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Optimized Features for Genetic Based Neural Network Model for Online Character Recognition

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Authors' contributions

This work was carried out in collaboration between all authors. All authors read and approved the final manuscript.

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Abstract

Feature extraction and feature selection place an important role in online character recognition and as procedure in choosing the relevant feature that yields minimum classification error. Character recognition has been a good research area for many years because of its potential applications in all the fields. However, most existing classifiers used in recognizing online handwritten characters suffer from poor selection of features and slow convergence which affect recognition accuracy. A genetic algorithm was modified through its fitness function and genetic operators to minimize the character recognition errors. In this paper Modified Genetic Algorithm (MGA) was used to select optimized feature subset of the character to extract discriminant features for classification task. Some of research works have tried to improve online character recognition and their works were based on learning rate and error adjustment which slow down the training process. Thus, to alleviate this problems, a genetic based neural network model was developed using MGA to optimize an existing Modified Optical Backpropagation (MOBP) neural network. Two classifiers (C1 and C2) were formulated from MGA-MOBP such that C1 classified using MGA at classification level while C2 employed MGA at both feature selection level and

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classification level. The experiment results showed that the developed C2 achieved a better performance with no recognition failure and 99.44 recognition accuracy.

Keywords: Artificial neural network; optical backpropagation; genetic algorithm; character recognition; feature extraction; feature selection; genetic operators.

1 Introduction

Feature extraction stage is the removal of redundancy from image character, before building the extraction procedure [1]. Feature extraction process as the set of features representing the pattern in the pattern space [2]. On the other hand, in feature selection, the most relevant features to improve the classification accuracy are selected. Feature extraction and feature selection are duo to perform the most effective feature reduction for classification [3]. Online handwritten recognition has been one of the most challenging research areas because of variability on size, different writing style, mood of writer, number of disconnected and cursive representation of character [4,5]. The aim of online handwritten character recognition system is to develop a user friendly computer assisted character representation, that will allow extraction of characters, from character image database to digitalize and translated the handwritten text into a machine readable form [6]. The increase in usage of handheld devices has created a growing demand for algorithm that would reduce the processing time and increase recognition accuracy [7,8,9]. Online handwritten character recognition can be classified into two categories: Optical Character Recognition (OCR) and Intelligent Character Recognition (ICR). OCR (offline) recognizes handwritten text that have been previously typed or scanned prior to recognition process or once the writing process is over [10,11] whereas in ICR (online), handwritten data are captured and recognized when character are under creation or during the writing. ICR is superior over OCR due to the temporal information available with the online, the two dimensional coordinates of successive points are represented as function of time and information on the ordering of strokes are available [12,13,14]. Many classifiers were used for character recognition, but Artificial Neural Networks (ANNs) outperform the other classifiers because of its flexibility, scalability, accuracy and learning. However, the backpropagation neural network is a popular algorithm for training a multilayer network, despite this, it has a lot of limitations: slow convergence and easily be trapped in local minima. These limitations are far from being solved and freely handwritten characters are still insufficient. This constitutes an open issues in character recognition system. Hence, this paper integrates the modified genetic algorithm and modified optical backpropagation to achieve a better performance of training time and recognition accuracy. MGA was used to optimized the global features to obtain a reduced form of features. Two classifiers (C1 and C2) were formulated form MGA-MOBP to check the performance of the system. Section two describes related work, while section three contains the material and methods and draw conclusion in section four.

2 Related Works

Online character recognition has been one of the most intensive and interesting research areas in the field of pattern recognition. Feature reduction techniques have been investigated and some have great performance. Feature reduction may be divided into two main categories, called feature extraction and feature selection [1,10]. The selection of appropriate feature extraction is the single most important factor in achieving high recognition performance [11,15]. [7] have extracted features based on different spatial and temporal features from strokes of the character and recognition was done by using genetic algorithm as a tool to find an optimal subset. The work produced a recognition rate of 83.1%. Also [16,17] developed a hybrid feature extraction technique using geometrical and statistical features and a multiple classification character recognition scheme was employed using modified counter propagation network (MCPN) and MOBP neural network. Similarly a novel and robust hybrid recognition system for Odia handwritten character, was designed based on the algorithm of feed forward Backpropagation Neural Network (BPNN) combined with Genetic Algorithm (GA) to perform the optimum feature extraction and recognition. A recognition accuracy of 94% was reported [18]. Furthermore, [19] presented an English character recognition system using the for recognition of uppercase alphabets. Recognition results was 91.1%. A backpropagation network algorithm combined with genetic algorithm was used [20] to achieve both accuracy and training swiftness for recognizing alphabets. The accuracy in recognizing character differ by 10, 77%, with a success rate of 90, 77% for the optimized backpropagation and 80% accuracy for the standard backpropagation network. Further [21] have presented a technique for recognition of an offline handwritten character using grip approach. Extracted features are trained by neural network as classifier of the character in classification stage. The overall experimental results in recognition rate was 96.9%. [22] proposed optical character recognition based on Genetic Algorithm, which partially emulate human thinking in the domain of artificial intelligence. The study generated the required character specification and after testing and evaluation of results, the percentage of OCR was 97%. Also, researchers have invested in improving backpropagation(BP) algorithm in many ways such as adjustment of learning rate and error adjustment [23]. However, these works were yet to deliver the desired results. Based on their limitations (Table 2.1), this research focused on integrating genetic algorithm into an existing MGA neural network to improve the performance of system in terms recognition time and recognition accuracy.

Table 2.1. Comparison analysis of existing techniques[1]

S/N	Author(s)	Strategy	Limitations	Performance %
1	Abed et al. [24]	Genetic algorithm	Slow training time	95
2	Ranpreet et al. [19]	Standard GA, BP	Scaling, local minima problems.	91
3	Padhi [18]	SBP, SGA	Local minima and loss of solution	94
4	Fenwa et al. [16]	MCPN, MOBP	Long training time	99
5	Noaman et al. [22]	Genetic algorithm	Not reported	97

3 Materials and Methods

Fig. 2 shows the block diagram of the character recognition system. In this paper, four main stages of online handwritten character recognition was developed namely character acquisition, preprocessing, feature extraction and selection, and classification.

3.1 Data acquisition and preprocessing

The first step is the acquisition of character images using pen digitizer (Genius Mousepen T34235) which has an electric pen with sensing writing board. 6200 characters was collected from 50 students from Yaba College of Technology, Nigeria who was requested to write each of the characters twice. Characters considered were 26 upper case (A-Z), 26 lower case (a-z) English alphabets and 10 digits (0-9) making a total of 62. Fig. 1 shows a sample of dataset used.

The second stage implements the preprocessing procedure by removing the noise from data and minimize the variations in character styles. The preprocessing techniques used were binarization, extreme coordinate measurement and grid resizing. The extracted feature provided the characteristics of input type to classifier by considering the description of the relevant properties of image into feature space.

3.2 Feature Extraction (FE)

In this research work, the process of features extraction was employed and tested on training set to determine the most optimal set of features for character recognition system. The features used were based on stroke information, invariant moments, projection count and zoning of the handwritten character to create a global feature vector. This research employed multiple properties of structural and statistical features to complement each other and handle style variations. Hence, a hybrid of feature extraction algorithm was developed to highlight different character properties that effectively identity a character as shown in Figs. 3 and 4 respectively. Sixteen (16) features were extracted in each string of character: stroke number, projection count, pressure, image centroid, zone centroid, distance between zone centroid, distance between image centroid, horizontal centre of gravity, vertical centre of gravity, skewness, kurtosis, higher order moments, hough and chain code transform, fourier transform and series, orientation elliptical parameters and eccentricity elliptical parameter respectively. The Hybrid (Struct-Statistical) Feature Extraction Algorithm proposed by [4] was used. The following stages were taken in the development.

Step 1: Stroke information of the image characters was obtained this include: pressure used, number of strokes and projection count of the character
Step 2: Apply invariant Moments to determine position, size and orientation of the character.
Step 3: Run Hybrid Zoning Algorithm on the character.
Step 4: Feature selection to reduce number of features by elimination of insignificant features was performed.
Step 5: The outputs of the extracted and selected features of the characters was fed into the digitization stage in order to convert all the extracted features into digital forms.

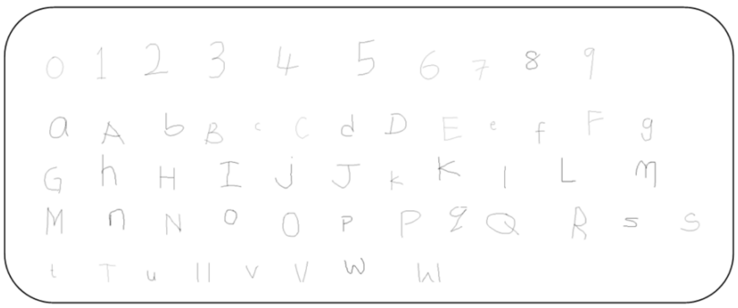

Fig. 1. Shows a sample of dataset used

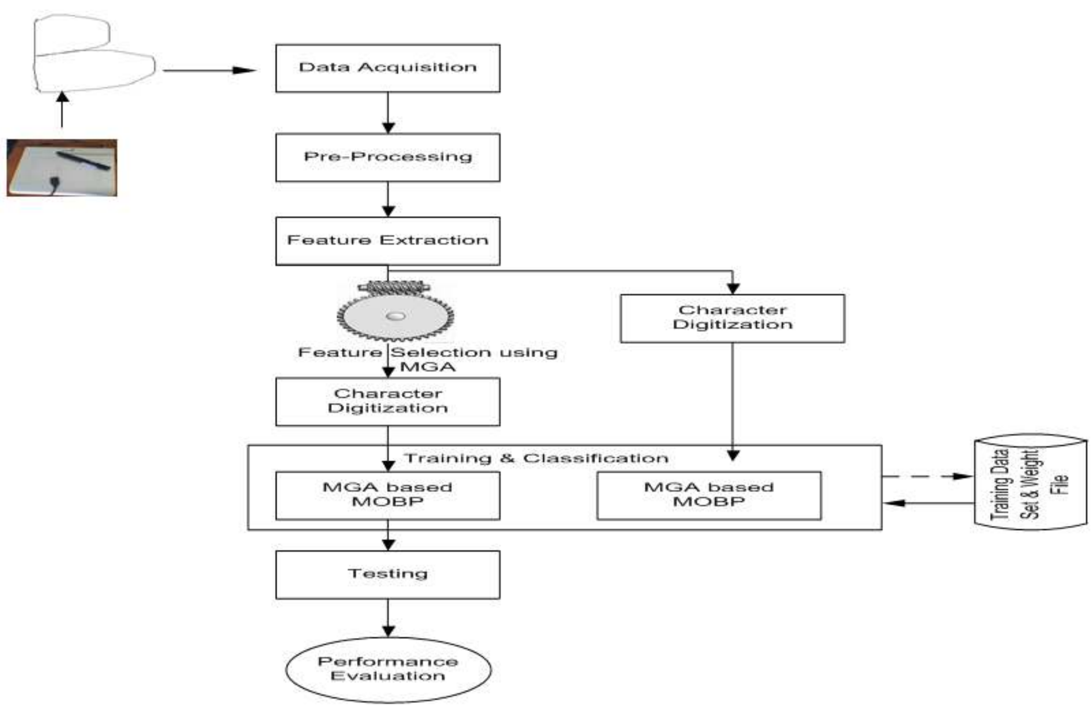

Fig. 2. Block diagram of the developed character recognition system

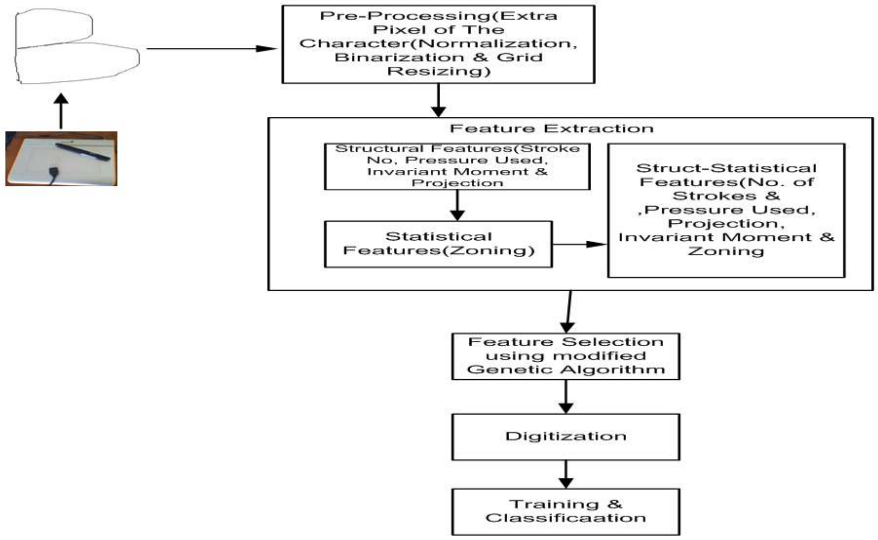

Fig. 3. Developed feature extraction model

3.3 Modified Genetic Algorithm (MGA)

The training of Neural network by backpropagation is time consuming and slow convergence due to local minimal. The loss of potential solution and slow convergence in standard genetic algorithm (SGA) is a common drawback in its application. To overcome these problems in this research, standard genetic algorithm was modified to speed up the convergence and reduce computational time for improving the training capacity of the network. Two unique strategies were modified to enhance the SGA.

Firstly, the main idea of Genetic Algorithm is to mimic the processes in nature, even though selection and crossover operators effectively work, there is a possibility that SGA may lose some potentially useful solution. Therefore, mutation is needed to prevent falling of all solutions into local optimum of character recognition. The genetic algorithm mutation operator was processed first, followed by selection and crossover. This led to a new modification denoted as MSC(Mutation, Selection Crossover).

Secondly, modification of fitness function is to determine the optimum subsolution and the fitness function was modified returned as equation (3.2) is the number of selected zero or approximately zero features from the algorithm and multiplied with the percentage of feature used. The fitness value defined by [25] is the number of recognition errors encountered multiplied by 10 and added with the percentage of feature used

$$\text{Fitness} = ((\text{number of errors}) * 10) + \%\text{Feature Used} \tag{3.1}$$

The equation (3.1) was manipulated mathematically and this further minimizing the negative by reduced the number of recognition errors and while reducing the number features extracted. The MGA is terminated when the total number of generation is encountered. In this research the %featured used was replaced with horizontal projection all over the downsample_height and downsample_width. This is shown in Equation 3.2 below.

$$\text{Fitness} = (\text{no of selected zero features}) * \%\text{FeatureUsed}) \tag{3.2}$$

Where

$\text{H} = \text{Hprojection}, \ \text{DH} = \text{Downsample\_Height}, \ \text{DW} = \text{Downsample\_Width}$ and

$$\text{FeatureUsed} = \left(\frac{\text{H}}{\text{DH} * \text{DW}}\right) * 100$$

3.4 Feature Selection (FS)

The resultant features representation serves as a suitable platform for selecting optimal subset of original features that are essential for the classification task. The extracted discriminant features that enhances classification performance was done by using MGA for feature selection. This reduces the computational burden in terms of memory utilization, training time and testing efficiency. In the research, MGA retained most of the intrinsic features of character data and initially starts with a number of chromosomes known as population(randomly generated). These chromosomes are represented using a string coding of fixed length. After evaluating each chromosome using a fitness function and assigning a fitness value to crossover to produce a new chromosome with better fitness, three different operators such as mutation, selection and crossover are used to update the population. A repetition of these three operators is known as a generation. The new chromosome will then replace the chromosome with the lowest survival rate. This process will be iterated until the desired error rate is achieved. The features with the bit value "1" are selected and the features with the bit value of "0", the corresponding one are rejected. The Algorithm proposed by [23] was used:

3.4.1 Feature selection (using modified genetic algorithm)

1. Start and get character features set
2. Set GA parameters (set gen<= numgen, set n <= population size, generation _gap)
3. Generate uniformly distributed chromosomes to form initial population
4. Encode features by a chromosome {using bit strings encoding}
5. Gencount <= 0
6. Rank chromosomes based on its uniqueness {i.e. first chromosome occurrence = 1, subsequence occurrence = 0 }
7. Arrange chromosomes based on their fitness value{ Accept features with bit value = 1 and reject features with bit value = 0}
8. Mutate selected chromosomes based on mutation tendency
9. Select chromosome with best fitness value using equation 3.2.
10. Perform crossover on parent chromosomes to form new offspring and replace the weak chromosomes with the new offspring based on generation_gap
11. Gencount <= gencount + 1 and repeat until total numgen
12. If gencount = gen then goto 13 else 6
13. Output chromosome with the highest fitness value(feature selected)

All the features extracted from the input images does not account for high accuracy. Hence, a feature selection process is highly essential for eliminating the insignificant features. Out of the sixteen features extracted, ten optimal set of features were selected by MGA. This optimization algorithm not only improved the training time but also improved the recognition accuracy results.

3.5 Development of hybrid MGA and MOBP model

The architecture of artificial neural network used in this research work describes the properties of individual neurons. Two hidden layers was adopted in this research work. The number of hidden neurons was calculated by 2/3 of the input layer size, plus the size of the output layer with image sizes of 5 by 7 (35 pixels). The output layer consists of 62 neurons; this is due to the fact that there are 62 characters to be identified. Thus each output neuron corresponds to every character and a binary code of size 6 was used to represent the output values. In this paper, a hybrid of MGA and MOBP neural network model was developed. The online character written is locally acquired using digitizer to get characters for processing. Then the extracted characters are resized for training the neural network which has undergone various processes like converting the grayscale into binary image, finding edge for feature extraction and normalization. During the preprocessing and feature extraction, the individual strokes are resampled to standard size. This helps to control the variations gap, noise and to avoid anomalous cases. Features are extracted from user's input pattern are stored and trained with different parameters and different sets of characters. The extracted features were subjected to optimization technique (MGA) for optimal features selection. Two classifiers (C1 and C2) were formulated from the MGA-MOBP. During training, the weights of the network are iteratively adjusted to minimize the error function. The set of outputs obtained during the acquisition are fed into the genetic algorithm to mutate based on mutation probability, select the best fittest and best solution and perform crossover to form new offspring until total number of generation. Output chromosomes with the highest fitness value are sent to the neural networks as input. The developed model was trained to recognize different types of handwritings. This was achieved by using highly efficient supervised learning algorithm. For each character, calculate the output of the feed forward network and compare with the desired output corresponding to the symbol and compute error. Back propagate error across each link to adjust the weights and then move to the next character and repeat until all characters were visited. The output obtained from the trained are stored as files. Match the introduced character with the one in the database template and classify the given character or pattern image. The extracted features are classified according to identify pattern to which it has been trained.

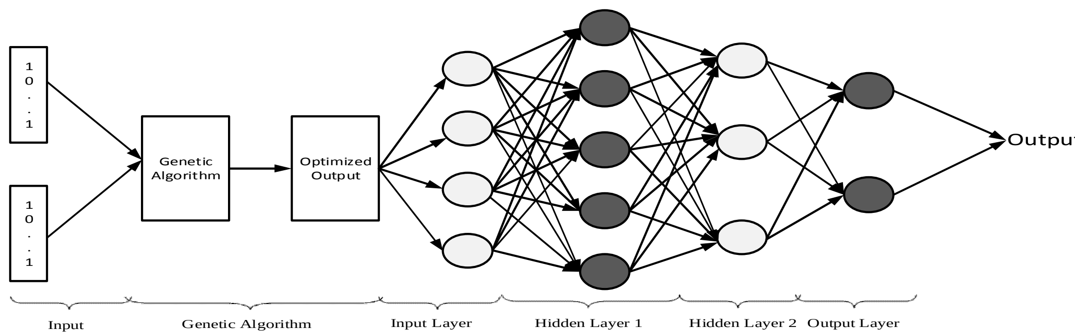

Fig. 4. The hybrid of MGA and MOBP model used

3.5.1 The genetic and neural network algorithm

This research work employed hybrid of modified Genetic Algorithm and Modified Optical Backpropagation neural networks for the training and classification of the input pattern. The training algorithm involves the following two stages:

Stage A: Performs the training of the character sample generated using Genetic Algorithm.

Step 1 : Select character samples collected from various people
Step 2 : Initial population, generation, set generation gap
Step 3 : Generate uniformly distributed random number with same size with feature matrix
Step 4 : Obtain fitness value of initial population
Step 5 : Mutate chromosomes based on mutation tendency
Step 6 : Select using roulette wheel selection
Step 7 : Crossover parents with best fitness values
Step8 : Replace a fraction of the old generation with new offsprings based on generation gap
Step 10: Insert the new offspring in the new population and use new generated population
Step 11: Re-run until generation is reached or best solution emerges in the population.

Stage B: Performs the training of the input from the genetic algorithm to the output layer. Assume there are *m* input units, *n* hidden units, and *p* output units. W^h_{ji} weight on the connection from the *i*th input unit to *j*th hidden unit.

1. Input vector, Equation 3.3 to the input units. Each value in input layer receive X_{pi} and forward to values in hidden layer.

$$X_p = X_{p1} + X_{p2} + X_{p3} \ldots + X_{pm} \quad (3.3)$$

2. Calculate the output of the feed forward network Equation 3.4

$$O_{pk} = f^{o}{}_{j}(\mathrm{net}^{o}{}_{pk}) \quad (3.4)$$

3. Compare with the desired output corresponding to the symbol and compute error

i) $\delta^{o}{}_{pk} = 3((1 + e^{t})^2 . f^{o'}{}_{k}(\mathrm{net}^{o}{}_{pk}))$ If $(Y_{pk} - O_{pk})2 >= 0$ (3.5a)

ii) $\delta^{o}{}_{pk} = -3((1 + e^{t})^2 . f^{o'}{}_{k}(\mathrm{net}^{o}{}_{pk}))$ If$(Y_{pk} - O_{pk})2 <= 0$ (3.5b)

iii) Using cubic error adjustment where

Y_{pk} = Desired output

O_{pk}= Network output

T = $(Y_{pk} - O_{pk})2$

4. Back propagate error across each link to adjust the weights, Equation 3.6

$$\delta^{h}{}_{pj} = f^{h'}{}_{j}(\mathrm{net}^{h}{}_{pj}) .(\textstyle\sum_{k=1}^{M} Modified\ \delta^{o}{}_{pk} . W^{o}{}_{kj}) \quad (3.6)$$

5. Move to the next character and repeat step 5 until all characters were visited

6. Compute the average error of all characters

Repeat steps from step 1 to step 6 until the error$(Y_{pk} - O_{pk})$ was acceptably small for each of the training vector pair. The developed algorithm is stopped when the cubes of the differences between the actual and target values summed over units and all patterns are acceptably small.

3.6 Classification and testing stage

Two types of classifiers were formulated. C1 (MGABased MOBP): classified using MGA at classification level and C2 (MGA and MGABased MOBP): employed MGA at both feature selection and classification levels. The classification stage is to recognize characters features that are extracted from raw data. This phase determined the overall performance of the developed algorithm. The recognition of character is done based on minimum distance classifier between two feature vectors which forms the character input pattern using Euclidean distance metric. That is template of testing and template of training vectors. The threshold is determined by the continuous modification of the threshold until significant accuracy is observed. When the minimum distance is less or equal to a threshold set implies correct match or a recognized character.

3.6.1 C1 (MGA based MOBP)

The performance of each of C1 and C2 was evaluated using recognition failure, training time and correct recognition accuracy. The best of the two classifiers was determined on the basis of correct training time and recognition accuracy. There was no optimization at feature selection at C1, therefore all the features were used. The MGA was used at classification level.

1. *Start*
2. *Character acquisition using Digitizer*
3. *Preprocessing of character images*
4. *Feature Extraction of the character images*
5. *Digitization*
6. *Training and Classification (using MGA and MOBP)*
7. *Testing*
8. *Performance Evaluation*
9. *Stop*

3.6.2 C2 (MGA and MGA based MOBP)

The second classifier used in this work is C2 and MGA is used as an optimization algorithm. The objective for using the optimization algorithm at feature selection level as stated: feature reduction which improves the convergence time, reducing computational burden, reducing storage requirements and improving data understanding. In this research work modified genetic algorithm was used for optimal feature selection. MGA was used during the training and classification: (i) to speedup the training process (ii) to solve the problem of local minima in backpropagation (iii) to rapidly locate region of optimal performance in relatively short time. and (iv) find those character features that minimize the recognition error. The extracted features were subjected to optimization test which finally yields the optimal feature set. The number of neurons used in the input layer for this classifier was reduced since the number of optimal features is less than the complete feature set. The mathematical calculations are minimized because of the reduced size of the weight matrix. Hence, a significant reduction in the time period was achieved for the weight adjustment of the hidden layer neurons. C2 is better than C1 based on the above justifications. The characters are classified according to similarity of their shapes and features from the data set collected of different person's handwritten characters using C2. The genetic feature output was projected into image space and stored in the database(template), were used for training and testing the classifiers. In this stage the feature extracted from the desired output was compared with those of actual output of the network for a particular input pattern. The character images were classified as correct recognition, false recognition and recognition failure.

4 Results and Discussion

The simulation tool used for this research is C# programming language, 64bits operating system, 8.00GB RAM and run under Windows 8 Operating system on Hp Pavilion i5-3230M CPU @2.60GHz processor. Experiments were performed with 6200 handwriting character samples for training and the system was tested with 540 character samples. The performance of the system was evaluated based on training time, recognition time and recognition accuracy. Figs. 5 and 6 show the results of feature extraction and recognition process displaying recognition status of characters M and A respectively.

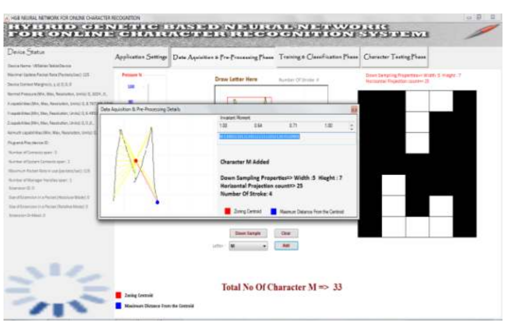

Fig. 5. Features extracted from sample character M

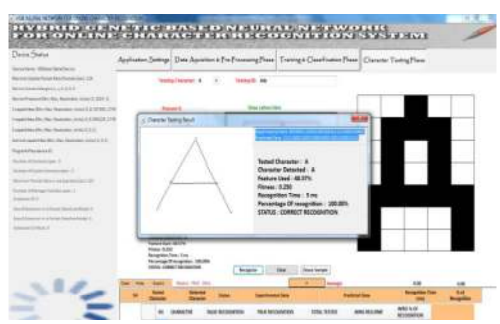

Fig. 6. Result of recognition process displaying recognition status

From Table 4.1 the recognition accuracy at database size 1240 is 97.04% and 99.44% at database size 6200 respectively. The recognition accuracy increases with increase in database size character images. This was due to the heuristic nature of the genetic algorithm and larger character samples in the vector space.

Table 4.1. Average recognition accuracy for various database size using 5 by 7 image size

Database size	Correct recognition	False recognition	Failure recognition	Total no testing images	Average recognition accuracy (%)
1240	524	14	2	540	97.04
2480	526	14	0	540	97.41
3720	530	9	1	540	98.15
4960	532	8	0	540	98.52
6200	537	3	0	540	99.44

From Table 4.2 the recognition accuracy obtained using C1 was 98.5% and the training time per character sample was 73.1 minutes. It can be concluded that the developed C2 is suitable for real-time character recognition considering the minimal training time and recognition accuracy achieved from the experiment. This is due to its stochastic probabilistic nature, ability to achieve feature selection reduction, removal of irrelevant features of character images and the use MGA during the training to solve the problem of local minima in backpropagation. Hence, a significant reduction in the time period was achieved for the weight adjustment of the hidden layer neurons. It also reveals that the less architecture of C2 is highly simplified, less number of mathematical computation operations and prone to recognition error than C1.

Table 4.2. Performance evaluation of the classification accuracies of two classifiers[1]

Character samples	Training time (minutes)	C1			Training time (minutes)	Developed system (C2)		
		CR (%)	FR (%)	RF (%)		CR (%)	FR (%)	RF (%)
1240	0.6	96.3	3.3	0.4	0.3	97.0	2.6	0.4
2480	4.6	96.7	3.1	0.2	3.6	97.4	2.4	0.0
3720	18.1	97.4	2.6	0.0	13.2	98.1	1.7	0.2
4960	38.3	98.2	1.8	0.0	27.7	98.5	1.5	0.0
6200	73.1	98.5	1.5	0.0	55.1	99.4	0.6	0.0

CR - Correct recognition, FR = Failure Recognition and RF = Recognition Failure

Correct recognition is the ratio of the number of correctly recognized images to the total number character images used for testing and vice verse. The result was compared with related works as shown in Table 4.3. The developed online character recognition system (CRS) took less period in training and recognition of characters when compared with existing online CRS. It was shown that the developed C2 achieved a better performance with no recognition failure. The best recognition performance was achieved in C2 because genetic algorithm was used to optimized the MOBP with result of 99.44% recognition accuracy (Table 4.1 and Appendix A). The C2 has better recognition accuracy than C1classifier.

Table 4.3. Performance evaluation of the developed system with related works

Author	Feature used	Method applied	Image used	% accuracy
Ranpreet and Singh [19]	Moments	SGA, BP	Character	91.10
Padhi et al. [18]	Zoning	SBP, SGA	Odia characters	94
Fenwa et al. [16]	Stroke no, counter pixel, projection and zoning	MCPN, MOBP	Characters and digits	99
Developed C2 [23]	Stroke no, projection, moments & zoning	FS, MGA, MOBP	Characters & digits	99.44

5 Conclusion

This research developed a hybrid of structural and statistical features used for extracting features from character images. This was developed to solve the problem of poor feature extraction and selection of online character recognition system. Two classifiers (C1 and C2) were formulated from MGA and MOPB algorithm for overall recognition accuracy. MGA was used as an optimization algorithm for feature selection to reduce the feature space which enhanced recognition accuracy and reduced training time. The results of the experiment revealed that the developed (C2) classifier signified a high performance that produced a robust and reliable online CRS. Future evaluation could be geared towards investigating the performance of other optimization techniques on modified optical backpropagation neural network.

Competing Interests

Authors have declared that no competing interests exist.

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Appendix A

Calculating average recognition accuracy (6200 samples)

SN	Character	False recognition	Recognition failure	Correct recognition	Total tested	AVRG REG. time	AVRG % of recognition
1	**A**	**0**	**0**	**15**	**15**	**100.00 ms**	**100.00%**
2	**B**	**0**	**0**	**15**	**15**	**100.00 ms**	**100.00%**
3	**C**	0	0	15	**15**	95.00 ms	**100.00%**
4	**D**	0	0	15	**15**	110.33 ms	**100.00%**
5	**E**	0	0	15	**15**	100.00 ms	**100.00%**
6	**F**	0	0	15	**15**	100.00 ms	**100.00%**
7	**G**	0	0	15	**15**	94.67 ms	**100.00%**
8	**H**	0	0	15	**15**	167.33 ms	**100.00%**
9	**I**	0	0	15	**15**	100.00 ms	**100.00%**
10	**J**	0	0	15	**15**	152.00 ms	**100.00%**
11	**K**	0	0	15	**15**	105.33 ms	**100.00%**
12	**L**	0	0	15	**15**	99.67 ms	**100.00%**
13	**M**	0	0	15	**15**	84.33 ms	**100.00%**
14	**N**	0	0	15	**15**	95.00 ms	**100.00%**
k15	**O**	1	0	14	**15**	157.00 ms	**93.33%**
16	**P**	0	0	15	**15**	105.33 ms	**100.00%**
17	**Q**	1	0	14	**15**	105.00 ms	**93.33%**
18	**R**	0	0	15	**15**	100.00 ms	**100.00%**
19	**S**	0	0	15	**15**	94.67 ms	**100.00%**
20	**T**	0	0	15	**15**	95.00 ms	**100.00%**
21	**U**	0	0	15	**15**	95.00 ms	**100.00%**
22	**V**	0	0	15	**15**	100.00 ms	**100.00%**
23	**W**	0	0	15	**15**	121.00 ms	**100.00%**
24	**X**	0	0	15	**15**	95.00 ms	**100.00%**
25	**Y**	0	0	15	**15**	121.00 ms	**100.00%**
26	**Z**	0	0	15	**15**	100.00 ms	**100.00%**
27	**1**	0	0	15	**15**	151.67 ms	**100.00%**
28	**2**	0	0	15	**15**	95.00 ms	**100.00%**
29	**3**	0	0	15	**15**	95.00 ms	**100.00%**
30	**4**	0	0	15	**15**	105.00 ms	**100.00%**
31	**5**	0	0	15	**15**	100.00 ms	**100.00%**
32	**6**	0	0	15	**15**	95.00 ms	**100.00%**
33	**7**	0	0	15	**15**	100.00 ms	**100.00%**
34	**8**	0	0	15	**15**	110.33 ms	**100.00%**
35	**9**	0	0	15	**15**	95.00 ms	**100.00%**
36	**0**	1	0	14	**15**	89.67 ms	**93.33%**
							99.44%

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