

A Hybrid Moth-Flame Optimization Technique for Feature Selection in Brain Image Classification and Image Denoising by Improved Log Gabor Filter

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ABSTRACT

In brain image classification, feature set reduction is essential to build an optimised feature subset that will lead to precise measurement. In this paper, an improved technique for feature selection by moth flame optimization with opposition-based learning (OBL) and simulated annealing (OB-MFO-SA) is proposed. The OBL strategy is used to create the optimum initial solution, while simulated annealing improves the search space. The proposed OB-MFO-SA shows improved performance from other well-known existing algorithms by eliminating getting stuck in the local optima. By using this hybrid moth flame optimization, the feature set is reduced to 40%. Also, image denoising is performed by dual tree complex wavelet transform (DTCWT) with an improved Log Gabor filtering technique. The filter bank of Log Gabor filter bank is tuned by genetic algorithm. The selected features from hybrid MFO algorithm are classified using SVM classifier. Experiments reveal that this hybrid algorithm shows more accurate classification outputs than the previous methods.

KEYWORDS

Complex Wavelet Transform, Feature Selection, Hybrid Moth Flame Optimization, Image De-Noising, Log Gabor Filter

INTRODUCTION

In recent image processing methods, de-noising has a major part. De-noising is the method of eliminating noise from the image and preserving all the relevant features of the image. While de-noising the images, the noises get suppressed without affecting the features such as important particulars of edges or textures from the images. Medical images are subjected to noise corruption during transmitting and receiving process. Every analog and digital recorder has noise susceptibility. Medical images are normally affected because of device/detector specifications and environment conditions. Henceforth, lessening of noise remains the same for conventional problem in medical imaging. The foremost objective lies in efficient de-noising of the high noisy dense images, with no additional computational expenses. Gaussian noise may also include salt, pepper and speckle noises. The removal of these noises is necessary for effective feature selection process.

However, de-noising the medical images to get the high quality is the greatest problem these days. The cause for this problem in de-noising of medical images is not unique. So, for effective noise

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removal in medical images, denoising is performed by DTCWT. It is the improved form of discrete wavelet transform and it also contains other important properties (Fan, 2019). The DWT can generate the real and imaginary coefficients if the filters are precisely planned, diverse from other filters (Selesnick et al. 2005). Thus, complex-valued filtering is used in the DT-CWT. The complex signals are disintegrated as real coefficients in the transform domain. It is needed for precisely explaining the energy localization of oscillating performance. Alternate method for implementing an expansive CWT includes the application of Hilbert transform initially. Here, the input and Hilbert transformed data are implemented with real wavelet transform and the wavelet transform coefficients are merged to get CWT. In case of dimensional signal, the redundancy factor of DT-CWT has 2 dimensions and is much smaller than static DWT (Naimi et al. 2015).

The de-noised images undergo segmentation and then the features are extracted. Following this, feature selection is performed to get the best features of images. The feature selection process consists of two methods, wrapper and filter techniques (Zhu et al. 2007). Here, the wrapper technique utilizes the learning process for analyzing the feature subset. But, this wrapper technique is not suitable for high dimensional images because it requires large computation time. Thus, the filter technique is more suitable for the feature selection process since it does not require learning process and the computation time is less.

The objective of selecting the features from the dataset is to improve the functioning of the classifier. It improves the accuracy of the classifier and also provides better result. The classification process becomes faster with feature selection. If the number of features in the image is more, then the size of the search space also increases exponentially. However, it is difficult to use complete search methods to obtain the finest result. Also, the feature selection methods undergo immobility in local optima (Zawbaa et al. 2016). Thus, a hybrid moth flame optimization algorithm is proposed for feature set reduction. MFO algorithm is based on the movement of moth towards the natural light. It is known as transverse orientation. Also for improving the functioning of MFO, the opposition based learning technique is used. Tizhoosh (2006) has proposed the OBL technique which is then utilized for reinforcement learning acceleration. This OBL technique helps the MFO algorithm to obtain the most appropriate features.

This paper is arranged as: Section 2 discusses the methodological background of the proposed method. Section 3 details the proposed framework. The methodology of proposed work is explained in the Section 4. Section 5 details the experimental results. Data validation is given in Section 6. At last, Section 7 concludes the paper.

METHODOLOGICAL BACKGROUND

Image Denoising

Image filtering or noise removal is an essential step in medical image classification as it helps the physicians to analyse accurately. Previously, methods such as Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), Weiner Filters (WF), Auto Enhancement Algorithm (AEA), Fast Fourier Transform (FFT) were used for denoising. However, the performances of these methods are not satisfactory. Techniques like, Kalman Filters, Hessian Based Filters (HBF) were also used, yet they have disadvantages such as differing variance, bad or fluctuating reaction for images of different sizes (Jerman et al. 2016; Pandey et al. 2017).

Gabor filter was also widely used for image filtering by getting localized frequency information of images. Anyhow, as DC component is present in this filter, maintaining wide bandwidth and minimized DC component is difficult. Alternatively, Log Gabor filter leads to improved contrast due to the absence of DC component. Also the transfer function provides spectral information of the image. However the design of filter banks of Log Gabor filter is a tiring process and time consuming (Wang et al. 2009).

As Log Gabor filter covers a certain frequency range. The orientation and information obtained from a single filter is not effective. Filter bank has large coverage in both scale and orientation, hence tuning of filter banks becomes essential. Since it is difficult to design filter bank by manual methods, tuning based on Genetic Algorithm (GA) is used in (Plodpradista et al. 2017).

The present research is the modification of (Naimi et al. 2015), where Wiener filter with DTCWT is implemented to de-noise the images. Here, DT-CWT is applied with wiener filter for Speckle Noise reduction and shrinkage. For de-noising the two dimensional images wiener filter is the good choice. Eventhough it is good at minimising MSE in inverse filtering and noise smoothening process, it has certain demerits because it has some problems when analysing power spectra and also while analysing blur transfer function. Also, it will not be suitable for mixture distributions because the results are mostly blurry and nearly invariant. Hence, to overcome all noises and to obtain better performance, Wiener filter has been replaced by log Gabor filter and the filter bank is tuned by GA. The log filter has been used with DT-CWT for de-noising the medical images. In log Gabor filtering, we can create an image filter at a precise frequency scale and specific orientation.

Image Denoising

Feature selection is a method of choosing best features that will be helpful in building a new feature subset and also results in minimum training time and accurate classification results. Artificial Bee Colony algorithm (ABC) based feature selection of Computer Tomography (CT) images is presented in the paper (Agrawal & Chandra, 2015). Classification results are obtained for both KNN and SVM classifiers. However, biasness in data has an effect in the result.

Hybridising optimal characteristics of different algorithms also results in better performance. A hybrid feature set reduction method for medical image classification is presented in (G et al. 2016). Tolerance Rough Set (TRS) and Firefly Algorithm are combined for feature selection to select distinguishable features of brain tumour. Anyhow, this also gives inaccurate results at certain instances.

A search based algorithm is used for feature selection in (Plodpradista et al. 2017). Moth Flame Optimization, a swarm intelligence optimization algorithm, is a searching method for selecting an optimal feature set. Since it is a search based technique, it has a chance of getting stuck in the local optima. So there is a need for modification in improving the search space of the algorithm. In (Sayed & Sayed, 2018), Moth flame optimization algorithm improved by simulated annealing is presented. The drawback of Moth Flame Optimization is rectified through Simulated Annealing, which has the ability to escape the local optima mechanism. However, it is not a feature selection algorithm. In (Elaziz et al. 2019), opposition based technique generates optimum initial solutions by creating opposite population and Differential Evolution is used for enhancing the exploitation ability. Anyhow, DE has the chances of lingering around the local optimal solutions (Das & Suganthan, 2011). In order to obtain optimal initial population and global optima precisely, OB-MFOA is proposed.

PROPOSED FRAMEWORK

Dual Tree Complex Wavelet Transform

There are many de-noising techniques used for noise removal in case of medical images and one of the typical techniques used in the process of de-noising is the Wavelet shrinkage. DT-CWT is one of the wavelet shrinkage methods and it is a bivariate shrinkage. It is a suitable tool for elimination of electrical noises. This DT-CWT method benefits the translational invariance and improves directionality (Wang et al. 2010). The DT-CWT is the enhancement of discrete wavelet transform proposed by Kingsbury in 1998. DT-CWT has additional properties other than DWT. The DWT has its application in signal processing and fault diagnosis of rotating machinery, but it contains some disadvantages because its shift-variant and the sparse sampling grid in the scale direction can loss some fault information (Hill et al. 2014). Hence, in order to overcome this disadvantage, discrete

wavelet transform is replaced by DT-CWT. The DT-CWT can signify the line singularities and plane singularities more efficiently than DWT (Yang et al. 2014).

To offer enhanced directional resolution and shift invariance, two dimensional DT-CWT is proposed and it is better than the regular discrete wavelet transform. This enhanced directional resolution and shift invariance have provided exceptional outcomes in de-noising, fusion and other image processing applications (Yang et al. 2014). Adelson et al. (2016) acknowledged that splitting of positive and negative frequencies is a necessary condition for human vision based processing. The 2-D wavelet transform is effective in representing the point edges. Anyhow, the optimality feature of images is not present in 2-D wavelet transform due to its inefficiency in representing the line and curve edges (Donoho, 1993; Vetterli, 2001).

Log Gabor Filter

Log Gabor filter (LGF) is a signal processing method which is a modification of Gabor filter. This log Gabor filtering is used for evaluating the frequency characteristic of the data (Gabor, 1946). It has an immense advantage in characterising medical images. In log Gabor filtering, we can create an image filter at a precise frequency scale and specific orientation.

Proposed Filter

Initially, for de-noising the images, DT-CWT and LGF were used in the proposed system. After blurring the images using low pass filter, the blurred images are recovered by using inverse filtering. But for inverse filtering, the additive noises in the images are sensitive. Thus, log Gabor filtering technique is used during de-noising process. The log Gabor filter performs optimal transaction among the inverse filtering and noise smoothening. The log Gabor filter eliminates the additive noise and also inverts the blurring in the images. During this process, the whole mean square error is reduced. This de-noising method gives the linear valuation of the original image.

Moreover, for completely developing log Gabor filtering, many parameters should be handcrafted for every unique problem (Plodpradista et al. 2017). The designing of filter bank requires more time and thus the brute-force search is not achievable. Also, if the dimension of the filter bank is more, the filtering process needs more computation time. Thus, to overcome this problem, the log Gabor filter is tuned with genetic algorithm for effective optimization. By this tuning process, the filter bank's size is reduced and the power of the filter bank is increased. Algorithm 1 details the pseudo code for optimizing Log Gabor filter bank.

```
Algorithm 1. Pseudocode for optimizing Log Gabor filter bank
Input: Image set, Number of genes, Number of chromosomes, Maximum
iterations, mutation rate, crossover rate.
Output: Optimized filter bank
//Optimization of Log Gabor filter bank
    Initialize population
    for n=1: Maximum iterations
        Calculate fitness      (minimization of number of filters
in LGB)
            for k=1:number of chromosomes (Chromosomes = LGF bank
parameters)
                Selection
                Crossover
                Mutation
            end
        Evaluate fitness of new population
        Replace previous population with new
    End
```

Image Segmentation

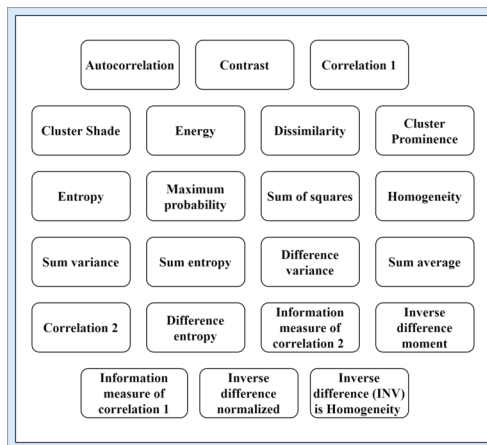
Image segmentation also plays a major part in brain image classification and shows a huge impact on the final output. It is the initial step in image feature extraction. The classification results depend on the features extracted after image segmentation (G et al. 2016). Threshold segmentation is a simple method that performs segmentation by choosing a threshold value (Agrawal & Chandra, 2015). In order to detect the tumour in the brain images, otsu threshold based segmentation and region growing methods were adapted. First of all, skull removal and conversion of image into binary image is performed. While region growing finds the region of interest, otsu thresholding gives acceptable segmentation result even in noisy image.

Feature Extraction

An image consists of numerous features which occupies large space and takes more time. Hence, feature extraction is essential to minimize the data, space and time. The obtained features hold the apt data of the image. These features were used in machine learning to test and train the classifier model. To obtain accurate classification output, representation of texture is essential as it explains the material surfacing. An image consists of both tone and texture.

Texture based feature extraction in images by Gray Level Co-occurrence Matrix (GLCM) was introduced by Harlick (Albertson, 2008). GLCM is the mixture of pixel brightness values present in the image (Thakare, 2013). A co-occurrence matrix is symmetric in nature and has a matrix of dimension N. Here N represents the total number of grey levels in the image. In this work, 22 texture based features are obtained by GLCM. The different features obtained from the brain images (www.kaggle.com) are shown in Figure 1.

Figure 1. Features computed using GLCM

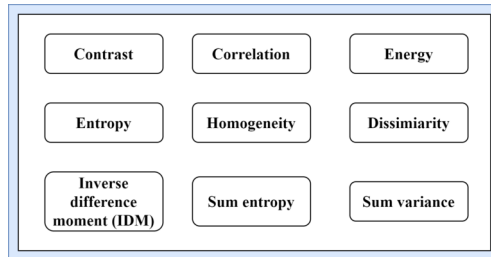


Hybrid Moth Flame Optimization for Feature Selection

By feature selection process, we can remove the noisy, redundant and irrelevant features from the dataset. Thus for better feature selection, an enhanced method is proposed by improving the moth flame optimization algorithm. It is achieved by combining opposition based learning method and simulated annealing with moth flame algorithm. To create the best initial conditions and to improve the search space of MFO, opposition based learning is utilized. Thus, like the conventional MFO

algorithm, the feature selection values do not linger around the local optima in this proposed algorithm. The best features selected from the feature set are presented in Figure 2.

Figure 2. Features selected using hybrid MFO



Initialization Phase

Opposition Based Learning (OBL) is a novel technique developed by Tizhoosh to enable the swarm intelligent optimization algorithms to obtain global optimal solution (Rahnamayan et al. 2008; Zawbaa et al. 2016). The basic concept of OBL method is to create a population opposite to the initial population in order to obtain best solutions. With this technique, the algorithm will be able to skip local positions while searching for best solutions. Based on the fitness function, this technique chooses the appropriate solution. Opposition based learning method is combined with moth flame optimisation in the proposed algorithm. The Equations (1-3) are used to create initial moth population.

$$X = l + (u - l) * rand(n, d) \quad (1)$$

Where, l and u denote lower and upper boundary, n is the solutions and d is the dimension of the solutions. Now, the opposite for the population, X' can be calculated as,

$$X' = u + l - X \quad (2)$$

Conversion of these values into binary values is performed by the equation given below.

$$y = \begin{cases} 1, & \text{if } \frac{1}{1 + e^{-y_i}} > thresh \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

Here, $thresh$ is the threshold which has the value of 0.55. Then the fitness function is evaluated. The objective function of our proposed method is the minimization of classification error.

Updating Phase

Moths update its position according to the flame, using the Equation (4).

$$M_i = d_i * e^{sr} * \cos(2r) + f_j \quad (4)$$

Where M_i indicates moth, d_i denotes the moth to flame distance, s is the shape constant, r generates a random number within a range of -1 and 1, and f is the flame. d_i can be calculated using Equation (5)

$$d_i = abs(M_i - f) \quad (5)$$

In case of Simulated Annealing (SA), the efficiency of finding the global optimum is unsatisfactory, but it is overcome by Moth Flame algorithm, which has the capability to lead the search by using intelligent learning mechanism. SA uses an acceptance mechanism in the updating phase, which decides the updating of the variable with the new value. The decision to select the new value depends on the probability value (Pr). Using this mechanism, the moth is able to attain global optima.

Classification Phase

Features corresponding to the best solution are chosen as the best features and the selected features are evaluated using the classifier. In this process, the classifier is used for ensuring the quality of the feature set. The data need to be partitioned into training and testing data, for which tenfold cross validation is utilized. This splits the data into ten parts. The classifier is trained with these 9 parts and tested with the remaining part. Here, classification is done with SVM. It is a simple classification process. The classification depends upon the trained dataset for feature selection. Initially, a trained model is created using the classifier and this will be used to predict the output of the test dataset. Algorithm 2 details the pseudo code for feature selection using OB-MFOA.

Algorithm 2. Pseudocode for feature selection using OB-MFOA

Input: Number of moth position (N), Maximum iterations (M), Temperature (T), Alpha (alpha)

Output: optimal feature set (F)

// Initialization (OBL strategy)

For i = 1: N

X = random moth position

X` = opposite of random moth position

y=XÈX` //best solution

Evaluate fitness

Find best solution

End

//Updating (SAMFO)

For n=Number of solution

Select new solution = M_{n+1}

If $M_{n+1} < M_n$

Calculate D

$M_{new} =$ Update moth position

Else

Δ Fitness = $M_{n+1} - M_n$

R= random (0,1)

Pr = Set probability

If R < Pr

Calculate D

$M_{new} =$ Update moth

position

```

        Else
             $M_{new} = M_n$ 
        End
    End

    Bound check
    Set T=alpha*T

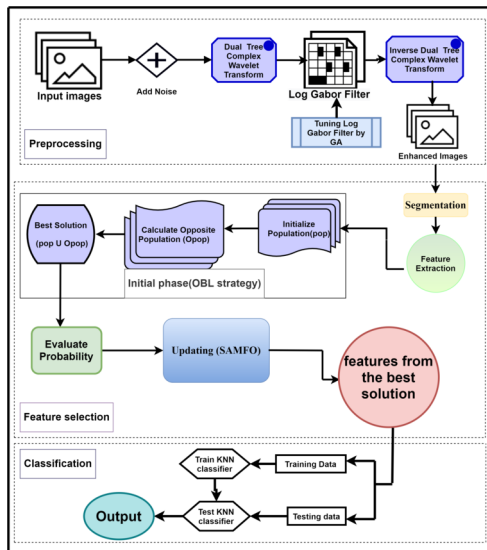
End

// Feature Selection
Features= Select features corresponding to best solution
    
```

METHODOLOGY

Process Description

Figure 3. Flowchart of the proposed system



At first, dual tree complex wavelet transform with log Gabor filtering is performed to remove all kind of noises including speckle noise. Then the image is segmented by otsu thresholding and the features are extracted from the image by GLCM. The hybrid Moth Flame Optimization algorithm is implemented for feature set reduction. After selecting the features for the best solution, the classification process is done. The classification process is carried out using SVM classifier. During the classification process, the classifier is initially trained with the training dataset and with the generated classifier model, testing is performed. This classifier model predicts the output of the test sample.

The detailed work flow of the proposed framework is explained in Figure 3. Initially, the input images are de-noised using the DT-CWT and log Gabor filter. Then the feature selection process is performed in the de-noised images using OB-MFSA algorithm. After selecting the features for the best solution, the classification process is carried out using SVM classifier and after the classification process, the output result is obtained.

EXPERIMENTAL RESULTS

For experimentation, 200 brain images were taken from Brain MRI Images for Brain Tumor Detection (www.kaggle.com). These images were Computed Tomography (CT) images. 100 normal brain images and 100 abnormal images were considered for experimentation. The proposed denoising technique of DTCWT with improved log gabor filtering was applied on these images. The original, noise added and denoised images of normal and abnormal brain images are shown in Figure 4 and Figure 5 respectively.

Figure 4. Normal brain Image (a) Input image (b) Noise added image (c) Denoised image

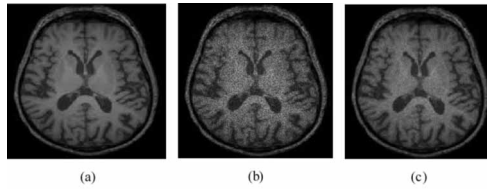
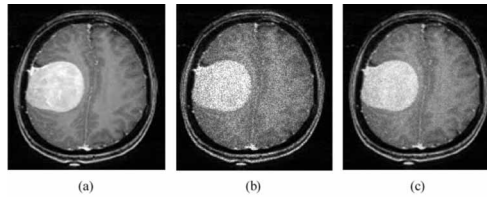


Figure 5. Abnormal brain Image (a) Input image (b) Noise added image (c) Denoised image



Performance Metrics

The parameters used to analyse the functioning of the proposed framework are given in Equations (6-12).

$$Accuracy = \frac{(tp + tn)}{(tp + tn + fp + fn)} \quad (6)$$

$$Precision = \frac{tp}{tp + fp} \quad (7)$$

$$f1score = 2 * Precision * \left(\frac{tp}{(tp + fn)} \right) / \left(\frac{tp}{(tp + fn)} + \frac{tp}{(tp + fp)} \right) \quad (8)$$

$$Kappa = \frac{Accuracy - Expected\ accuracy}{1 - Expected\ Accuracy} \quad (9)$$

Here, expected accuracy can be calculated as:

$$Expected\ Accuracy = \frac{((tp + fn) * (tp + fp)) + ((fp + tn) * (fn + tn))}{(tp + tn + fp + fn)^2} \quad (10)$$

$$Sensitivity = \frac{tp}{tp + fn} \quad (11)$$

$$Specificity = \frac{tn}{fp + tn} \quad (12)$$

Here tp denotes true positive, fp denotes false positive, tn denotes true negative and fn denotes false negative.

The capability of the proposed filtering model is analysed in terms of Peak Signal to Noise Ratio (PSNR), Mean Squared Error (MSE), and Structural Similarity Index (SSIM), which can be calculated using the following equations (13-15).

$$mse = \frac{1}{n} \sum_{x,y} (A_{x,y} - B_{x,y})^2 \quad (13)$$

$$psnr = 10 \log_{10} \frac{(2^n - 1)^2}{\sqrt{mse}} \quad (14)$$

$$ssim = \frac{(2\mu_a\mu_b + D_1)(2\sigma_{ab} + D_2)}{(\mu_a^2 + \mu_b^2 + D_1)(\sigma_a^2 + \sigma_b^2 + D_1)} \quad (15)$$

Here n represents the size of the image, x, y represents the pixel position and A, B denotes the original and noise removed image. μ_a, μ_b indicates the average of original image (A) and denoised image (B), whereas σ_a and σ_b denote the variance of A and B. σ_{ab} is the covariance of A and B, D_1 and D_2 are variables.

Performance Analysis

The proposed method is evaluated in this section. The proposed model is implemented in MATLAB R2018a software. The model parameters used in the proposed technique to analyse the performance of different algorithms in feature selection are given in Table 1.

Table 1. Parameters used in algorithm

| Parameter | Value |
|--------------------------|----------------------------------|
| OB-MFOSA | |
| Search agent | 40 |
| Maximum iterations | 500 |
| Problem Dimension | Equal to feature set's dimension |
| Shape constant (s) | 0.75 |
| Random number (R) | [-1 1] |
| Initial Temperature (T) | 90 |
| Cooling schedule (alpha) | 10 |
| Thresh | 0.55 |
| PSO | |
| Maximum iterations | 500 |
| Weight maximum | 0.9 |
| Number of particles | 40 |
| Weight minimum | 0.2 |
| Constant1 (c1) | 2 |
| Constant2 (c2) | 2 |
| GA | |
| Maximum iterations | 500 |
| Number of chromosomes | 40 |
| Gamma (G) | 0.2 |
| Crossover rate (Cr) | 0.8 |
| Mutation rate (MR) | 0.01 |
| Procreating rate (pCR) | 0.8 |
| ALO | |
| Maximum iterations | 500 |
| Number of search agent | 40 |
| Number of antlions | 20 |

The convergence curve of Genetic Algorithm (GA), Particle Swarm Optimisation (PSO), Ant Lion Optimisation (ALO) and proposed OBMFOSA algorithm is presented in Figure 6. Results reveal the capability of the proposed hybrid MFO algorithm to attain global optima and better convergence rate.

The experimental results are compared with different algorithms like ALO, PSO and GA and from the results of different algorithms, the effectiveness of proposed algorithm is known. The

performances of various algorithms are presented in the Table 2 and Figure 7, 8 and 9. The proposed hybrid MFO based feature selection shows better performance than the other existing techniques.

Figure 6. Convergence curve of different algorithms

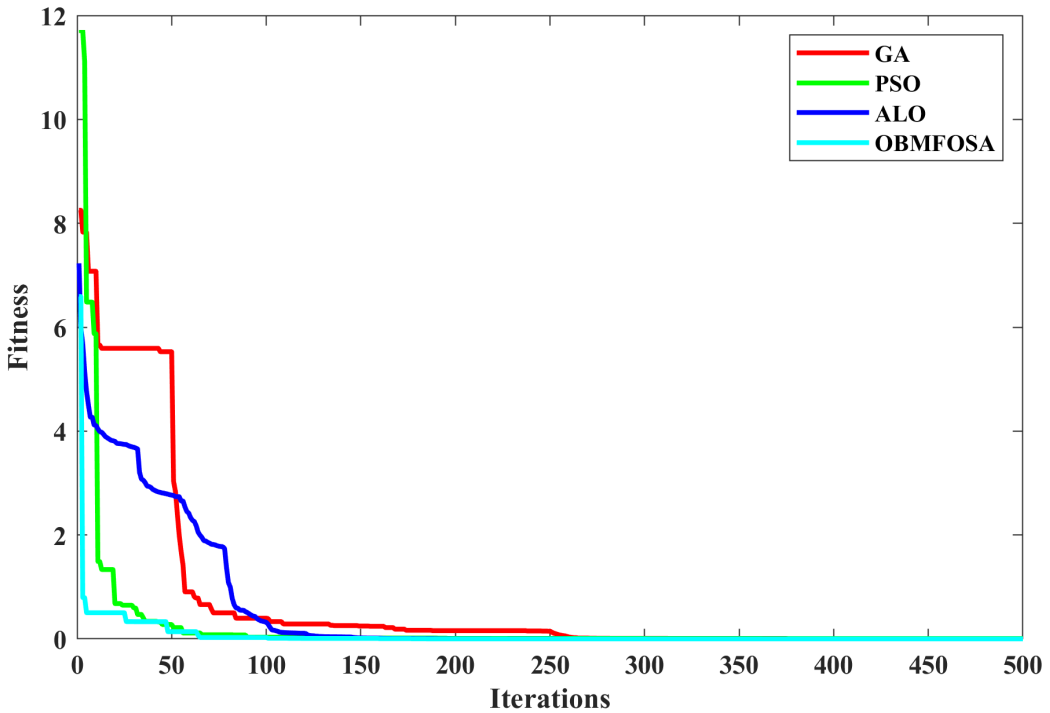


Table 2. Performance of algorithms

| Parameters | OBMFO-KNN | OBMFO-SVM | ALO-KNN | ALO-SVM | PSO-KNN | PSO-SVM | GA-KNN | GA-SVM |
|-------------|-----------|-----------|---------|---------|---------|---------|--------|--------|
| Accuracy | 0.9166 | 1 | 0.7500 | 0.8314 | 0.8333 | 0.8333 | 0.7916 | 0.7284 |
| Precision | 1 | 0.9998 | 1 | 0.8333 | 0.9666 | 0.7500 | 0.8888 | 0.7000 |
| F1 Score | 0.9230 | 0.9952 | 0.8000 | 0.8333 | 0.7324 | 0.8571 | 0.8422 | 0.8235 |
| Kappa | 0.8333 | 0.9954 | 0.5000 | 0.6633 | 0.6624 | 0.6666 | 0.5500 | 0.4370 |
| Sensitivity | 0.8571 | 1 | 0.6666 | 0.8333 | 0.8333 | 1 | 0.8000 | 0.1000 |
| Specificity | 1 | 1 | 1 | 0.8333 | 0.8333 | 0.6666 | 0.5000 | 0.4000 |

Figure 7. Accuracy and precision values

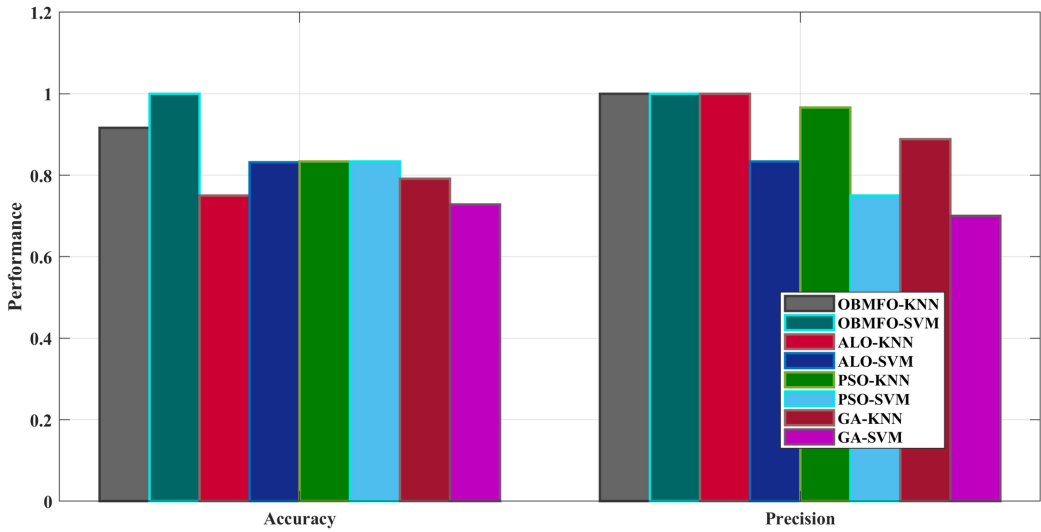


Figure 8. F1 score and kappa values

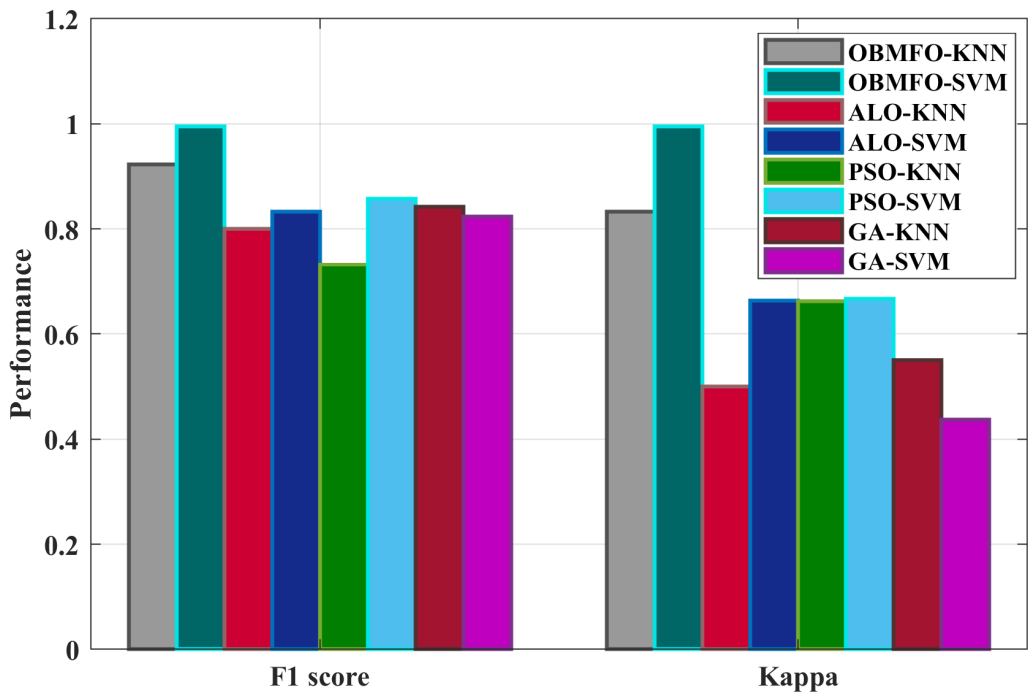
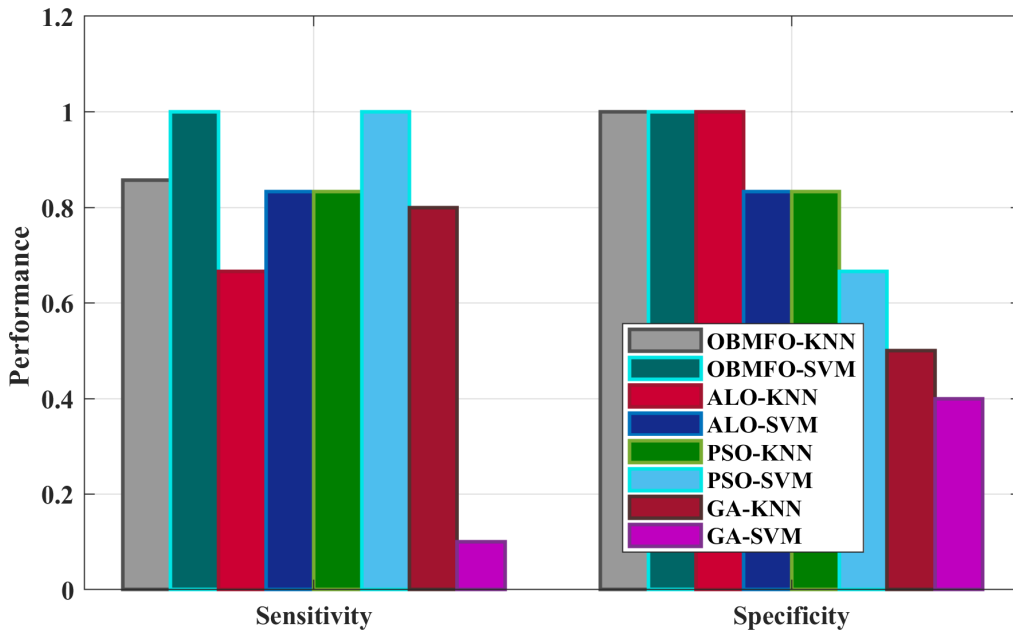


Figure 9. Sensitivity and Specificity for different algorithms

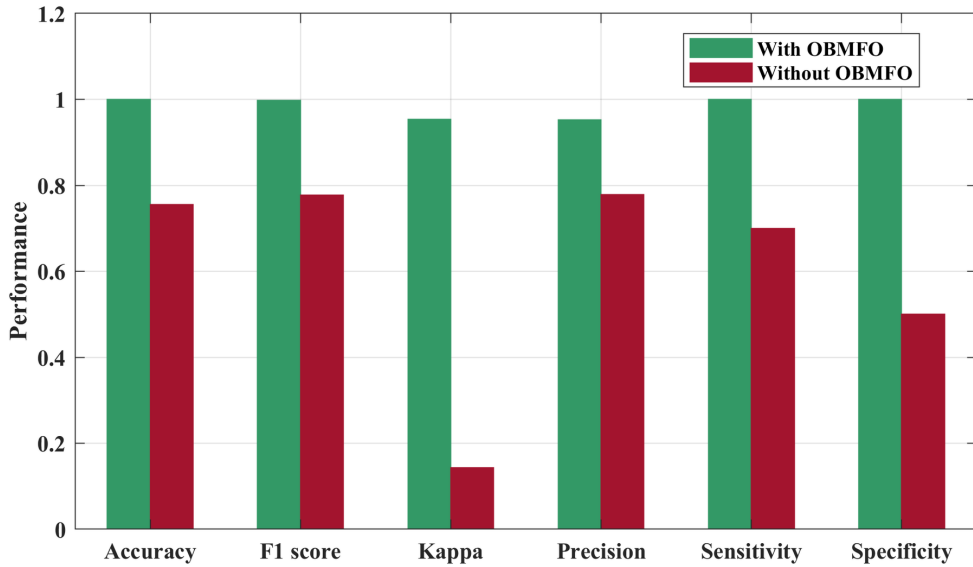


The feature selection process increases the accuracy of the classifier. Here, the parameters are compared with and without feature selection to analyse the difference in the performance of the classifier. The parametric values of the classifier vary based on the feature selection. The comparison process shows that the classifier gives better result with feature selection. The comparison table with and without feature selection is given in Table 3 and Figure 10.

Table 3. Comparison table of performance with and without feature selection

| Parameters | With MFO Feature Selection | Without Feature Selection |
|-------------|----------------------------|---------------------------|
| Accuracy | 1 | 0.755 |
| Precision | 0.9998 | 0.7777 |
| Fmeasure | 0.9952 | 0.7778 |
| Precision | 1 | 0.8755 |
| Kappa | 0.9954 | 0.14285 |
| Sensitivity | 1 | 0.70000 |
| Specificity | 1 | 0.50000 |

Figure 10. Parametric values with and without OBMFO

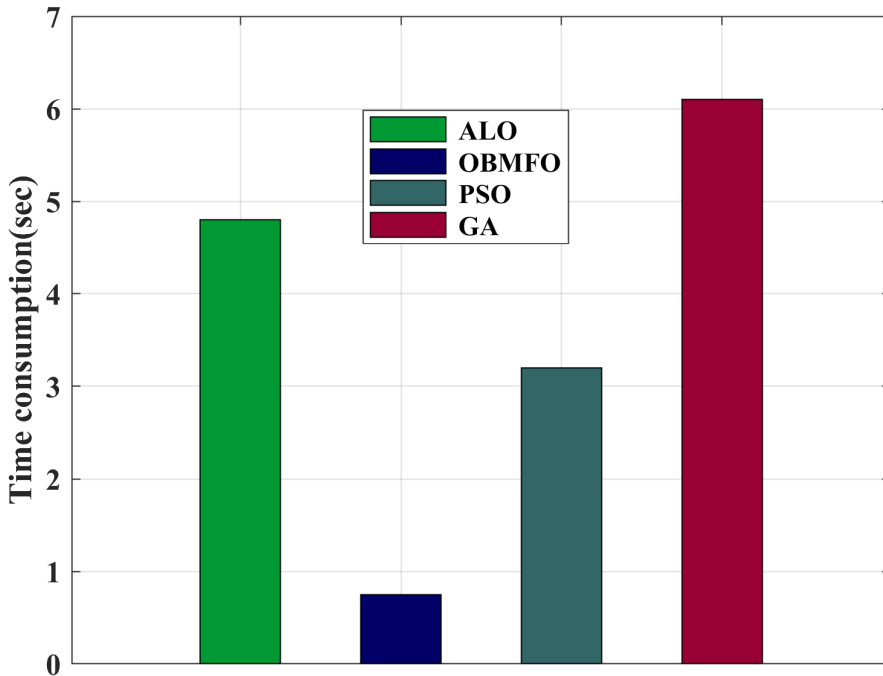


Also, the time consumed for feature extraction by different algorithms such as ALO, PSO and GA are compared with proposed algorithm and preciseness of the proposed algorithm is known. Time consumed for feature selection by various algorithms is given in Table 4 and Figure 11. This shows that the proposed techniques take lesser time than all the existing algorithms.

Table 4. Time consumed by different algorithms

| Algorithm | Time Consumed |
|-----------|---------------|
| OBMFOSA | 0.61841 |
| ALO | 47.0048 |
| PSO | 3.2403 |
| GA | 61.241 |

Figure 11. Para Time consumption of different algorithms



DATA VALIDATION

In the proposed method, the feature selection process is carried out using opposition based moth flame algorithm with Simulated Annealing. The feature selection result is also compared with other relative algorithms like ALO, PSO and GA. A total of 22 texture based features were extracted using GLCM and the best features that can give precise results are selected using feature selection algorithm. The total number of features selected by each algorithm is given in Table 5.

Table 5. Comparison table of different feature selection algorithms

| Algorithm | Features Present | Features Selected |
|-----------|------------------|-------------------|
| OBMFL | 22 | 9 |
| ALO | 22 | 10 |
| PSO | 22 | 5 |
| GA | 22 | 12 |

The de-noising process in the proposed system is performed by DT-CWT with log Gabor filter. In medical image classification, the pre-processing part is also a crucial step as it has a huge impact

on the classification output. The PSNR, MSE and SSIM values for different noise variation are given in Table 6 and Figures 12, 13 and 14. Comparison is made between the output of the proposed technique and the well-known Weiner filter method. Figures 12, 13 and 14 depict that the improved log Gabor filtering method is far superior than the Weiner filter.

Table 6. Noise variation in proposed filter and weiner filter

| Noise variation | 0.02 | 0.04 | 0.05 | 0.06 | 0.08 |
|---------------------|---------|---------|---------|---------|---------|
| PSNR-proposed | 40.0790 | 37.8796 | 35.4437 | 34.6687 | 32.1687 |
| PSNR-Weiner filter | 35.2470 | 34.2140 | 31.5100 | 31.0070 | 28.9650 |
| MSE-proposed | 0.00021 | 0.0002 | 0.0003 | 0.0005 | 0.0006 |
| MSE -Weiner filter | 0.0005 | 0.0007 | 0.0009 | 0.0013 | 0.0015 |
| SSIM-proposed | 0.9404 | 0.9324 | 0.9136 | 0.8868 | 0.8774 |
| SSIM- Weiner filter | 0.8542 | 0.8215 | 0.7854 | 0.7721 | 0.7541 |

Figure 12. PSNR values for proposed method and weiner filter

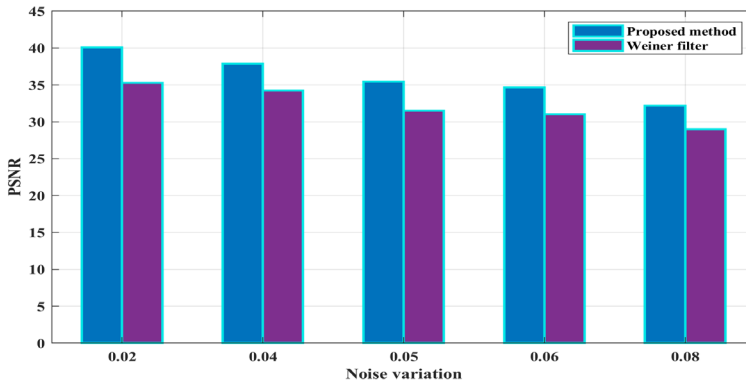


Figure 13. MSE value for proposed method and weiner filter

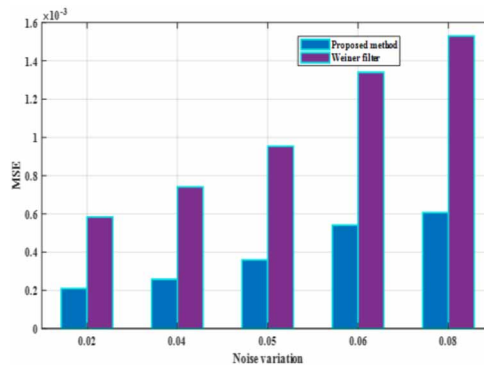
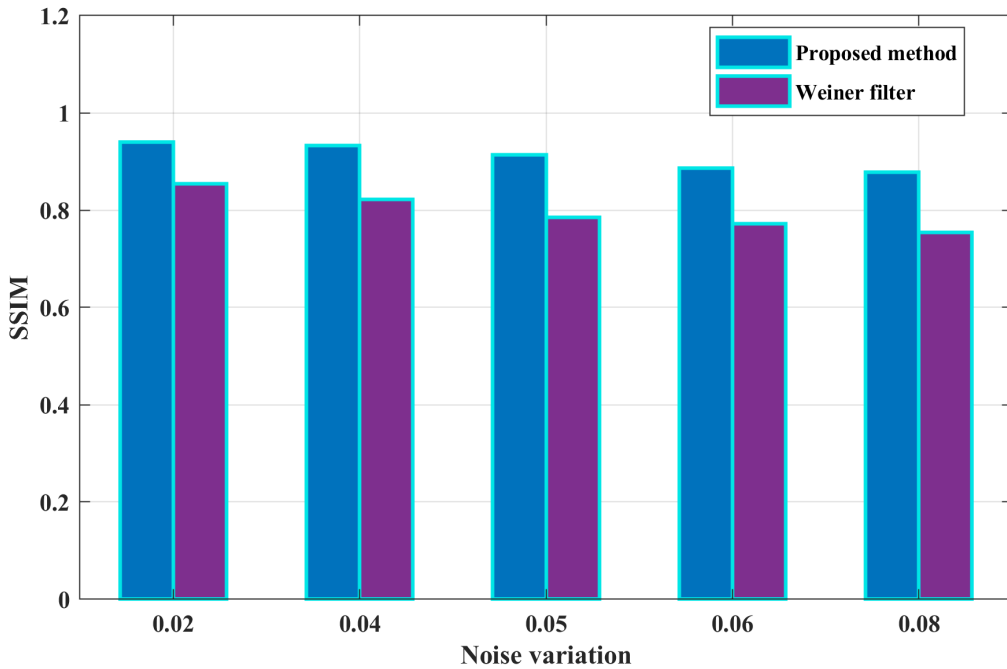


Figure 14. SSIM values for proposed method and weiner filter



CONCLUSION

In this paper, a novel Moth Flame Optimization with Simulated Annealing and OBL technique is presented to obtain better convergence characteristics and to improve the search space. This hybrid moth flame optimization technique takes the advantage of both OBL and SA algorithms: ideal initial population by OBL and escaping the local optima by SA. This also has the capability of fast exploration and learning ability for leading the search (Sayed & Sayed, 2018). Moreover, we compared the proposed algorithm with other existing algorithms to analyse the results of the system. The computation time for the proposed algorithm is also calculated. The result reveals that the proposed hybrid moth flame algorithm is superior to other existing algorithms. For future work, the proposed algorithm can be modified and tested for complex optimization problems.

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