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№ 291

Handwritten Bangla Digit Recognition Using Chemical Reaction Optimization

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June 21, 2018

HANDWRITTEN BANGLA DIGIT RECOGNITION USING CHEMICAL REACTION OPTIMIZATION

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***Abstract*—Handwritten character recognition, an active research field of Artificial Intelligence and Pattern Recognition, has gained enormous attention in recent years. However, much of the works were concentrated on recognition of few economically important languages; limited attention had been paid for character recognition of Bengali, the 5th ranked language of the world. In this paper, we propose a new methodology to recognize handwritten Bengali numerals using a recently established metaheuristic algorithm known as Chemical Reaction Optimization (CRO) in order to increase the recognition accuracy. The proposed method produces a higher accuracy rate, 98.96% which is higher than the outcome of any other proposed method. Unquestionably, the result shows that our proposed technique outperforms all previously developed methodologies.**

Keywords—Chemical Reaction Optimization algorithm; Feature extraction; Handwritten Bangla digit recognition; Support vector machine; Operator design.

I. INTRODUCTION

Nowadays as Artificial Intelligence (AI) has entered into our daily-life sphere through its various applications, the need for natural language processing inevitably has gained tremendous attention. Not surprisingly, recognition of handwritten scripts has become one of the most powerful research areas of natural language processing in recent years. While a large volume of work related to handwritten script recognition has been reported in the literature, majority of them focused on European Languages (e.g., Latin, English, German) and more recently Sino-Tibetan Language Family (e.g., Mandarin and Japanese) due to the economic importance of these languages; only a few were focusing on Indic Languages, like Hindi, Bengali, Punjabi and others, and Dravidian Languages (e.g., Telugu, Tamil, Malayalam). Bengali (also known as Bangla to the natives) being the 5th ranked language in the world [1] and official language of Bangladesh and some states in India, exploration of script recognition techniques for Bangla is an urgent need. In this work, we focus on handwritten character recognition for Bangla numerals only.

Handwritten character recognition problems fall directly under pattern recognition field of AI. In recent years, various feasible techniques for character recognition have been proposed in the literature [2-15]. These techniques involve identification of predominant features from (handwritten) digit images and classification of those features into digit classes. However, all area of an image does not contain similar discriminant information; rather some regions contain more discriminant features than others. Distinguishing of such discriminant regions during handwritten digit recognition incurs little cost in terms of computing time. At the same period, such optimization may also improve the classification accuracy.

Das et al. [3] proposed a region sampling methodology for identification of local regions containing maximum discriminating information using a genetic algorithm (GA). They randomly generated seven sets of local regions and from every set, GA selected an optimal group of local regions which provided best recognition performance by using support vector machine (SVM) based classifier. Similar experiments with other well-known optimization algorithms like Simulated Annealing (SA) and Hill Climbing (HC) with same data set produced worse recognition accuracies, 96.7% in both cases than the accuracy obtained using GA (97%). In this approach, they acquired a very high recognition accuracy, but the recognition cost was not considered. Whereas, Sarkhel et al. [15] proposed a cost-effective methodology for handwritten character and numeral recognition structure. A multi-objective region sampling technique was developed for handwritten Bangla characters and digits recognition in their work. A non-dominated sorting harmony search algorithm (NSHA) based region sampling methodology and a non-dominated sorting genetic algorithm (NSGA-II) based region sampling methodology was developed. An AFS methodology, based on

fuzzy logic was applied to build a model for combining the Pareto-optimal outcomes from two multi-objective heuristics algorithms. Highest recognition accuracies of 86.65% and 98.23% were obtained with 0.23% and 12.60% reduction in recognition cost for handwritten Bangla characters and numerals individually. In this method, they applied metaheuristics algorithms for region sampling. But Salah et al. [2] used a genetic algorithm to extract and enhance features. They proposed a technique for Arabic digit recognition which requires no preprocessing actions and uses genetic algorithms to extract and enhance features of the unknown patterns and classify them simultaneously. On the other hand, for selection of feature subsets GA had been used by Oliveira et al. [8] They focused on the feature subset selection for handwritten digit recognition through a modified wrapper based multi-criterion approach using a genetic algorithm which was connected to a multilayer perceptron neural network model. They explored two different versions of the genetic algorithm, simple genetic algorithm, and iterative genetic algorithm respectively.

Rajashekararadhya et al. [9] proposed an efficient zone-based feature extraction technique for handwritten Kannada, Telugu, Tamil and Malayalam numeral recognition. Wen et al. [7] discovered a new classifier which is based on Bayesian discriminant. But for classifying Alom et al. [11] used a deep learning based neural network. They proposed a methodology for recognizing Bangla handwritten digits which were constructed on several filter techniques includes Deep Belief Network (DBN), Convolutional Neural Networks (CNN), CNN with dropout, CNN with dropout and Gaussian filters, and CNN with Gabor filters and dropout. They obtained the highest accuracy of 98.78%.

Recognition of handwritten Bangla numerals is a tough task. Few Bengali numerals have similar shapes; for example, "১" (one) and "৯" (Nine) in Bangla numerals are about the same except the lower middle portion of the digits [3]. Although various techniques using nature-inspired metaheuristic algorithms have been proposed, in this paper we propose yet another methodology for Handwritten Bangla Digit Recognition (HBDR) with another optimization algorithm called Chemical Reaction Optimization (CRO) algorithm. CRO algorithm has been used to find solutions for several NP-hard problems and this meta-heuristic algorithm has shown its superiority to other algorithms in solving such problems [16]. Major advantages offered by CRO are flexible design for both local and global search, multiple operators, variable population size, and ability to work with variables in both the discrete and continuous domains. CRO was applied to the population transition technique in peer-to-peer live streaming [17], artificial neural network training [18], CROG for 0–1 Knapsack problem [19], and Network coding optimization problem [20].

In this paper, we show that when CRO is used in recognition of handwritten Bangla numerals, it outperformed other heuristic and metaheuristic optimization algorithms. In the following sections, we provide a short description of the CRO algorithm in Section-II; we present the materials and methodology used this work in Section-III. Section-IV discusses the results. At the end, in Section-V we give our concluding remarks.

II. Chemical Reaction Optimization

Chemical reaction optimization (CRO) is a metaheuristics optimization algorithm. It is based on the behavior of chemical reactions. It is one of the latest optimization algorithm reported by Lam and Li [21]. The property of chemical reaction is to transform any unsettled molecule to settled one through a natural process. To do that it occurs two types of collision: either on the wall of the jar where it remains or with other molecule exists in that jar [22]. By colliding, the molecule is decomposed or synthesized and reaches the stable position. Applying this technique, the CRO algorithm has been introduced. In CRO two types of energy has been introduced, which are the energy of molecules and the energy of surroundings. Potential energy (PE) and Kinetic energy (KE) are the energy of molecules. PE prescribes objective function(s) and KE prescribes the minimum amount of energy required for any reaction to take place. CRO algorithm comprehends any change in a chemical reaction if the following equation is satisfied [21].

$$\sum_{l=1}^{q}(PE_{bl}+KE_{bl}) \geq \sum_{l=1}^{w} PE_{b'l} \;\; where 1 \leq l \leq q \qquad (1)$$

Here, q represents the total number of reactants in b and w represents the total number of products in b'. By colliding with each other, reactants form new products.

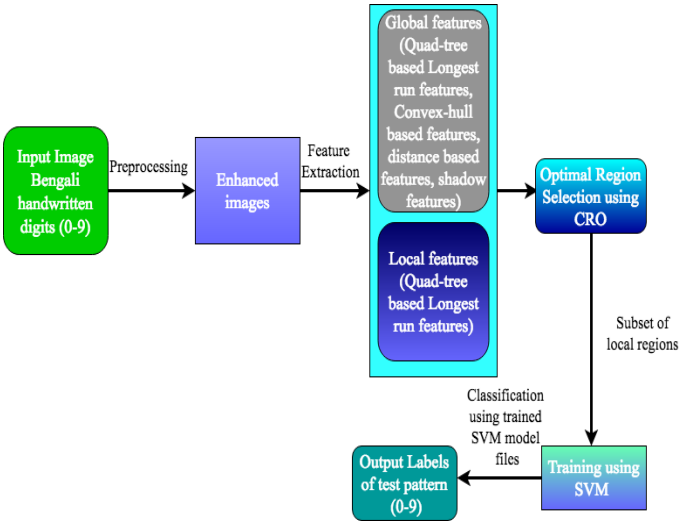
In general, in a chemical reaction, two types of collisions occur. Out of them, the first one appeared between a molecule and its neighborhood and is known as unimolecular. The other one is between two or more molecules that is termed as an inter-molecular collision. The unimolecular reaction contains On-wall ineffective collision and decomposition. On the other hand, the inter-molecular collision also contains two: inter-molecular ineffective collision and synthesis. The inter-molecular ineffective collision is applied to a regional search. The reactant molecules face a few numbers of modification in the molecular area. The next inter-molecular reaction is known as Synthesis in which two or more molecules collide with each other and make a unique molecule.

III. Design of CRO-HBDR

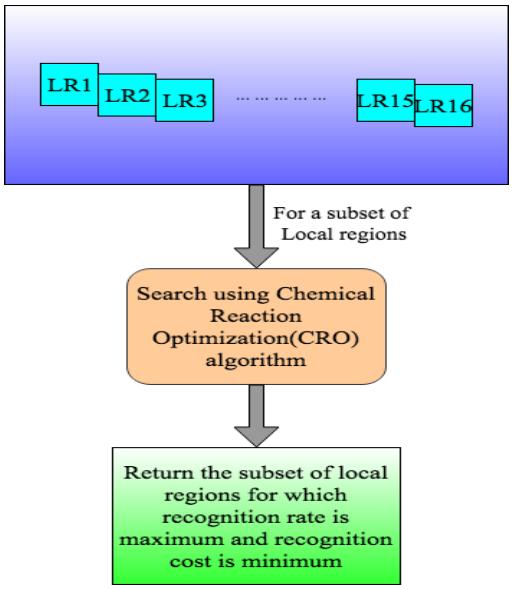
In our methodology, the images were preprocessed and then features were extracted from the images. We used SVM as our classifier. CRO was used for searching the sub-images with the most discriminating features. To find an optimized set of local regions and train and testing data an SVM classifier was used.

A. Definition and Notation

Let $\mathrm{Im}_{r\times c}$ is a 2D array that denotes a digital image of dimensions $(r \times c)$ such that, $\mathrm{Im}_{r\times c} = \{f(i,j), 0 \le i \le r-1 \text{ and } 0 \le j \le c-1\}$. Where $f(i,j)$ denotes the intensity of the pixel at coordinate (i,j). In our current method, only binary images of Bangla handwritten numerals were examined. For a binary image the value of $f(i,j) \in [0,1]$. A 2D binary image is considered as the association of regions which can't be overlapped to each other. Let, the region R_n, where $n = \{1, 2, 3....., m\}$. Here $\mathrm{Im} = U_n R_n$.



Block diagram of CRO-HBDR



Optimal region selection using CRO

Fig. 2 Workflow of CRO-HBDR

Our target is to find the optimized subset S_l, where $S_l \subseteq S$ and S_l defines the set of those regions which fulfill the criteria of optimization i.e. the maximum recognition accuracy and minimum recognition cost. Fig. 2 shows the workflow of the proposed technique.

B. Image Preprocessing

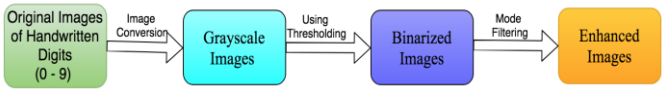


Fig. 1 Block diagram of Image Processing

We transformed RGB images into grayscale images. In order to binarize an image, we split foreground pixels from their background using a threshold. The midpoint of image histogram was used as the threshold value. The binarized images have been enhanced by mode filtering method. Then enhanced images are resized to 128×128 pixels. Fig. 1 shows the complete system of image preprocessing.

C. Feature Extraction Technique

The extracted features, applied in the current work can be classified into two categories: global and local. While the number of global features extracted from a handwritten digit image is fixed, in the instance of local features it may vary based on the number of local regions evaluated. The extraction of global features are computed from the whole image, on the other hand, local features are computed from a sub-region or local region [12] of the image being considered.

1) Global features: For our experiment, 186 global features were used in total. From those global features, there were 125 convex-hull based features, 25 quad-tree based longest run features, 12 distance-based features, and 24 shadow based features.

Convex-hull based features contain the maximum distance from the convex hull boundary to the boundary of the foreground of the image (d_{cp}), the total number of rows having $d_{cp} > 0$, average d_{cp}, number of visible bays, mean row coordinate, and the total number of rows where there is no gap between convex hull boundary and foreground boundary i.e. $d_{cp} = 0$. These six features have been calculated from all four sides of the image i.e. top, bottom, left and right boundaries. Total summation of the rows where $d_{cp} = 0$ has been added with the earlier ($4 \times 6 = 24$) features as the 25th feature [13].

Center of gravity (CG) based quad-tree partitioned longest-run attributes were also constructed in the present technique. (Five) Longest run features extracted from the root node and the first-level child-nodes of the resultant quad-tree also contribute to the global feature set ($4^0 \times 5 + 4^1 \times 5 = 25$) [14].

Shadow features were calculated by examining the lengths of projections of the digit image on three sides of each octant dividing triangles within the minimal bounding box wrapping the image. Addressing all the 8 octant triangles dividing the

minimal bounding box, 24 shadow features in total were extracted from every image [3].

In case of distance-based features, highest horizontal, vertical and diagonal distances from image border to digit border were calculated for every quadrant and then normalized. Thus, for four quadrants the total number of distance features was *3×4=12* [14].

2) Local features: The features extracted from the second level of child nodes of the CG based quad-tree construct the local feature set. The total number of nodes in the second level of the quad-tree is $4^2=16$. Longest run based features were computed from each and every local region. Those local regions were represented by the nodes in the quad-tree. Each local region has 4 local features along with four axes: horizontal, vertical and two diagonals. The fifth longest-run feature has been calculated by scalarizing -previous four longest-run features. For scalarization technique, we used the proposed method of Sarkhel et al. [15]. Hence, a total number of local features in the feature set of our present work is *16×5=80* and the aggregated number of features in the integrated feature set of the experimental setup is 266 (*125 + 25 + 24 + 12 + 80 = 266*).

D. Region Sampling using Chemical Reaction Optimization

Chemical reaction optimization works in three stages: Initialization, Iteration, and final stage.

1) Initialization: The algorithm is initialized with an empty set *F*; upon termination, the population contained in *F* would represent the Pareto-front. The population size is fixed initially. In our current method, the population size of CRO based region sampling methodology is 20. The parameter 'molecoll' is set to 0.6 which is applied to select single molecule operation or multiple molecule operations. If the 'molecoll' is less than the randomly selected value of 'molecoll' between 0 and 1 and hit difference is greater than gamma, decomposition will be held else it will be on wall-ineffective collision. If the kinetic energy is less than or equal to delta, it will choose synthesis. Or, it will choose inter-molecular ineffective collision. The parameters values for the experimental setup are given in Table 1.

2) Objective Function: The objective of the algorithm is to gain the highest recognition accuracy and lowest recognition cost. To formalize, the optimization problem can be described as following:

$$\begin{cases} Maximize\, R_a \\ Minimize\, R_L \end{cases}$$

With respect to following constraints:

$$\begin{cases} R_a \geq 0 \\ R_L = \left| V_{R_L} \right| \\ 1 \leq R_L \leq 16 \end{cases}$$

Where V_{R_L} symbolizes the region-vector representing the encoding of local regions returned by the algorithm, R_a symbolizes the recognition accuracy achieved by the SVM based classifier using the features extracted from the global feature set and the local feature set R_L extracted from V_{R_L}, R_L symbolizes the number of local regions used to represent each handwritten digit.

3) Termination Criteria: The algorithm terminated when it successfully reproduced 10 generations of population. Hence, the maximum number of iterations of the algorithm was 10.

It is to be noted that the algorithm discussed above are developed independent of any specific dataset and can be successfully applied to any region sampling based pattern recognition task.

E. Production of Molecule

Sub-images generated from quad-tree are represented as local regions. Let, *l* represents the partition level of an image, where $l \in \{0, 1, 2\}$. z_l symbolizes the set of local regions at l^{th} level of the quad-tree. For *l* = 2, 16 regions of quad-tree are generated which are considered as the local regions. Participation of local regions is denoted by '0' and '1'; where '0' represents that the region is deactivated and '1' represents that the region is activated. Fig. 3 shows a molecule of local regions. Here 'LR' represents local regions which are the sub-images of the root image.

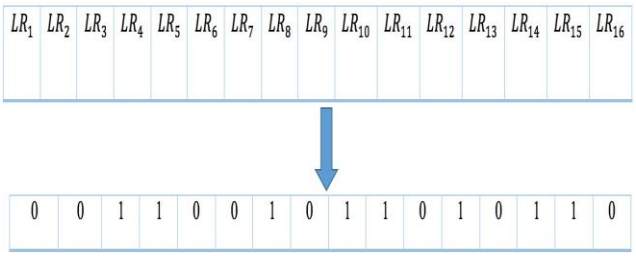


Fig. 3 Molecule generation

F. Reaction Operators

We adopted four reaction operators of CRO. They are described in the following sub-sections. In sub-sections, we used 10 zones instead of 16 for the shake of simplicity.

1) On-wall Ineffective Collision: This is a molecular reaction. From the population, a molecule *M* is taken randomly as input. Then local regions are activated or deactivated randomly from the molecule according to the Fig. 4. Recognition accuracy is calculated for the newly generated molecule *M′*, i.e. the new set of active local regions. If the

accuracy rate is higher than that of the old molecule *M* the old molecule *M´* is replaced by the new one.

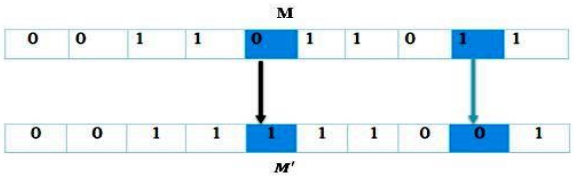


Fig. 4 On-wall ineffective collision

2) Decomposition: In decomposition, we follow the half-total exchange operation. Two new molecules ($M_1^{'}$ and $M_2^{'}$, as in Fig. 5) are produced in decomposition from a single molecule (M). One half (either first half or the last half) of the parent molecule remains intact in the new child molecules, while the other half is generated with random values. We measured recognition accuracy for child molecules. Massive changes occur in the molecule structure of the newly produced molecules $M_1^{'}$ and $M_2^{'}$. Here, *M* is duplicated into two forms. The first half is passed to $M_1^{'}$ and the second half to $M_2^{'}$. Then, comparing the new recognition accuracies with the previous accuracy, we decided whether to reject or accept the newly generated molecules. From the parent molecule and both child molecules, one with the best accuracy is accepted. Fig. 5 shows the illustration of the decomposition reaction.

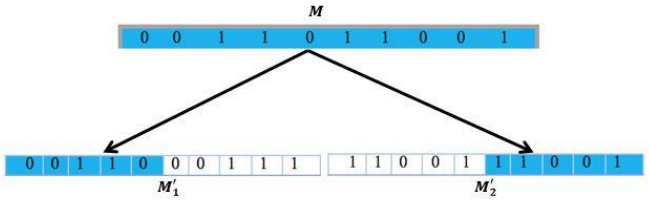


Fig. 5 Decomposition

3) Inter-molecular ineffective collision: This operator takes two molecules M_1, and M_2 as input and generates two new molecules $M_1^{'}$ and $M_2^{'}$ as output. On the parent molecules a position is selected randomly, then the values at those positions are swapped to each other and the child molecules are generated. In this operation, child molecules change slightly from parent molecules. Fig. 6 shows the illustration of inter- molecular ineffective collision reaction.

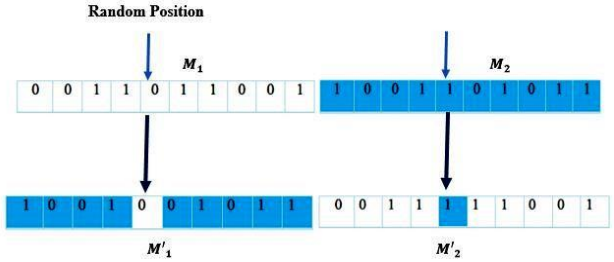


Fig. 6 Inter-molecular ineffective collision

4) Synthesis: Two molecules are combined to generate a new molecule in a synthesis operation. In this operation, two molecules from the population are chosen randomly which are used as parent molecules. The first part of the first parent molecule is appended with the last part of the second parent molecule to produce a child molecule. For example, two molecules M_1 and M_2 from the population are combined to form a new molecule. It is worked as opposite of decomposition reaction. Fig. 7 shows the illustration of the synthesis reaction.

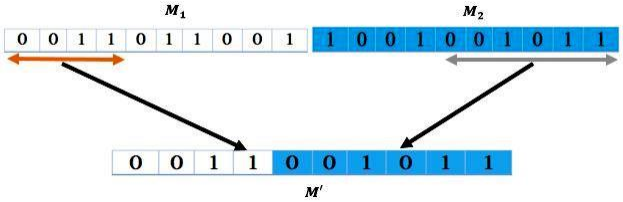


Fig. 7 Synthesis

The reaction operators are selected according to some parameters. A random variable *v* is generated to decide either the reaction is unimolecular or intermolecular. If *v* > MoleColl, the reaction is unimolecular, otherwise intermolecular. If the reaction is unimolecular and satisfies the condition of decomposition (as discussed in section V-D), the reaction is decomposition; otherwise, it is an on-wall ineffective reaction. Finally, if the reaction is inter-molecular and satisfies the condition of synthesis, it is synthesis; otherwise, it is an inter-molecular ineffective collision. The effectiveness of the CRO algorithm highly relies on these parameters. Among other parameters, CRO includes Pop-Size, KElossRate, MoleColl, Buffer, InitialKE and two thresholds, α and β.

TABLE I.
INITIAL VALUES OF CRO PARAMETERS USED IN HBDR PROBLEM-

Symbol	**Meaning**
Population size	20
KELossRate	2
Molecoll	0.6
InitialKE	Population size
Alpha (α)	Population size / 5
Beta (β)	(4 * Population size) / 5
NumHit	0
MinHit	0

IV. EXPERIMENTAL RESULT

In the proposed method, we applied CRO based optimization approach to find the optimized subset of local regions. For classification purposes, SVM classifier with radial basis function (RBF) kernel with gamma (γ) value 0.00009 has been used in our proposed method. Among different tools, one of the openly accessible scikit-learns library from Python 3.5.2 was used on this method.

For evaluating the performance of our experiment, we used CMATERdb dataset [23]. There are 6000 images in the dataset, from which 4000 images were used as train purpose and other 2000 images were used for testing. Table II displays the highest and average recognition accuracy with and without the application of CRO. Table III shows the confusion matrix for the highest recognition performance for the proposed technique. A confusion matrix contains information about

effective and predicted classifications achieved by a classification technique. The Outcome of this type of system is generally evaluated using the data in the matrix. From the confusion matrix TP (True Positive), FP (False Positive), TN (True Negative), and FN (False Negative) values are obtained. The diagonal values of the confusion matrix represent the number of digit images that are accurately classified and non-diagonal values represent the digit images that are misclassified. By using the values of confusion matrix and applying the following equation [24], we get the overall recognition accuracy of the proposed system.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100\% \qquad (2)$$

Fig. 8 shows the comparative analysis among some renowned meta-heuristic evolutionary algorithms and our proposed method.

TABLE II
FINAL OUTPUTS ON THE DATASET OF HANDWRITTEN BANGLA NUMERALS

Dataset Index	Dataset type	Highest recognition performance (%) in the current technique		Average recognition performance (%) in the current technique		Number of local regions applied	
Dataset (CMATERdb)	Isolated handwritten Bangla numerals	Without CRO	Using CRO	Without CRO	Using CRO	Without CRO	Using CRO
		98.8	**98.96**	98.57	98.9	16	10

TABLE III. CONFUSION MATRIX REPRESENTATION FOR THE HIGHEST RECOGNITION PERFORMANCE OF THE PROPOSED TECHNIQUE

Digits	0	1	2	3	4	5	6	7	8	9
0	200	0	0	0	0	0	0	0	0	0
1	0	198	1	0	0	0	1	0	0	0
2	0	0	200	0	0	0	0	0	0	0
3	3	0	0	197	0	0	0	0	0	0
4	0	0	0	0	198	1	1	0	0	0
5	1	0	1	0	0	198	0	0	0	0
6	0	0	0	1	0	3	196	0	0	0
7	0	0	0	0	0	0	0	199	1	0
8	0	1	0	0	0	0	0	0	199	0
9	0	5	0	0	0	1	0	0	0	194

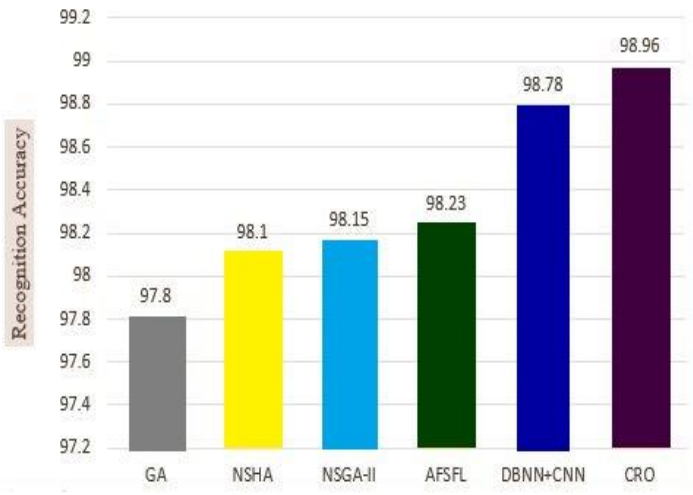


Fig. 8 Comparison of recognition accuracy (%) with some existing algorithms

According to Fig. 8, our proposed methodology outperforms other methods found in the literature. The recognition rate in our proposed methodology is 98.96% which is the best result, comparing with some well-known algorithms. As CRO was used in proposed methodology to sample the regions, it tried to search for the best regions both locally and globally. For a molecule of CRO, it gives the best result if it hits multiple times. In that case, lower kinetic energy loss rate promotes a local search which in effect produces a better result. But GA or other evolutionary algorithms only perform a global search. At the same time, the hit difference of CRO makes the molecules more stable, as a result, CRO finds the regions which are most discriminating. This is another reason why CRO could improve the performance significantly compared to other algorithms.

V. Conclusion

Since the last decade, handwritten digit recognition has obtained a crucial attention to the researchers, as it has an important role in the field of Artificial intelligence. In the present work, we proposed an advanced technique for handwritten Bangla digit recognition. The main intention was to improve the recognition performance of handwritten Bangla numerals. We chose a recently established optimization algorithm, CRO, which reportedly outperformed other similar algorithms. We observed a significant improvement in the recognition accuracy when we applied CRO for handwritten Bangla digit recognition. From the dataset, we gained an overall accuracy of 98.96%. We compared our digit recognition technique with the techniques using a genetic algorithm (GA) in [3,15] and deep learning in [11]. Unquestionably our proposed technique outperformed the recognition performance of those techniques. Although we applied the proposed technique for only one publicly available dataset (i.e. CMATERdb), we expect that the method would produce better recognition rate in other datasets as well.

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