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Optimal Feature Selection-Based Medical Image Classification Using Deep Learning Model in Internet of Medical Things

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ABSTRACT Internet of Medical Things (IoMT) is the collection of medical devices and related applications which link the healthcare IT systems through online computer networks. In the field of diagnosis, medical image classification plays an important role in prediction and early diagnosis of critical diseases. Medical images form an indispensable part of a patient's health record which can be applied to control, handle and treat the diseases. But, classification of images is a challenging task in computer-based diagnostics. In this research article, we have introduced a improved classifier i.e., Optimal Deep Learning (DL) for classification of lung cancer, brain image, and Alzheimer's disease. The researchers proposed the Optimal Feature Selection based Medical Image Classification using DL model by incorporating preprocessing, feature selection and classification. The main goal of the paper is to derive an optimal feature selection model for effective medical image classification. To enhance the performance of the DL classifier, Opposition-based Crow Search (OCS) algorithm is proposed. The OCS algorithm picks the optimal features from pre-processed images, here Multi-texture, grey level features were selected for the analysis. Finally, the optimal features improved the classification result and increased the accuracy, specificity and sensitivity in the diagnosis of medical images. The proposed results were implemented in MATLAB and compared with existing feature selection models and other classification approaches. The proposed model achieved the maximum performance in terms of accuracy, sensitivity and specificity being 95.22%, 86.45 % and 100% for the applied set of images.

INDEX TERMS IoMT, classification, deep learning, medical image, features, Crow search algorithm, optimization.

I. INTRODUCTION

In recent days, medical informatics has become a hot research topic in which Information Technology meets the needs of human healthcare requirements. Many research activities have been conducted in the area of 'investigation of medical images' with the intention of diagnosis as well as clinical studies [1]. The images are retrieved from computer-aided investigation analysis through various imaging systems such as Magnetic Resonance Imaging (MRI), Computer Tomography (CT) scan as well as ultrasound B-scan. To achieve better classification performance, both descriptiveness as well as discriminative power of the extracted features are critical when it comes to image classification problems. This machine learning section is necessary because of its wide range of applications in the field of data mining, forecasting models, recovery of media information, etc.

The medical image databases are used for image classification and for teaching purposes. It frequently contains images with various qualities pictured under diverse conditions,

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along with precision explanation. In medical diagnosis, it is important to recognize the most significant risk factor with disease identification. The fundamental feature of conventional medical image classification algorithms are many, for example, color, texture and shape features. The subset of best feature is given in a way for improving the classification performance or regression model, particularly when managing a high-dimensional feature space by optimization [2]. The optimized representation of the identified feature subset represents new problems. Now, one of the newly proposed swarm intelligence-based algorithms is explained herewith. If the feature extraction algorithm defers a huge number of features, the manual selection of optimal feature becomes critical. Thus, the optimal feature selection is explained to computerize this process. Various researches have been carried out about lung cancer images classification.

The computational complexity is comparatively high and these techniques require clear information about the image structure. Majority of the classification processes find an efficient connection between the membership function [3] and the feature of the object. Moreover, the accurate identification of this fundamental function is highly critical [4]. The proposed work i.e., Deep Neural Network (DNN) is effectively applied to real world classification approaches, for example speech recognition, fault detection, medical diagnosis etc., [5]. It is a subfield of machine realization which utilizes a lot of calculations that endeavor to demonstrate the abnormal state in the present information by utilizing a [6] deep arrangement that has few layers with direct and nonlinear change capacities [7]. Some of the advantages in deep learning model are reduction in the need for feature production and it is deemed to be one of the most time-reducing parts of machine learning approach. In case of huge data and images, it can easily recognize, understand the spoken language, overcome issues and work more efficiently [8].

By using deep learning methods, it is possible to avoid common problems which generally consumes too much of time. Image classification is an important area and poses great challenge for an image to be classified with the medical expert knowledge. The main aim of this paper focuses only on the analysis of miming the medical image classification approach [9].

The authors have introduced an Optimal Feature Selection based Medical Image Classification using Deep Learning model, by incorporating preprocessing, feature selection and classification. The main goal of the article is to derive an optimal feature selection model for effective medical image classification. In order to achieve this goal, a set of Gray-level co-occurrence matrix (GLCM) and Gray-level Run Length Matrix (GLRLM) were used. With the use of texture features like GLCM and GLRLM, the best subset of features are extracted from pre-processed medical images. Traditionally, the extracted features are provided to the classification process. But, in the proposed method, it is not directly given to the classification process since it consumes more computational time to execute. Hence, the optimal feature selection module is preferred where most of the significant features are selected using Opposition-based Crow Search optimization algorithm i.e. OCS. The application of OCS algorithm in the selection of GLCM and GLRLM features show the novelty of current work. Finally, the DL technique was utilized to categorize the given medical image as whether malignant or benign. Besides, the consistent performance of the proposed model was validated against brain, lung, and Alzheimer disease identification and classification processes.

The paper is ordered as follows: Section 2 explains the review of recent literature about medical image processing, section 3 explains the current problems, section 4 provides a brief explanation of methodology, section 5 discusses the implementation result of image classification models, and finally, the conclusion section explains with possible future scope.

II. LITERATURE REVIEW

In 2018, Singh and Singh *et al.* [10] created the engineered medical images with the help of newly proposed deep learning Generative Adversarial Networks (GANs). The classic data expansion was performed by training the Convolutional Neural Network (CNN) whereas the synthetic data expansion and performance comparison were done. The results obtained were 78.6% sensitivity and 88.4% specificity for the classification performance utilizing classic data expansion. By adding the synthetic data expansion, the results got improved by 85.7% sensitivity and 92.4% specificity.

A Computer Aided Diagnosis (CAD) was introduced in the research work by Frid-Adar *et al.* [11] for the categorization of liver ultrasound image. The image features were separated using seven particular surface models to describe the surface of Region of Interest (ROI). The Mutual Information (MI) feature selection strategy was utilized after it was chosen by its exceptional segregation highlights. The proposed CAD framework was able to yield 95.55% precision and affectability of 97.77% with 20 best features chosen by the MI including the determination method.

Sharma *et al.* [12] conducted a research study in which the Firefly Algorithm (FA) was adjusted in selecting the components of characterization as well as regression techniques to support the fundamental forms with the help of data-based learning models. To assess the effectiveness of the proposed FA method, an aggregate of 29 characterizations and 11 relapse benchmark informational indexes were utilized. The proposed FA adjustment offered a proficient strategy to perceive ideal element subsets in classification as well as regression models for supporting the information-based basic leadership forms.

The CT output of lung images was examined with the help of Optimal Deep Neural Network (ODNN) along with Linear Discriminate Analysis (LDA) by Zhang *et al.* [13]. The profoundly highlighted sections were removed from CT lung pictures after which the dimensionality of the feature was reduced using LDR to categorize lung nodules as two types: malignant or benign. In order to recognize the lung malignant growth arrangement, ODNN was connected to CT scans and was upgraded using Modified Gravitational Search Algorithm (MGSA).

To enhance the analysis of Parkinson's ailment, the advanced variant of Crow Search Algorithm was introduced (OCSA) by Lakshmanaprabu *et al.* [14]. The outcomes were against the primary Chaotic Crow Search Algorithm (CCSA) whereas the execution of OCSA was estimated for minimum standard datasets. The proposed nature-motivated calculation found an ideal subset of features from the test result and expanding the exactness and diminishing various features were chosen for further study.

In the research conducted by Gupta *et al.* [15], in the instance of medical data possessing bigger hierarchal connections in the information, the upside of machine learning can be found through algorithms without relentless hand-making features. Lately, the astounding accomplishment of machine learning calculations in image recognition intersects with a period of significantly expanded usage of electronic medical records and image diagnosis.

A deep learning technique was introduced by Ker *et al.* [16] in 2018 to classify the lung images. Here, the dataset utilized was VGG-16 CNN learning design with convolutional channel of (3×3) that was actualized on mammograms' ROIs from IRMA. For the main completely-associated layer, the deep element grid was processed. The outcome shows that 10 folds on SVM was utilized with two-fold trees, straightforward coordination and KNN (with $k = 1, 3, 5$) classifiers. The final result was achieved with 100% classification accuracy with AUC 1.0.

To overcome these problems, novel meta-heuristic optimizer, namely CCSA was proposed by Gardezi *et al.* [17]. The CSCA performance was compared with other known techniques like metaheuristic algorithms. In order to discover an optimal feature subset, to increase the performance of classification and to minimize the number of selected features, the study was conducted and the experimental result was analyzed with the ability of CSCA.

III. PROBLEM IDENTIFICATION

After analyzing the existing literature related to the field of image classification and feature selection, the authors found several issues in the existing classifiers which are detailed as below:

- The explanatory power of ANN is not satisfactory whereas optimization of the network can be challenging, especially in avoiding the overtraining of data
- In case of an SVM classifier, it leads to omissions and misclassification when identifying small and irregular-sized cancers
- Tumor diagnosis is a basic criteria that needs to be met. In imaging test, finding the right tumor part is a mind-blowing test. In addition, the image mining systems are present only to find the exact tumor cells by following numerous techniques.
- Existing feature determination models display challenges i.e., optimization [13], [14] and dimension reduction joining features from various information models [17]. Further, the potential challenges of performing feature selection in little sample estimate situations need to be exhibited.
- By analyzing the existing papers, it was inferred that several researchers took efforts to develop methodologies so as to overcome these challenges. Yet, some specific problems related to optimization algorithm still exist such as high computational time, misdetection because of small size, etc., The motivation to overcome these issues paved the way to propose a new method.

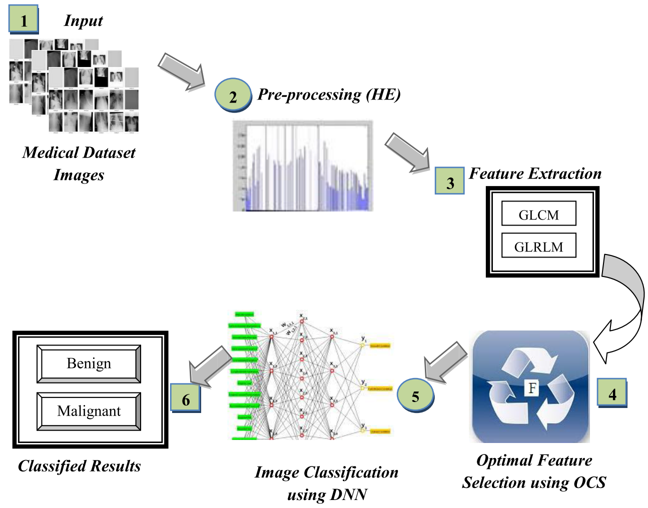


FIGURE 1. The overall process of medical image classification.

IV. METHODOLOGY

In the domain of medical image classification, diagnosing the individual's disease from medical dataset is a promising computation. The current research work considered four datasets for image classification analysis and the main aim is to achieve maximum accuracy in disease prediction. The three datasets considered were brain, lung, breast cancer and Alzheimer's disease. From these datasets, the stages of each patient's image were classified as Benign and Malignant at an early stage by the proposed classification (DL) technique. This medical image classification consists of three stages such as pre-processing, feature selection, and classification. Figure 1 depicts the diagrammatic representation of medical image classification.

- Preprocessing: The purpose of image preprocessing is to get a better quality of images. Here, the histogram equalization is used to enhance the input image quality.
- Optimal Feature Selection (OCS): One of the significant image processing steps is feature selection; this makes the image classification, a simple process.
- Classification: According to the selected best features, it classifies medical images into benign and malignant.

TABLE 1. Features of GLCM and GLRLM.

Feature Description	Features	Description
GLCM (10 features)		
F1	Autocorrelation	It defines the link in an image subdivided by various time durations
F2	Contrast	Contrast is a proportion of variations exhibited in an image.
F3	Correlation	Correlation is a proportion of direct dependency of gray dimensions with adjacent pixels.
F4	Dissimilarity	It calculates the irregularity of the features using Eigenvector
F5	Cluster Prominence	It evaluates the value of asymmetry
F6	Cluster Shade	Determination of skewness of the matrix on the basis of uniformity.
F7	Entropy	Entropy loans denote the surface image and decide the circulation change in an area of the image.
F8	Energy	Entropy is a proportion of turmoil inside a district and is a characteristic trademark to fuse into a division assessment technique.
F9	Homogeneity	It measures the uniformity of non-zero entities
F10	Maximum Probability	Maximum probability describes the combination of its distributive action as well as possible density function of an image.
GLRLM (5 features)		
F11	Gray-Level Nonuniformity (GLN)	GLN determines gray level values of the image.
F12	Run Length Non uniformity (RLN)	RLN measures the length's similitude that is often implemented throughout the image; RLN is acquired when run lengths could not be differentiated in all images.
F13	Run Percentage (RP)	The homogeneity as well as the course of continued running in a specific direction of RP is greatest, if the length is 1 for every dark dimension's explicit way.
F14	Short Run Emphasis (SRE)	The SRE is very dependent on the event of short runs and is normally vast for fine surfaces.
F15	Long Run Emphasis (LRE)	Long Run Emphasis computes the long runs. LRE is based on the event of long runs that are targeted for maximum textures respectively.

A. PRE-PROCESSING

This section consist of Histogram Equalization (HE) which is used to enhance the image quality. This is performed by leveling the image pixel gray-levels in order to reorganize them constantly in the spatial space. The general execution steps of HE [18] is depicted in the figure 1. The histogram of the input image is evaluated, normalized for sum evaluation and at last, the input image is transformed to an output image while the sample HE image is shown in the figure 2 below.

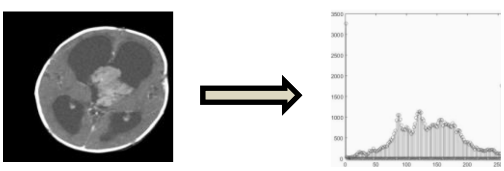


FIGURE 2. HE for medical image.

The HE formula, for transforming an input image into an output image, is depicted in the following equation (1).

$$HE(image) = round\left(\frac{cdf(image) - cdf_{\min}}{(W_{image} \times H_{image}) - cdf_{\min}} \times (G-1)\right) \tag{1}$$

The expansion of equation (1) is: Cumulative Distribution Function of the medical image is abbreviated as cdf, the minimum non-zero value of cdf is represented as $cdf_{\min}$ while W_{image} and H_{image} indicate the image width and height value respectively. The image gray level is denoted as G. Table 1 shows the pre-processing results of the medical image.

B. FEATURE SELECTION MODULE

Feature selection is a dimensionality reduction method used in datasets; it eliminates irrelevant or redundant features from the pre-processed image. The feature selection strategy implies less data transmission. Usually, several feature-extraction models are applied in data mining process. In the proposed study, two techniques were used to extract the desired features i.e., GLCM and GLRLM.

- Gray-level Co-occurrence Matrix (GLCM): It is a measurable technique of examining the texture that considered spatial correlation of pixels in GLCM or else it is also termed as gray-level spatial dependence matrix. The GLCM [19] portrays the ascertaining of the pixel with explicit qualities in a predefined spatial relationship that take place in an image, making it a GLCM. After this process, the factual measures are separated from the matrix. The matrix component $m(a, b|d_1, d_2)$ signifies the proportionate separated by a pixel distance (d1 and d2).
- Gray-level Run Length Matrix (GLRLM): The GLRLM technique is a method for removing higher order statistical texture data. In maximum gray dimensions G, the image is frequently reduced by prior re-quantizing in order to aggregate the network. The features which are

TABLE 2. Performance measures.

Confusion Matrix for Classification		Real Class	Predicted Class C1	Predicted Class C2
		C1	RP: Real Positive	RN: Real Negative
		C2	WP: Wrong Positive	WN: Wrong Negative
Accuracy	$\frac{RP+WN}{RP+WP+RN+WN}$	FPR	$\frac{WP}{WP+RN}$	
Sensitivity	$\frac{RP}{RP+WN}$	FNR	$\frac{WN}{RP+WN}$	
Specificity	$\frac{RN}{RN+WP}$	FDR	$\frac{WP}{RP+WP}$	

isolated with the help of GLRLM and GLCM are listed in the table 1. GLRLM is created as follows:

$$K(\theta) = (r\,(u, v)/\theta), 0 \leq u \leq N_r, \quad 0 \leq v \leq K \max \quad (2)$$

where N_r implies maximum gray level values, K max denotes more length as well as u, v indicate the sizes of the matrix values.

C. OPTIMAL FEATURE SELECTION USING OCS ALGORITHM

By using texture features like GLCM and GLRLM, the best subset of features (i.e. depicted in the tables 2 and 3) were extracted from the pre-processed medical image. The extracted features were not directly provided to the classification process since it consumes more computational time to execute. So, the optimal feature selection module was chosen where most of the significant features are selected using the optimization algorithm i.e. OCS.

1) CROW SEARCH (CS) ALGORITHM

The researchers [20] developed CS algorithm on the assumptions of nature of crow with respect to hiding and grabbing the food. By seeking the crow's nature, the features of CSA is illustrated as follows (a) It is in the form of a flock, (b) it saves food hiding places, (c) for the purpose of stealing, they follow each other along with (d) by probability, and they guard their caches against being pilfered. The original and new positions of the two crows are described in figure 3.

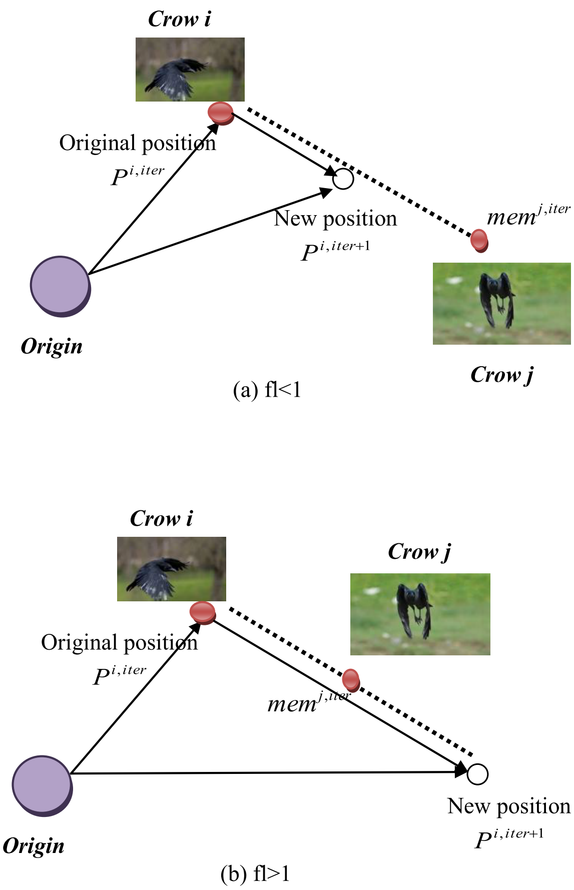


FIGURE 3. Inspiration of CS algorithm.

2) OPPOSITION BASED CS (OCS) ALGORITHM

To develop the efficiency of traditional CS technique, the contrast operation was added. For every initiated solution, the adjacent opposite operation also starts working. If the solutions are compared, better solution can be selected to obtain the optimal solution.

The implementation procedure of OCS algorithm is described in the steps below:

3) INITIALIZATION OF CROW'S POPULATION

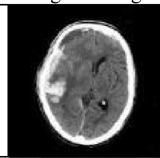
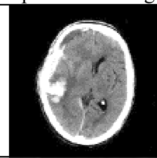
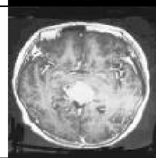
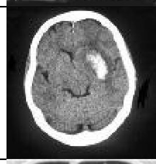
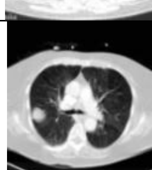
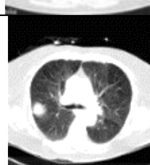
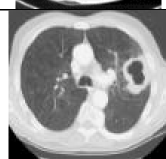
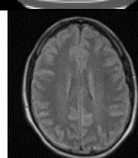
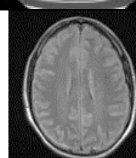
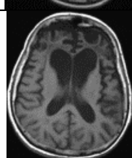
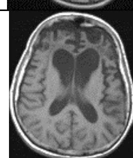
Assign the population of crows (features extracted from the medical image) with respect to F_i whereas the initialized crows (features) are arbitrarily located in a search space.

$$F_i = F_1, F_2, \ldots\ldots.F_n, \quad \text{where } i = 1, 2, 3 \ldots n. \quad (3)$$

4) OPPOSITION PROCESS

Generally, the metaheuristic optimization models start with few initial solutions and try to improve it by simultaneously monitoring the contrast solution. While comparing the solutions, the optimal one could be selected as an initial solution. For example, let $f \in (g, h)$ is a real number. By applying

TABLE 3. Preprocessed results.

Type of Medical image	Original Image	Preprocessed Images
		
Brain		
		
		
Lung image		
		
Alzheimer disease		
		
		

the opposite point definition, it can be written as

$$\tilde{f}_j = g_j + h_j - f_j \tag{4}$$

5) FITNESS EVALUATION

The fitness function of OCS algorithm is calculated on the basis of objective function of the research work. Here, the contribution of optimization is to attain optimal features from the given dataset images.

$$OF_i = MAX\ (Accuracy) \tag{5}$$

6) GENERATE NEW POSITION

Assume a crow to form a novel position in a random manner by choosing one of the flock crows in such a way that the crow 'j' has its own position as well as storage space. The innovative position of the crow $P^{i,\,iter}$ is attained by the following equation (6).

$$P^{i,iter+1} = \begin{cases} P^{i,iter} + r_i \times fl^{i,iter} \times (mem^{j,iter} - P^{i,iter}) \\ \qquad\qquad if\ r_j \geq AP^{j,iter} \\ rand\ P \qquad otherwise \end{cases} \tag{6}$$

The expansion of equation (6) is explained here: r_i and r_j indicate random number of crows i and j respectively, between [0 and 1], $fl^{i,\,iter}$ represents the flight length of crow i, P symbolizes the position of crow, $mem^{j,\,iter}$ denotes the memory location of jth crow and $AP^{j,iter}$ indicates the attentiveness probability of crow j at iteration.

7) MEMORY RENEWAL

The currently upgraded crow's place and memory value are updated with the application of equation (7).

$$mem^{i,iter+1} = \begin{cases} P^{i,iter} & f(P^{j,iter+1}) > f(mem^{j,iter}) \\ mem^{i,iter} & otherwise \end{cases} \tag{7}$$

8) TERMINATION CONDITION OF OCS

It is monitored that the fitness value for the new location of a crow is superlative in sustained position. The crow often updates the storage space by novel position. If more than one iteration is attained, the optimal location of the memory, which corresponds to objective, is addressed as the best solution of filtered set of features. The well-defined patterns of OCS technique are denoted in the figure 4.

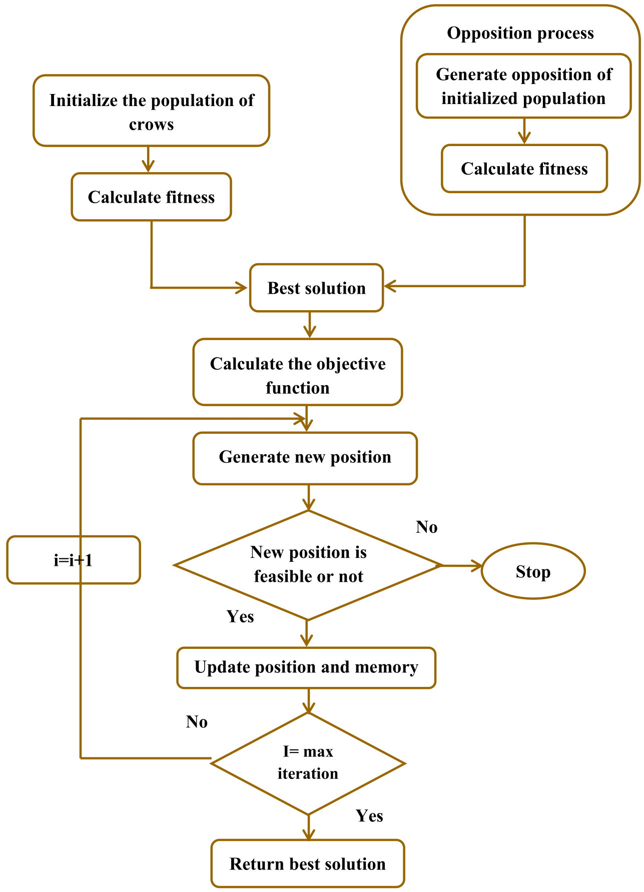


FIGURE 4. Flowchart of OCS algorithm.

D. IMAGE CLASSIFICATION

Followed by optimal feature selection, DL technique was employed to divide the image into two levels:

- Benign
- Malignant

The alleviated feature set was induced for classification method. Hence the accomplished image, including the best features, designs the precision of classification operation while comparing the classification performance of actual images [24]–[26].

1) DEEP LEARNING (DL)

Artificial Neural Network (ANN) strategy is generally modeled using various layers of hidden units as well as outputs which are named as DL. It consists of two levels, namely

- Pre-training
- Fine-tuning stages

a: PRE-TRAINING STAGE

Being a deep structure as well as crucial feed forward network, the Deep Belief Network (DBN) is employed where the instance gets originated from input layer to output layer through maximum number of hidden layers along with additional layers. Based on the application of DBN [13] technique and in accordance to the hidden units which differentiate the network itself, the network produces activation functions.

In addition, Restricted Boltzmann Machine (RBM) is established to resolve the problems of viable activation function production.

2) RESTRICTED BOLTZMANN MACHINE

RBM is a sort of Markov arbitrary domain which consists of single layer of (commonly Bernoulli) stochastic hidden units including a single layer of (ordinarily Bernoulli or Gaussian) stochastic visible units.

Step 1: Initiate the clear units v to train the RBM vector

$$F(v,h) = -\sum_{k=1}^{K}\sum_{l=1}^{L} W_{kl} v_k h_l - \sum_{k=1}^{K} \alpha_k v_k - \sum_{l=1}^{L} \beta_l h_l \tag{8}$$

The expansion of equation (8) is as follows; W_{kl} denotes the symmetric communication among the visible unit v_k and the hidden unit h_l, α, β are the bias terms, K, L are the number of visible and hidden units. The subordinate of the log likelihood of a preparation vector concerning a weight is inconsistently simple. From the hidden units of RBM, there is no sudden response that tends to obtain simple impartial sample from $(V_k, h_l)_{data}$

$$\rho(h_l = 1 \mid v) = \delta\left(\sum_{k=1}^{K} W_{kl} v_k + \alpha_l\right) \tag{9}$$

where $\delta(x)$ is the logistic sigmoid function. $\frac{1}{(1+\exp(x))}$, v_k, h_l is the unbiased sample.

3) UPDATING PROCESS

The hidden unit is updated whereas the visible units are assumed to be concurrent from the provided visible as well as hidden units. It leads to route a complex procedure as follows.

$$\Delta W_{kl} \theta\, (v_k h_l)_{data} - (v_k h_l)_{reconstruction} \tag{10}$$

At this point, RBM undergoes training. A divergent RBM could be stacked across a frame using multilayer technique. Every time, there is a distinct RBM available which is stacked. While the input visible layer is arranged as a vector, the qualities for units, which are efficiently deployed with RBM layers, have been shared with the application of shared models in current weights as well as biases. Hence, the finishing layer, which is trained officially, is locked to be in novel RBM. Therefore, the accomplished DNN weights are filled with fine-tuning phase. The architecture of DL along with n-hidden units are shown in the figure 5.

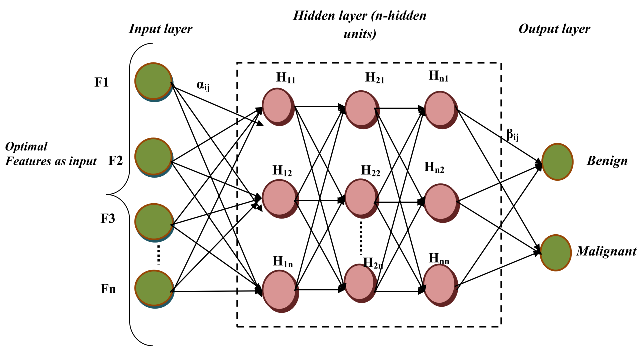


FIGURE 5. Structure of DL.

a: FINE TUNING PHASE

The fine tuning level is performed according to back propagation technique.

In order to segregate the medical images into two stages, output layer is organized from top of DNN. Also, N number of input neurons as well as three hidden layers are applied in DL method. The enhanced weight should be obtained during training phase, along with the help of training data set, in such a way that the back propagation is initialized with the weights that are gained from pre-training level. Finally, using equation (8), the minimum error value was calculated; also the maximum accuracy of DL classification was achieved by the optimized weight. At last, based on this optimal weight (optimal feature sets), the medical images such as brain, lung, breast cancer and Alzheimer were classified as two categories: Benign and Malignant.

V. RESULT ANALYSIS

The proposed medical image classification and the implementation results are discussed in this section. It was simulated in MATLAB 2017a with i7 processor and 4GB RAM. The parameter setting of the proposed model is given here; Number of input nodes: 100, hidden layer 1 node: 50, average activation: 0.5, weight decay is 0.0001, M: 30, upper bound: 1, lower bound: 0 and maximum iteration count: 60. Here multi-medical image database was considered for analysis such as brain, lung, and Alzheimer disease as shown in the figure 6 [21]–[23]. The proposed optimal features, with DL model, were compared with other optimizations and classifiers such as CS [14], FA [12], Support Vector Machine (SVM), CNN [10] and NN with different performance measures as listed in the able 2.

Table 3 explains the pre-processed result using HE. It was performed with three types of medical image databases such as brain, lung and Alzheimer disease. In all the three types of the image database, some of the sample images were taken for pre-processing. First, the original image was taken in which the HE technique was applied as a result of which the pre-processed image is attained. HE is a technique used to enhance the contrast of the image. At the end of this step, a clear medical image was obtained for further processing.

Figure 7 demonstrates the accuracy analysis of various medical images, analyzed with different features. The considered features were F1, F2, F3, F4, F5, F6 etc., whereas the considered algorithms were CS, FA and OCA. For each algorithm, different optimal feature values were obtained. In feature F1, the CS algorithm attained 72%, 65% for FA algorithm and the OCA algorithm attained 79.9% accuracy. In feature F2, 79% was attained for CS algorithm, 75.5% for FA algorithm and the OCA algorithm achieved the maximum accuracy at 90%. Similarly, the entire feature provided various optimal values and the OCS algorithm yielded better accuracy compared to existing algorithms.

Figure 8 explains the feature selection process with various optimization algorithms. In CS algorithm, the number of features was 15 in which the selected features obtained were 10. The number of features for FA was 15 and the selected feature was 13. Here, the number of features was the same for all the algorithms and the selected features were different. In the proposed OCS algorithm, the number of features was 15 and the selected feature was 6.

Table 4 explains the image classification outcome for the proposed DL algorithm. For all pre-processed images, the accuracy (%), sensitivity (%) and specificity (%) were calculated. In this study, nine sample images were considered. Using different medical images, the disease has been predicted as benign or malignant. Here, some of the pre-processed images are shown and the class of such images was predicted to be benign or malignant for all the pre-processed images. The analysis predicted the class as malignant for brain image with 92.23% accuracy, 86.45% sensitivity with 100% specificity for the first image. The first lung image proved to be benign and the predicted class was benign with 91.22% accuracy, 83.1sensitivity and 94.5% specificity. The second and third images were classified to be malignant and the predicted class was benign. In this case, different accuracy values were obtained. In 1stAlzheimer disease,

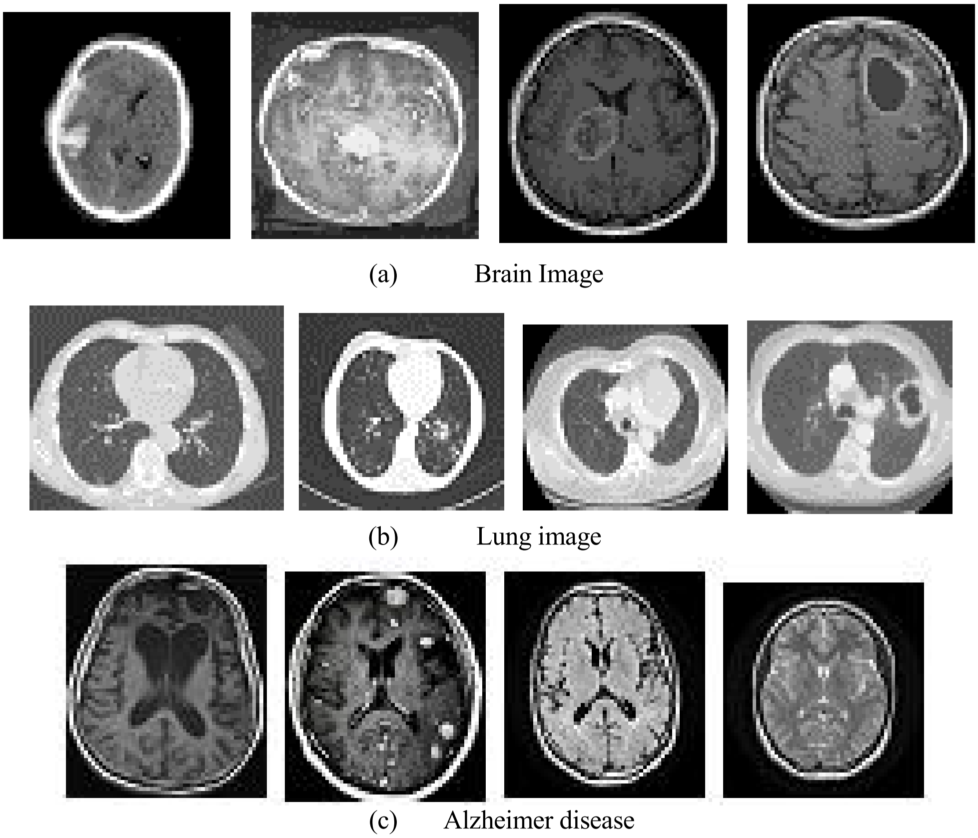


FIGURE 6. Sample database medical images.

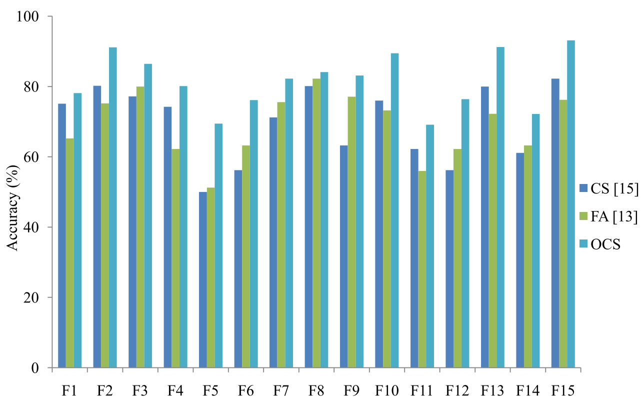


FIGURE 7. Accuracy for feature selection.

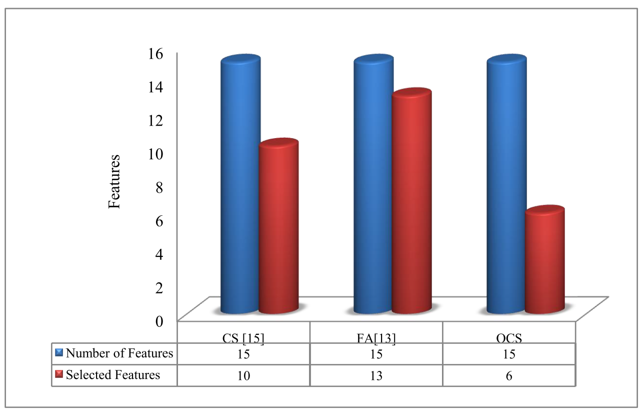


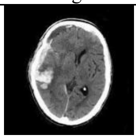
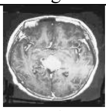
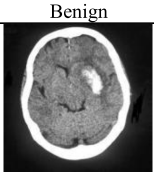
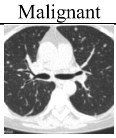
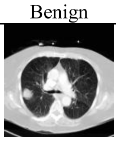
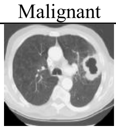
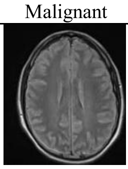
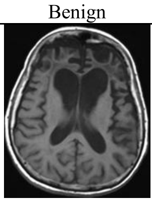
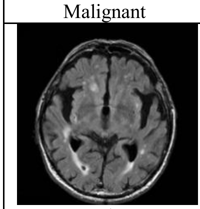
FIGURE 8. Feature selection based Comparison.

the image was benign and the predicted class was benign with 92.22 % accuracy, 86.45% sensitivity and 83.12 specificity. The 2nd image was malignant and the predicted class was malignant with 93.11% accuracy, 79.45% sensitivity and 89.11% specificity. Similarly, the third image was benign and the predicted class was also benign with different accuracy values obtained from the analyses.

Table 5 explains the training and testing result for the proposed (OCS-DL) algorithm. Here, the sample lung images were considered for analysis. The image was trained and the accuracy, specificity, and sensitivity were calculated. The accuracy was 86.2% with 91.22% specificity and sensitivity being 96.12% for 90% training and 10% testing. In case of 80% training and 20% testing, the accuracy obtained was 83.22%, specificity was 85.22% with 51.2% sensitivity. The training image was 70% and the testing image was 30% with 90.1% accuracy, 72.2% specificity and 53.22% sensitivity. The training image was 60% and the testing image was 40%. The accuracy was 69.22% with specificity being 79.2% and 51.2% sensitivity. For 40% training and 60% testing, the accuracy obtained was 56.11%, specificity was 43.4 % and sensitivity was 46.2.2%.

Figure 9 (a) represents the performance analysis for image classifier. The performance was compared with various

TABLE 4. **Proposed (DL) medical image classification results.**

Preprocessed Target Images	Predicted Class	Accuracy (%)	Sensitivity (%)	Specificity (%)
 Malignant	Malignant	92.23	86.45	100
 Benign	Malignant	91.22	82.11	100
 Malignant	Malignant	86.45	79.45	96.45
 Benign	Benign	91.22	83.1	94.5
 Malignant	Benign	86.2	91.22	96.12
 Malignant	Benign	89.77	85.45	86.45
 Benign	Benign	92.22	86.45	83.12
 Malignant	Malignant	93.11	79.45	89.11
 Benign	Benign	94.45	79.45	83.22

algorithms. The compared algorithms were DL, CNN, SVM and NN. The performance is represented in (%). The accuracies obtained for DL, CNN, SVM and NN were 92, 8, 85 and 79. The sensitivity values for DL, CNN, SVM and NN were 83.2, 79, 100 and 60 respectively. For specificity analysis, the respective values for DL, CNN, SSVM and NN were 100, 82, 75 and 90 respectively. Figure 9(b) explains the

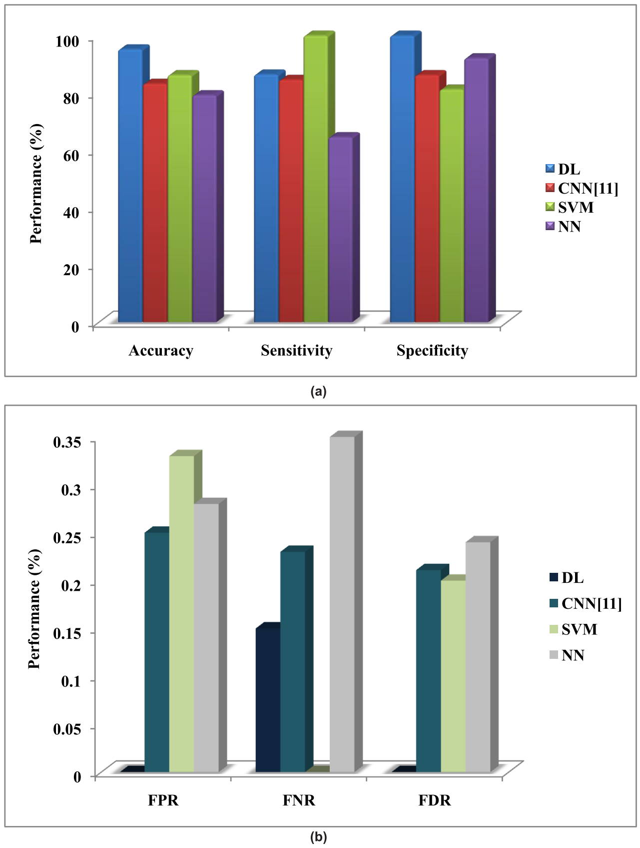


FIGURE 9. **Feature selection based comparison.**

performance measures such as FPR, FNR and FDR. For DL algorithm, the FPR and FDR attained 0, FNR attained 0.14. The FPR value for CNN was 0.23, FNR was 0.23, and FDR was 0.2. For SVM classification, FNR attained the value 0, FPR attained 0.34 and FDR achieved 0.19. Similarly, for NN classification, various performance values were obtained.

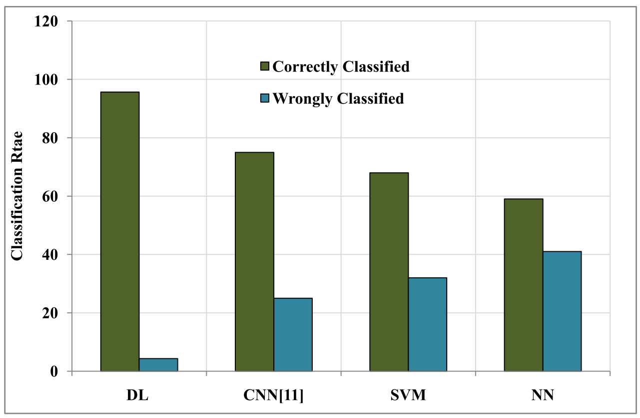
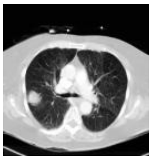


FIGURE 10. **Classification rate analysis.**

Figure 10 demonstrates the classification rate analysis for various medical images. This section discusses whether the image classification was correct or wrong using optimization algorithms and classification techniques. The selected images

TABLE 5. Sample training and testing result for the proposed model.

Sample Image	Training/Testing	OCS-DL		
		Accuracy	Specificity	Sensitivity
	90%-10%	86.2	91.22	96.12
	80%-20%	83.22	85.22	51.2
	70%-30%	90.1	72.2	53.22
	60%-40%	69.22	79.2	51.2
	50%-50%	68.22	62.22	56.4
	40%-60%	56.11	43.4	46.22

were classified correctly using the DL algorithm with classification rate being 89.9% whereas the classification rate for being wrongly classified was 0.3%. In CNN, the image was correctly classified at 68.9% and wrongly classified at 20.12%. In SVM, the classification rate was 60.56% for correctly classified and 20.35% for wrongly classified. The classification rate was 59.9% for correctly classified and 40% as wrongly-classified in case of NN.

VI. CONCLUSION

A novel classification method was proposed to classify the medical images by choosing the best features from the images. Thus, a novel system of clinical image classification was presented on the basis of soft set to accomplish better execution regarding accuracy, precision and computational speed. The performance measures of the proposed DL achieved 95.22% accuracy, 86.45% sensitivity and 100% specificity in DL classifier with optimal features (OCSA) model. The present strategies can be modified by including other measurable features so as to get expanded unwavering quality in the classification of difficult medical images. The technique presented here incurred maximum cost. Though it yielded the optimal result, the precision must be improved under the application of eliminating massive features and prolonging the training dataset. In future investigations, the segmentation systems and some automatic classification techniques should be used to identify the tumor part in medical images and furthermore feature reduction strategy is likewise to be considered.

CONFLICT OF INTEREST

No author expresses any conflict of interest about the publication of this paper.

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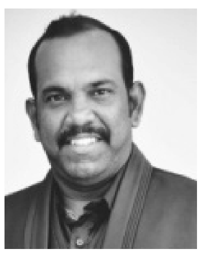

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