporting binary classification and separating data points into classes. The latest phase of the proposed MSVM approach is the classification process which determines the recognition output of the given Kannada handwritten images with the dynamic process instability using multi-class classification. MSVM classifiers using various extracted features outperform KNN and NN classifiers. For optimization of SVM, the kernel parameter setting is utilized to tune the parameters for enhancing the accuracy of classification. The classification model is trained using the feature vectors from the previous phase that are produced from the self-constructed dataset. The HOG descriptors are utilized in MSVM for the classification in the approach based on the recognition of handwritten Kannada and English numerals. 4000 isolated handwritten Kannada and English numerical images are utilized in experiments which use the template matching technique to compare portions of input character images with training character images. *Table 1* represents the parameter setting of various classifiers.

Table 1 Parameter setting of various classifiers

Methods	Parameter	Range	Selected value
RF	Criterion of trees	(Gini and Entropy)	Gini
	Max Depth	(1,10)	5
	Max Features	(5,50)	10
DT	Criterion	(Gini and Entropy)	Gini
	No. of trees	(10,100)	10
K-nearest neighbor (K-NN)	K-neighbours	(100,2000)	500
NN	No. of layers	(2,8)	2
	No. of iterations	(100,500)	100
SVM	Gamma	(0.1,1)	0.1
	C	(0.1,5.0)	1.0
	Kernal		RBF

4.Results

The proposed method is tested using two different datasets namely, real time datasets and Chars 74 K datasets generated above. The dataset is guaranteed to include photos in formats of grayscale, jpg, and png that are potentially all well-known. The proposed method is analysed with MATLAB R2020B, with a RAM of 16GB, Intel core i7 processor and Windows 10 operating System. The output images are utilized to construct the results. The suggested WOA-OTSU depends on the correctness of the accuracy, and it performs best with skew-free images. true positive (TN), true negative (TN), false positive (FP), and false negative (FN) values are among the fundamental parameters computed. The chars74K dataset is created and labelled manually as a component of framework. The total amount of characters in labelled ligature images is counted and contrasted with the performance metrics of accuracy, precision and sensitivity as given below.

Accuracy

The accuracy is defined as the sum of TP and TN to the total number of values.

The equation for accuracy is shown in Equation 12

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (12)$$

Precision

In terms of positive observations, precision is the proportion of accurately anticipated observations to all predicted positive observations.

The equation for precision is shown in Equation 13.

$$Precision = \frac{TP}{TP+FP} \times 100 \quad (13)$$

Sensitivity

It refers to the probability of a positive test, conditioned on truly being positive of the function.

The equation for sensitivity is shown in Equation 14.

$$sensitivity = \frac{TP}{TP+FN} \quad (14)$$

Specificity

It refers to the probability of a negative test, conditioned on truly being negative of the function.

The equation for specificity is shown in Equation 15.

$$Specificity = \frac{TN}{TN+FP} \quad (15)$$

F1-Score

The weighted average of Precision and Recall is the F1 Score. Therefore, both FP and FN are considered while calculating this score.

The equation for F1-score is shown in Equation 16.

$$F1 - Score = \frac{2TP}{2TP+FP+FN} \times 100 \quad (16)$$

4.1 Real-time dataset in Kannada image segmentation

In the Real time data sets of the system, a piece of data is immediately available after it is created or acquired by the recognition function. Data is sent to users immediately after it is collected and is instantly accessible without any lag, which is essential for supporting real-time, on-the-spot decision-making. On online datasets like real-time datasets, the proposed WOA-OTSU model for character recognition is studied. The real-time dataset is a handwritten Kannada dataset. The examples of the real-time dataset's handwritten Kannada characters are shown in the *Figures 8* and *9*.

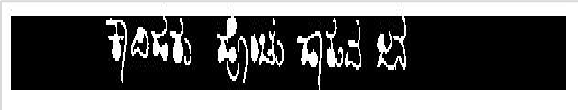

Figure 8 Image of the Kannada Characters

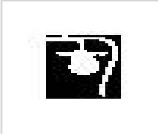

Figure 9 After segmentation image of the Kannada character

4.2 Chars74 dataset in English character

On online datasets like the chars74k datasets, the proposed WOA-OTSU'S model for character recognition is studied. The chars74k dataset is a collection of 60,000 training and 10,000 testing handwritten graphics in English that are created by 700 different writers. The numbers from 0 to 9 are typed by every person ten times. English characters are divided into 64 classes, including digits, lowercase letters, and uppercase letters (0–9, a-z, and A-Z). The English characters in the real-time dataset are represented by 3410 images, 62,992 artificial descriptions, and 7705 real photos. The English sample typescripts from the chars74k dataset are shown in the *Figures 10* and *11*.

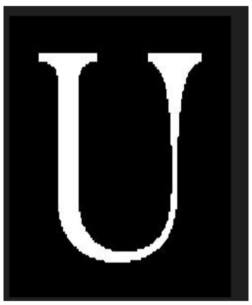

Figure 10 Image of the English character

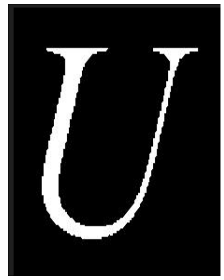

Figure 11 After segmentation image of the English character

The comparison of the real-time dataset of various classifiers is shown in *Table 2*. The existing methods taken for evaluating the performance of proposed method are KNN, NN, DT, and RF. The comparison of the image segmentation of the proposed model with various classifiers are shown in *Table 3*. The proposed method attains a high accuracy of 98.23%, which is comparatively higher than other existing methods such as KNN, NN, DT and RF. The comparison of the English chars74k dataset on various classifiers is tabulated in *Table 4.* The comparison of the Kannada chars74k dataset of various classifiers is shown in *Table 5.* The comparison of training time and error rate of various classifiers is shown in *Table 6.* The comparison of the various features utilized in research is shown in *Table 7.*

Table 2 Comparison of the real time datasets with different classifiers

Classifiers	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1_score (%)
K-NN	90.40	90.29	89.13	90.34	90.31
NN	89.54	89.23	88.71	88.56	88.89
DT	94.26	94.98	93.89	95.90	95.44
RF	96.54	97.40	96.05	97.89	97.64
MSVM	98.32	98.20	98.60	99.02	98.61

Table 3 Segmentation comparison of the proposed model

Classifiers	PSNR (%)	SSIM	Accuracy (%)	Sensitivity (%)	Specificity (%)
PSO	43.78	0.94	90.32	89.35	91.02
Grey wolf optimizer (GWO)	45.09	0.90	94.43	93.21	93.16
WOA	47.21	0.89	95.72	96.34	94.89
Proposed	56.78	0.97	98.32	98.32	98.60

Table 4 Comparison of the English chars74k dataset

Classifiers	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1_score (%)
KNN	89.20	88.56	87.05	89.19	88.88
NN	90.40	90.53	89.88	91.25	90.89
DT	88.10	88.27	88.02	89.15	88.71
RF	94.26	94.98	93.89	94.70	92.78
MSVM	99.20	98.99	99.01	98.43	97.54

Table 5 Comparison of the Kannada Char74k dataset

Classifiers	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1_score (%)
KNN	88.12	87.34	86.02	87.11	88.87
NN	87.14	89.53	86.88	88.45	90.84
DT	85.11	84.28	87.02	86.94	88.70
RF	92.28	91.96	93.90	92.10	92.58
MSVM	97.53	96.28	98.08	97.28	97.54

Table 6 Comparison of training time and error rate of various classifiers

Classifiers	Training time (sec)	Error rate (%)
KNN	7,950	13.73
NN	7,456	12.89
DT	6,834	12.35
RF	6,267	11.22
MSVM	4,203	7.77

Table 7 Comparison of combinations used in feature extraction methods

Features extraction methods	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1 Score (%)
GLCM	83.67	82.56	82.37	81.92	82.56
HOG	83.75	82.67	82.24	81.49	82.03
SF	84.03	83.15	81.94	80.76	81.49
SPT	84.28	83.48	81.72	80.38	81.14
GLCM+HOG	86.53	84.98	83.34	84.23	83.45
SF+SPT	86.01	84.81	83.45	85.65	85.56
HOG+SPT	85.92	84.22	84.56	85.20	86.87
GLCM+HOG+SF	87.99	86.12	86.88	86.98	87.90
HOG+SPT+GLCM	88.54	87.23	87.99	87.45	87.67
GLCM+HOG+SF+SPT	89.98	88.73	89.43	89.12	88.24

The comparison of proposed and existing classifiers in terms of various parameters is shown in *Table 8*. The proposed method is compared with other existing methods such as HFE with MSSAE [33], Siamese Network [34] and hybrid convolutional neural network – recurrent neural network (CNN-RNN) [35] in Chars74k dataset. The introduced model attained the highest accuracy of 99.20% when compared to the existing methods.

Table 8 Comparative table

Methods	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
HFE-MSSAE [33]	Chars74k	96.73	95.18	97.30	94.08
Siamese Network [34]	(Kannada	85.6	98.5	79.3	N/A
Hybrid CNN-RNN [35]	characters)	84.69	N/A	N/A	N/A
Proposed		99.20	98.43	98.99	97.54

N/A*-Not Available

5.Discussion

From the overall analysis, the performances of proposed method are compared with different existing methods such as HFE-MSSAE [33], Siamese Network [34] and Hybrid CNN-RNN [35] in terms of accuracy, sensitivity, specificity, precision, and F1-score. The existing methods have limitations such as: HFE-MSSAE method [33] attaining high accuracy by utilizing a huge number of features is challenging, Siamese Network method [34] the fine-tuning of AlexNet in English and Kannada takes more time for training, Hybrid CNN-RNN method [35] attaining high accuracy by utilizing a huge number of features is challenging. To overcome these limitations, the MWO-OTSU method is proposed in this research for recognizing the handwritten characteristics. Initially, the results are evaluated for MSVM classifier to compute the effectiveness while classifying the handwritten images. The obtained results at the time of classification show that MSVM achieved better classification accuracy of 98.32%, and the segmentation efficiency of proposed MWO-OTSU is evaluated with some existing optimization techniques. The results from the process of segmentation shows that the proposed approach achieved better segmentation accuracy of 56.78% which is relatively higher than the existing techniques. Moreover, the performance of the MSVM classifier is evaluated for two datasets such as English Chars 74k dataset and Kannada Chars 74k dataset. The comparative results show that the proposed approach achieves a classification accuracy of 98.43%, which is comparatively higher than the existing classifiers such as LSTM (93.3%), multi-level feature fusion (MLFF) (91.0%) and sequential minimal optimization (SMO) (91.0%). The overall results hence show the efficiency of the proposed method for overall metrics, and help in better recognition of handwritten characters.

5.1Limitations

The suggested hand recognition framework is incapable to recognize the presence of joint letters. Moreover, the accuracy of the proposed approach was diminished while recognizing joint letters. When there is sounder in the data set (i.e.) when the target classes overlap, the proposed method does not perform as well. Even if a kernel method is employed, the suggested classification will be difficult because of the high computational difficulties and previously mentioned reasons. This is because the computations involved will require a significant amount of processing time. The datasets themselves will take a long time to train as a result. Also, the proposed method will perform worse if there are more attributes for each data point than there are training data specimens.

A complete list of abbreviations is shown in *Appendix I.*

6.Conclusion

The HCR of Kannada, English and Arabic through OCR is a tedious task in the pattern identification field. In this paper, deep and machine learning-based new techniques are developed for the identification and detection of unnatural handwritten characters in natural images. This work mainly focuses on the segmentation of the individual features of the system. Moreover, the relevant data are accumulated based on real time and Chars 74k digital datasets, while pre-processing is done using image enhancement with binarization techniques. In addition, segmentation is applied to effectively segment the singular characters such as line, word, and character using optimization based skew line techniques of the modified MWOA algorithm. In addition, the features are extracted effectively in the textual images using HOG, and GLCM techniques, and finally classification is performed using MSVM classifiers. Specifically, the MWOA-MSVM outperforms the existing character recognition techniques, and the final accuracy of the introduced method is 98.60% which is high when compared to the WOA. In the future, a network can be developed using deep transfer learning techniques with numerous datasets.

Acknowledgment

None.

Conflicts of interest

The authors have no conflicts of interest to declare.

Author’s contribution statement

Keerthi Prasad Ganeshaiah: Conceptualization, methodology, background work, dataset collection, implementation, result analysis and comparison, preparing and editing draft and visualization. **Vinay Hegde**: Supervision, background work, dataset collection, review of the work, project administration, and editing draft.

References

[1] Tong G, Dong M, Sun X, Song Y. Natural scene text detection and recognition based on saturation-incorporated multi-channel MSER. Knowledge-Based Systems. 2022; 250:109040.

[2] Moudgil A, Singh S, Gautam V, Rani S, Shah SH. Handwritten Devanagari manuscript characters recognition using capsnet. International Journal of Cognitive Computing in Engineering. 2023; 4:47-54.

[3] Alwaqfi YM, Mohamad M, Al-taani AT. Generative adversarial network for an improved Arabic handwritten characters recognition. International Journal of Advances in Soft Computing & Its Applications. 2022; 14(1):1776-95.

[4] Anggraeny FT, Via YV, Mumpuni R. Image preprocessing analysis in handwritten Javanese character recognition. Bulletin of Electrical Engineering and Informatics. 2023; 12(2):860-7.

[5] Chen X, Jin G. Preschool education interactive system based on smart sensor image recognition. Wireless Communications and Mobile Computing. 2022; 2022:1-11.

[6] Ahsan S, Shah TN, Sarwar TB, Miah MS, Bhowmik A. A machine learning approach for Bengali handwritten vowel character recognition. IAES International Journal of Artificial Intelligence. 2022; 11(3):1143-52.

[7] Naiemi F, Ghods V, Khalesi H. Scene text detection and recognition: a survey. Multimedia Tools and Applications. 2022; 81(14):20255-90.

[8] Rahman MM, Akhand MA, Islam S, Shill PC, Rahman MH. Bangla handwritten character recognition using convolutional neural network.

International Journal of Image, Graphics and Signal Processing. 2015; 7(8):42-9.
[9] Das M, Panda M, Dash S. Enhancing the power of CNN using data augmentation techniques for Odia handwritten character recognition. Advances in Multimedia. 2022; 2022:1-13.
[10] Guo Z, Zhou Z, Liu B, Li L, Jiao Q, Huang C, et al. An improved neural network model based on inception-v3 for oracle bone inscription character recognition. Scientific Programming. 2022; 2022:1-8.
[11] Dan Y, Zhu Z, Jin W, Li Z. PF-ViT: parallel and fast vision transformer for offline handwritten Chinese character recognition. Computational Intelligence and Neuroscience. 2022; 2022:1-11.
[12] Motamedisedeh O, Zagia F, Alaei A. A new optimization approach to improve an ensemble learning model: application to Persian/Arabic handwritten character recognition. In international conference on document analysis and recognition 2023 (pp. 180-94). Cham: Springer Nature Switzerland.
[13] Saqib N, Haque KF, Yanambaka VP, Abdelgawad A. Convolutional-neural-network-based handwritten character recognition: an approach with massive multisource data. Algorithms. 2022; 15(4):1-25.
[14] Sahay R, Coustaty M. An enhanced prototypical network architecture for few-shot handwritten Urdu character recognition. IEEE Access. 2023; 11:33682-96.
[15] Tan YF, Connie T, Goh MK, Teoh AB. A pipeline approach to context-aware handwritten text recognition. Applied Sciences. 2022; 12(4):1-17.
[16] Hu M, Qu X, Huang J, Wu X. An end-to-end classifier based on CNN for in-air handwritten-Chinese-character recognition. Applied Sciences. 2022; 12(14):1-12.
[17] Albattah W, Albahli S. Intelligent Arabic handwriting recognition using different standalone and hybrid CNN architectures. Applied Sciences. 2022; 12(19):1-23.
[18] Zhang Y, Li Z, Yang Z, Yuan B, Liu X. Air-GR: an over-the-air handwritten character recognition system based on coordinate correction YOLOv5 algorithm and LGR-CNN. Sensors. 2023; 23(3):1-23.
[19] Geng S, Zhu Z, Wang Z, Dan Y, Li H. LW-ViT: the lightweight vision transformer model applied in offline handwritten Chinese character recognition. Electronics. 2023; 12(7):1-10.
[20] Li Y, Yang Q, Chen Q, Hu B, Wang X, Ding Y, et al. Fast and robust online handwritten Chinese character recognition with deep spatial & contextual information fusion network. IEEE Transactions on Multimedia. 2022: 2140-52.
[21] Chandure S, Inamdar V. Handwritten MODI character recognition using transfer learning with discriminant feature analysis. IETE Journal of Research. 2023; 69(5):2584-94.
[22] Rasheed A, Ali N, Zafar B, Shabbir A, Sajid M, Mahmood MT. Handwritten Urdu characters and digits recognition using transfer learning and augmentation with AlexNet. IEEE Access. 2022; 10:102629-45.
[23] Islam MS, Rahman MM, Rahman MH, Rivolta MW, Aktaruzzaman M. RATNet: a deep learning model for Bengali handwritten characters recognition. Multimedia Tools and Applications. 2022; 81(8):10631-51.
[24] Ahmed G, Alyas T, Iqbal MW, Ashraf MU, Alghamdi AM, Bahaddad AA, et al. Recognition of Urdu handwritten alphabet using convolutional neural network (CNN). Computers, Materials & Continua. 2022; 73(2):2967-84.
[25] Rani NS, BR P. Robust recognition technique for handwritten Kannada character recognition using capsule networks. International Journal of Electrical & Computer Engineering (2088-8708). 2022; 12(1):383-91.
[26] Ramteke SP, Gurjar AA, Deshmukh DS. A novel weighted SVM classifier based on SCA for handwritten Marathi character recognition. IETE Journal of Research. 2022; 68(2):845-57.
[27] Pughazendi N, Harikrishnan M, Khilar R, Sharmila L. Optical handwritten character recognition for Tamil language using CNN-VGG-16 model with RF classifier. Optical and Quantum Electronics. 2023; 55(11):976.
[28] Prashanth DS, Mehta RV, Ramana K, Bhaskar V. Handwritten Devanagari character recognition using modified Lenet and Alexnet convolution neural networks. Wireless Personal Communications. 2022; 122(1):349-78.
[29] Elkhayati M, Elkettani Y. UnCNN: a new directed CNN model for isolated Arabic handwritten characters recognition. Arabian Journal for Science and Engineering. 2022; 47(8):10667-88.
[30] Kathigi A, Honnamachanahalli KK. Handwritten character recognition using skewed line segmentation method and long short term memory network. International Journal of System Assurance Engineering and Management. 2022; 13(4):1733-45.
[31] Dey R, Balabantaray RC, Mohanty S. Sliding window based off-line handwritten text recognition using edit distance. Multimedia Tools and Applications. 2022; 81(16):22761-88.
[32] Arun M, Arivazhagan S. A unified feature descriptor for generic character recognition based on zoning and histogram of gradients. Neural Computing and Applications. 2022; 34(14):12223-34.
[33] Ganeshaiah KP, Hegde V. Handwritten character recognition using morlet stacked sparse auto encoder based feature dimension reduction. International Journal of Intelligent Engineering & Systems. 2023; 16(2):454-63.
[34] Elaraby N, Barakat S, Rezk A. A novel Siamese network for few/zero-shot handwritten character recognition tasks. Computers, Materials & Continua. 2023; 74(1):1837-54.
[35] Siddanna SR, Kumar A, Dubey A, Govind B, Dixit D. Kannada handwritten character recognition using hybrid RNN. International Journal of Progressive

Research in Engineering Management and Science. 2022; 2(7):5-9.
[36] Lee SH, Yu WF, Yang CS. ILBPSDNet: based on improved local binary pattern shallow deep convolutional neural network for character recognition. IET Image Processing. 2022; 16(3):669-80.
[37] Zanwar SR, Bhosale YH, Bhuyar DL, Ahmed Z, Shinde UB, Narote SP. English handwritten character recognition based on ensembled machine learning. Journal of the Institution of Engineers (India): Series B. 2023:1-5.
[38] Ali AA, Mallaiah S. Intelligent handwritten recognition using hybrid CNN architectures based-SVM classifier with dropout. Journal of King Saud University-Computer and Information Sciences. 2022; 34(6):3294-300.
[39] Kavitha BR, Srimathi CB. Benchmarking on offline handwritten Tamil character recognition using convolutional neural networks. Journal of King Saud University-Computer and Information Sciences. 2022; 34(4):1183-90.
[40] Khan MM, Uddin MS, Parvez MZ, Nahar L. A squeeze and excitation ResNeXt-based deep learning model for Bangla handwritten compound character recognition. Journal of King Saud University-Computer and Information Sciences. 2022; 34(6):3356-64.
[41] Sonthi VK, N K. An intelligent Telugu handwritten character recognition using multi-objective mayfly optimization with deep learning–based DenseNet model. ACM Transactions on Asian and Low-Resource Language Information Processing. 2023; 22(3):1-16.
[42] Abdalla PA, Qadir AM, Shakor MY, Saeed AM, Jabar AT, Salam AA, et al. A vast dataset for Kurdish handwritten digits and isolated characters recognition. Data in Brief. 2023; 47:1-13.
[43] Dan Y, Li Z. Particle swarm optimization-based convolutional neural network for handwritten Chinese character recognition. Journal of Advanced Computational Intelligence and Intelligent Informatics. 2023; 27(2):165-72.
[44] Omayio EO, Indu S, Panda J. Word spotting and character recognition of handwritten Hindi scripts by integral histogram of oriented displacement (IHOD) descriptor. Multimedia Tools and Applications. 2023:1-28.
[45] Maray M, Al-onazi BB, Alzahrani JS, Alshahrani SM, Alotaibi N, Alazwari S, et al. Sailfish optimizer with deep transfer learning-enabled arabic handwriting character recognition. Computers, Materials & Continua. 2023; 74(3):5467-82.
[46] Alheraki M, Al-matham R, Al-khalifa H. Handwritten Arabic character recognition for children writing using convolutional neural network and stroke identification. Human-Centric Intelligent Systems. 2023:1-13.
[47] https://www.kaggle.com/datasets/supreethrao/chars74kdigitalenglishfont?select=EnglishFnt.tgz . Accessed 20 October 2023.
[48] Jadhav S, Inamdar V. Convolutional neural network and histogram of oriented gradient based invariant handwritten MODI character recognition. Pattern Recognition and Image Analysis. 2022; 32(2):402-18.
[49] Alemayoh TT, Shintani M, Lee JH, Okamoto S. Deep-learning-based character recognition from handwriting motion data captured using IMU and force sensors. Sensors. 2022; 22(20):1-15.
[50] Alwagdani MS, Jaha ES. Deep learning-based child handwritten Arabic character recognition and handwriting discrimination. Sensors. 2023; 23(15):1-21.
[51] Gader TB, Echi AK. Attention-based deep learning model for Arabic handwritten text recognition. Machine Graphics and Vision. 2022; 31(1/4):49-73.
[52] Niharmine L, Outtaj B, Azouaoui A. Tifinagh handwritten character recognition using optimized convolutional neural network. International Journal of Electrical & Computer Engineering (2088-8708). 2022; 12(4):4164-71.

Keerthi Prasad Ganeshaiah is currently pursuing his Ph.D. at RVCE, Bengaluru, under VTU Belagavi. His research focuses on "Natural Language Processing." Additionally, he serves as an Assistant Professor in the IS&E Department at GMIT, Davanagere.
Email: logon2keerthi@gmail.com

Vinay Hegde is working as Associate Professor in CS&E Dept. RVCE, Bengaluru. His area of interest includes Natural Language Processing, Word sense Disambiguation, Language Analyzer and Cognitive Aspects of NLP. He has published 10+ papers in International Journals and 20+ papers in International Conferences.
Email: vinayvhegde@rvce.edu.in

Appendix I

S. No.	Abbreviation	Description
1	CNN-RNN	Convolutional Neural Network – Recurrent Neural Network
2	DB	Decibels
3	DCNN	Deep Convolutional Neural Network
4	DT	Decision Tree
5	DWT	Discrete Wavelet Transforms
6	FN	False Negative
7	FP	False positive
8	GLCM	Grey Level Co-occurrence Matrix
9	GWO	Grey Wolf Optimizer
10	HCR	Handwritten Character Recognition
11	HFE	Hybrid Feature Extraction
12	HOG	Histogram of Gradients
13	HFPSO	Hybrid Firefly Particle Swarm Optimization
14	IHOD	Integral Histogram of Oriented

		Displacement
15	ILBPSNet	Improved Local Binary Pattern (LBP) With Shallow Deep Convolution Neural Network
16	K-NN	K-Nearest Neighbor
17	LBP	Local Binary Pattern
18	LSTM	Long Short-Term Memory
19	MLFF	Multi-Level Feature Fusion
20	MMP	Modified Mutualism Phase
21	MSE	Mean Square Error
22	MSSAE	Morlet Stacked Sparse Auto-Encoder
23	MSVM	Multi-class Support Vector Machine
24	MWOA	Modified Whale Optimization Algorithm
25	NN	Neural Network
26	OCR	Optical Character Recognition
27	OTSU	Operational Test Support Unit
28	PSNR	Peak Signal Noise Ratio
29	PSO	Particle Swarm Optimization
30	ROI	Region of Interest
31	RF	Random Forest
32	RNN	Recurrent Neural Network
33	SE	Squeeze and Excitation
34	SF	Skeleton Feature
35	SNR	Signal-to-Noise Ratio
36	SMO	Sequential Minimal Optimization
37	SOS	Symbiotic Organism Search
38	SPT	Steerable Pyramid Transform
39	SSIM	Structural Similarity Index
40	SVM	Support Vector Machine
41	TN	True Negative
42	TP	True Positive
43	WOA	Whale Optimization Algorithm