CERTAIN INVESTIGATION ON IMPROVING THE CLASSIFICATION PERFORMANCE OF BRAIN TUMOR IMAGE PROCESSING

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ABSTRACT

In the contemporary world, many dangerous diseases which are affecting human beings and new pandemic disease is also raising alarm to have an effective health care system. In this aspect the technology plays a major role in improving and optimizing the health care system. The technologies are used in health care systems for diagnosis, prognosis, planning of treatment, In recent days, the hyperspectral imaging technique is used in numerous applications like remote sensing, medical images and so on. The reason behind the implementing the hyperspectral imaging is to get more information of the location or region through large number of bands by varying the bandwidth of the image acquisition system. In general, the medical images are captured using the multispectral band which is useful for the first level of diagnosis. But, the deeper analysis of the regions in the medical images the multispectral image is not that much efficient. Hence, to overcome this drawback the hyperspectral imaging technique is introduced in the medical imaging system. It is mainly used in the brain tumour detection. The localization of brain tumour is performed by applying the parallel K-means clustering to the hyperspectral images. The drawback of the parallel K-means clustering is to select the cluster numbers manually and the evaluation is not performed. This Project taken these two things as an objective to propose an automatic approach to detect the number of clusters and to evaluate the performance. In this project, the localization of tumour is detected by using the hybrid approach called moth flame optimization and K-means clustering. The optimization algorithm role is to detect the optimal number of clusters to segment the medical images using K-means clustering. The evaluation of tumour localization is done by calculating the mean absolute error and the peak signal to noise ratio. The results of these works are compared using the performance metrics such as accuracy, sensitivity, specificity and precision. Based on the comparison, the dragonfly optimized FCM and the dragonfly optimized SVM out performs all other models and it gives best results for the classification of MRI brain tumor images.

KeyWords: **Brain tumor, Classification, K-means clustering, FCM, MRI, SVM**

I INTRODUCTION

The medical field has extremely improved from ancient days to recent days. Due to this improvement, the diseases which are considered as untreatable can be healed now a days. Now almost all the diagnostics are done with the engineering and technological equipment.

The diagnostic has to be perfectly done so that proper treatment will be given to the patients. This improvement in medical field technology has cured very dangerous diseases like tumour, cancer, and blood clots at initial stages. These very dangerous diseases are identified with the support of images of the affected region and biopsy. Mostly, the images of the affected region are the first step of diagnosis of the diseases. For this the image processing is used. In this work the Magnetic Resonance Imaging (MRI) is chosen.

Brain tumor is one of the most mortal type of cancer infections. It has its high effects because it is very close to the main neuronal motor of the human being where every small defect can cost a lot. For this reason, it is important to find methods of early detecting or alarming the possibility of the existence of brain tumor. This importance comes from the fact that early detection increases significantly the possibility of curing the disease and saving the life of patients. Recently, the treatments of cancer have greatly developed especially in the early stages of infection. Survival possibilities are very high for those patients receiving early treatments compared to those people who don’t have this chance in the early stages of sickness.

Brain tumor is a mass or accumulation of biological cells in the brain. These cells are classified as abnormal cells that differ from the normal brain cells. These cells grow and increase in size inside the rigid skull that encloses the brain. This growth of the cells mass inside the hard structure of the skull forces the brain cells and causes serious pains and problems. Generally, tumors of the brain or any tumor can be classified into two types of tumor. The first is called benign tumor or noncancerous tumor; whereas the second is very dangerous and cancerous that is said to be malignant tumor. The growth of these two types of tumor inside the skull forces the brain and can be very harmful for life of patient.

Based on the origin of tumor, tumors can also be classified into two categories. These are the primary and secondary tumor. Primary tumor is originated in the brain and generally it is benign tumor type. Secondary tumor or also called metastatic is originated in other body organs like lungs and spread into brain through blood or lymph.

Image processing provides high significant advantages in the medical field. By using image processing techniques, the tumors will be identified in the early stage as well as the location of the tumor. The image processing combined with machine learning algorithms has shown many improvements in the medical image processing and more helpful in diagnosing the disease. Image processing and machine learning have wider applications like surveillance, environment monitoring, military, remote sensing, industrial automation, agriculture, automotive and medical etc.

II LITERATURE REVIEW

Yamany et al. proposed moth flame optimizer (MFO) to train multilayer perceptron (MLP). This algorithm performs better with minimum error and high classification rate compared with algorithms like genetic algorithm, particle swarm optimization, ant colony optimization and evolution strategy for the datasets XOR, iris, heart, breast cancer and balloon.

S.Said et al. proposed the moth flame optimization algorithm to segment the MRI liver images of the abdomen. They used the algorithm to cluster the intensity values of the image. The implementation of this algorithm made the clustering better with average accuracy rate of 95.66%. .

H.Faris et al. proposed the moth flame optimization algorithm in training Radial Basis Function Network (RBF). They used MFO as a global optimizer to find the optimal values for the parameters to minimize the objective (MSE). The datasets they used are blood, heart, breast, Parkinson's, planning relax, diagnosis I and diagnosis II. In all the datasets the MFO gives better performance compared with other meta heuristics algorithms such as GA, PSO and BA. MFO algorithm flexibly handles the problem of local optima stagnation with a reasonable convergence speed when training RBF networks.

M.Ghorbani et al. introduced hybrid firefly algorithm based support vector machines for prediction of soil field capacity and permanent wilting point. They compared the proposed hybrid model with ANN and SVM. Compared with ANN and SVM the hybrid firefly based SVM gives better results with RMSE of 2.402% and relative RMSE (RRMSE) of 7.677%.

Alsmadi et al. proposed a hybrid firefly based fuzzy C-means algorithm to segment the MRI brain tumor images. By hybridizing the FCM with the firefly algorithm, it overcomes the drawbacks of FCM such as low convergence rate, getting stuck in the local minima and vulnerable to initialization sensitivity.

S.Kumar et al. proposed a method for firefly optimization based improved fuzzy clustering for CT/MR images. The proposed optimization yields better results with other optimizations like Cuckoo, artificial bee colony and simulated annealing coupled with FCM. It gives better performance of cluster validity performance metrics to find the optimal number of clusters.

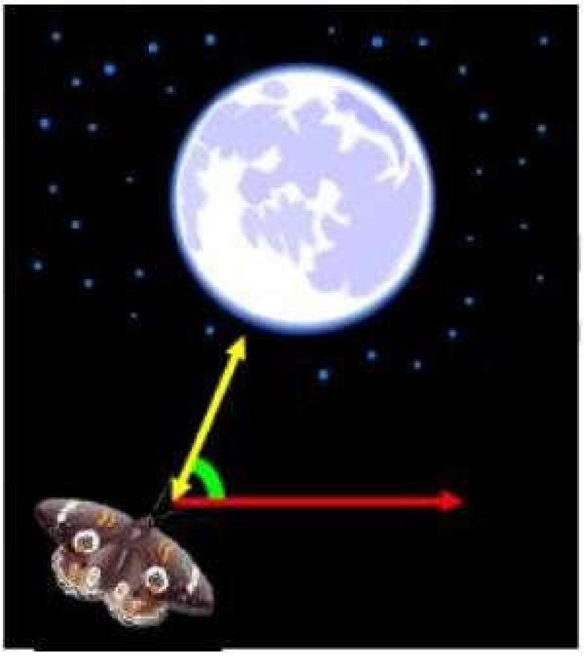
III EXISTING SYSTEM

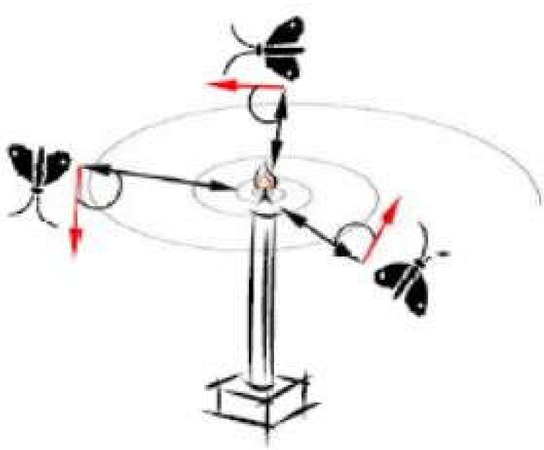
Brain tumor is a mass or accumulation of biological cells in the brain. These cells are classified as abnormal cells that differ from the normal brain cells. These cells grow and increase in size inside the rigid skull that encloses the brain. This growth of the cells mass inside the hard structure of the skull forces the brain cells and causes serious pains and problems. Generally, tumors of the brain or any tumor can be classified into two types of tumor. The first is called benign tumor or noncancerous tumor; whereas the second is very dangerous and cancerous that is said to be malignant tumor. The growth of these two types of tumor inside the skull forces the brain and can be very harmful for life of patient. MRI is non-invasive, cost effective, provides good contrast, has less acquisition time compared with PET and X-RAY. It provides better details of bone structure and organs behind them like lungs and brain beneath the skull.

IV DISADVANTAGES

The methodology for image classifications of brain tumor images are reviewed. It is found that most of the brain tumor image classifications are done in stages, first preprocessing, then clustering, feature extraction and finally classification. The metrics mostly used for calculating the performance of the classification are mainly: accuracy, sensitivity, specificity and precision. In the literature, it is found that the clustering algorithm, artificial neural network and support vector machines performance increases when it is hybridized with any natural inspired algorithms.

V BLOCK DIAGRAM (MOTH FLAME ALGORITHM)





VI PROPOSED METHODOLOGY

Level I
In the level I low level image processing, the input as well as output both will be in image. This process involves operations like image preprocessing to reduce noise, contrast enhancement and image sharpening. Gonzalez.
Level II
In the level II mid-level image processing, the input to the process is image but the output will be in the form of image attributes. It involves segmentation, image description and image classification of individual objects.
Level III
In the level III high level image processing, the input itself an image attribute and output will give the analysis of the particular image field. It involves process that make sense of an ensemble of recognized objects as in image analysis.

the hybrid Moth Flame optimized K-means and FCM clustering with single layer feed forward neural networks are discussed. In order to improve the performance a model is proposed based on the existing work of Arvinder et al. who proposed a new algorithm using hybridization of

K- Means and Firefly Algorithm for anomaly detection. The proposed model uses the neural network classifier. This chapter, discuss about the proposed hybrid Firefly optimized K-means clustering with multilayer feed forward neural network and the proposed hybrid Firefly optimized FCM with multilayer feed forward neural network.

DEVELOPMENT OF MODEL The development model of the hybrid Firefly optimized K-means clustering and multilayer feed forward neural network is depicted in the figure

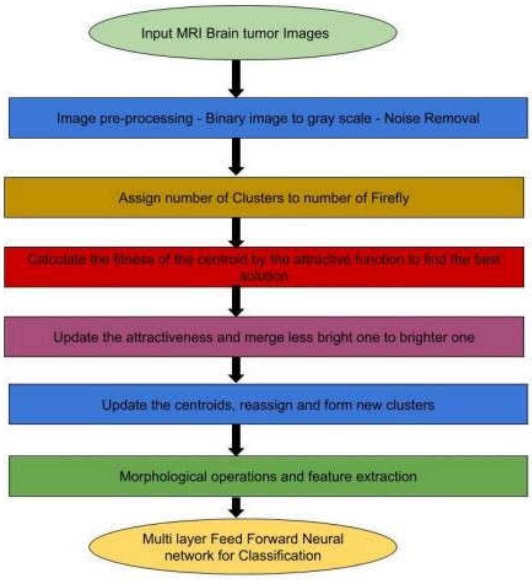


Figure: Development model of the hybrid firefly optimized K-means clustering and neural network

Initially the image pre-processing is done. The binary images are converted to gray scale images. Then the noises are removed by using the Medav filter.

FIREFLY ALGORITHM Firefly Algorithm (FA) was a natural inspired algorithm developed by Xin-She Yang in late 2007 and 2008 at Cambridge University, it was based on the flashing patterns and behaviour of fireflies. FA uses the following three rules:

- Fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex.
- The attractiveness is proportional to the brightness, and they both decrease as their distance increases. Thus for any two flashing fireflies, the less brighter one will move towards the brighter one. If there is no brighter one than a particular firefly, it will move randomly.

HYBRID FIREFLY OPTIMIZED K-MEANS CLUSTERING AND MULTILAYER FEED FORWARD NEURAL NETWORK

1. Initialized the population of fireflies, N, and related parameters.

2. Randomly assigned K clusters for each of the N fireflies.

3. For each firefly, K objects are selected from S data objects as initial centroids, by taking the mean values of the attributes of the objects within their given clusters.

4. Calculated the fitness of the centroid in each firefly, and found the best solution that is represented by the total fitness values of centroid in a firefly.

5. For each firefly, its light intensity is updated according to its fitness value based on equation.

6. For each firefly, its attractiveness is updated by varying the distance r via $e^{-\gamma r^2}$.

7. The fireflies are merged by allowing the less brighter one to be attracted by the brighter one based on equation.

8. The centroids are updated in each firefly according to their latest positions

9. The fireflies are ranked according to the light intensity and the current best is found out.

10. The clusters are reassigned according to the best solution.

11. Output the best cluster configuration that is represented by the firefly that has the greatest fitness.

12. Exit criteria is the total number of iterations.

VII ADVANTAGES

The main objective of the projects is to

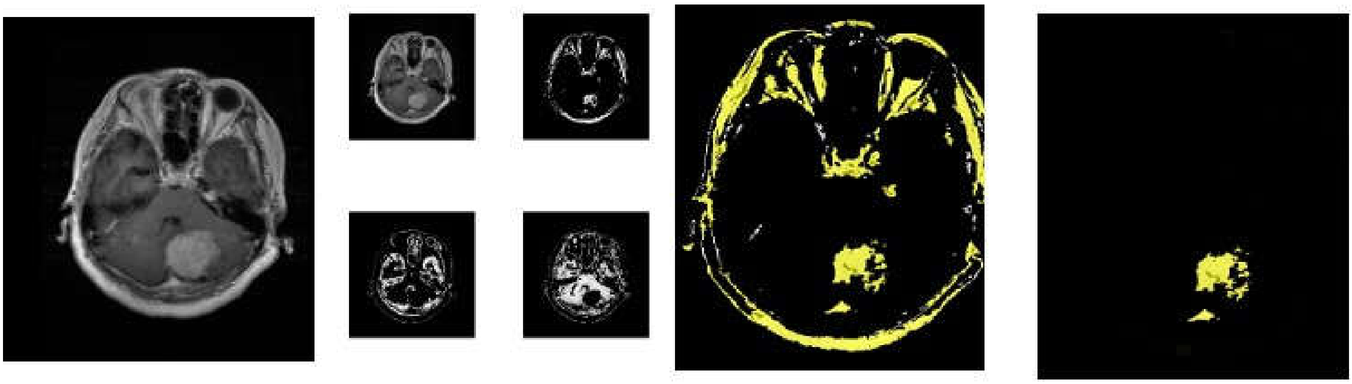
1. To improve the classification performance of the brain tumor images by making hybrid models FCM clustering with Artificial Neural Network (ANN) and Support Vector Machines (SVM) with bio-inspired algorithms.
2. To compare the bio-inspired FCM algorithm performance with ANN and SVM.
3. To Find out the best hybrid model to improve the classification of brain tumor.

VIII APPLICATION

1. Image sharpening and restoration
2. Medical field
3. Remote sensing
4. Transmission and encoding
5. Machine/Robot vision
6. Color processing
7. Pattern recognition
8. Video processing
9. Microscopic Imaging

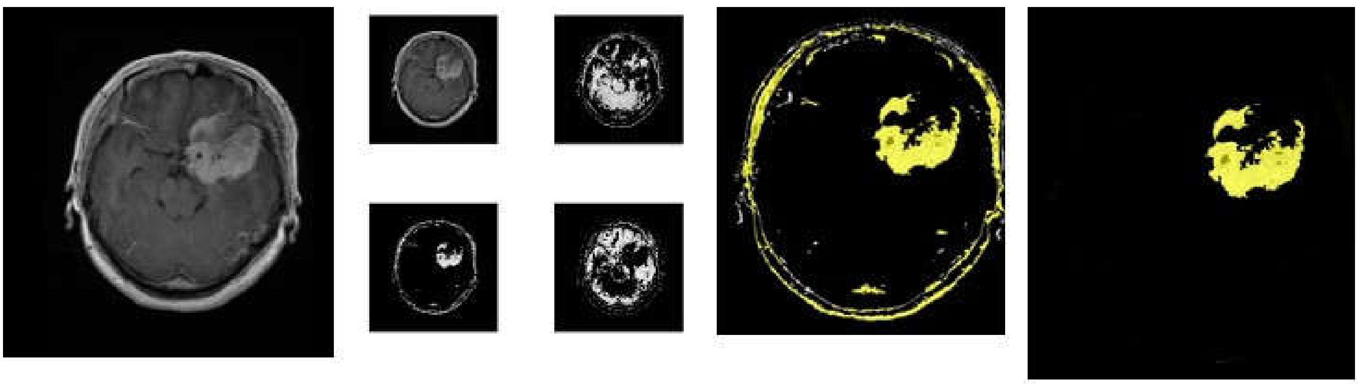
IX RESULTS AND CONCLUSION

In the proposed work, the brain tumor classification is done mainly by two approaches, one with neural network and the other with support vector machines. This classifiers are hybridized with natural inspired meta heuristics algorithms to improve the results. In the approach, the FCM algorithm is hybridized by the meta heuristics algorithm MFO, FA and DFA. The features are extracted from the clustered and it is given to the neural network for classifying as tumor or non - tumor. The classification performance is measured by the parameters: accuracy, sensitivity, specificity, precision and mean absolute error. By comparing the above three hybrid model performance, it is found that the Dragonfly optimized model gives better result compared with MFO and FA algorithm.



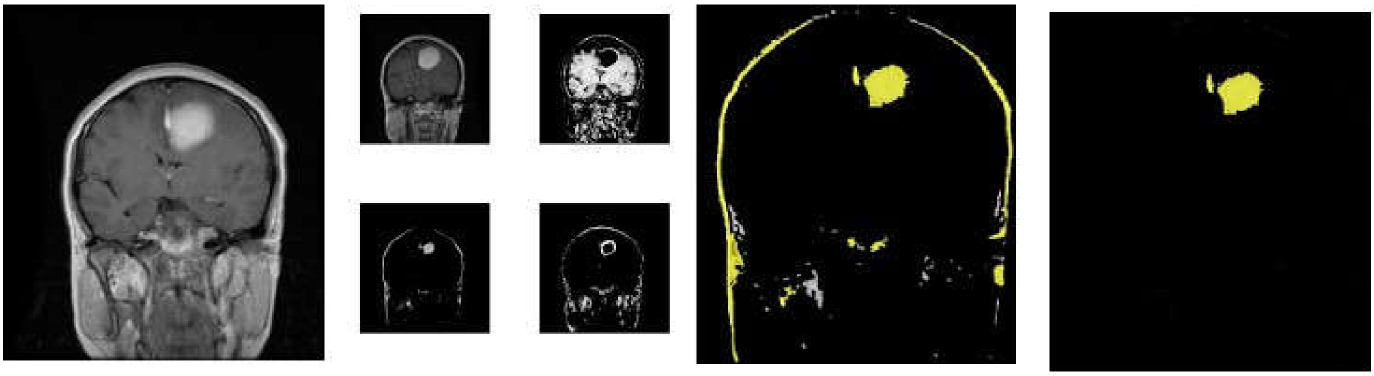
a) Input image b) Clustered output c) Selected cluster output d) Tumor recognition

Figure: Intermediate results of the proposed algorithm for Meningioma tumor



a) Input image b) Clustered output c) Selected cluster output d) Tumor recognition

Figure: Intermediate results of the proposed algorithm for Glioma tumor



a) Input image b) Clustered output c) Selected cluster output d) Tumor recognition

Figure: Intermediate results of the proposed algorithm for Pituitary tumor

Metrics	Moth Flame optimized FCM clustering and single layer feed forward neural network			Moth Flame optimized FCM clustering and hybrid moth flame optimized SVM		
	Meningioma	Glioma	Pituitary	Meningioma	Glioma	Pituitary
Accuracy	92.39%	92.39%	92.39%	96.09%	96.09%	96.09%
Precision	87.26%	90.14%	89.22%	93.30%	94.86%	93.37%
Sensitivity	95.23%	96.60%	96.10%	97.76%	98.15%	98.05%
Specificity	98.11%	97.92%	97.90%	99.06%	99.02%	98.90%

X FUTURE SCOPE

The suggestion for the future work is that the brain tumor MRI images are multispectral images. This can be extended to hyperspectral images by non-linear band dimension expansion method. So that it will have more number of images got from different wavelengths. Therefore, more data will be got for the classification. The spectral data got from this will be more precise and the classification will be the best with higher sensitivity and accuracy.

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