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Research Article

Ex-RSFO: Exponential Rider-based Sun Flower Optimization enabled Deep Convolution Neural Network for Image Classification

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Abstract

The collection of large set images is easily obtainable from web pages from huge video datasets. The progression of automatic approaches for handling large amount of images is the most significant one in daily life. However, retrieving and indexing the data is a major challenge in web pages. In addition, automatic organization and indexing of images is also a most important problem. In this paper, Exponential Rider Sun Flower Optimization (exp RSFO)-based Deep Convolution Neural Network (Deep CNN) is developed for image classification. Here, a weighted shape size pattern spectra is employed for extracting the significant features and analysing the patterns. The weighted shape size pattern spectra is considered by adapting weight shape decomposition and gray scale decomposition. Furthermore, Fuzzy Local Information C-Means Clustering (FLICM) technique is applied for clustering process. Besides, Deep Convolution Neural Network (Deep CNN) is utilized for image classification, and the classifier is trained by developed exp RSFO technique. The proposed exp RSFO algorithm is devised by incorporating Rider-based Sun Flower Optimization (RSFO) method and Exponential Weighted Moving Average (EWMA) scheme, whereas RSFO model is the combination of Rider Optimization Algorithm (ROA) and Sun Flower Optimization (SFO) technique. Conversely, the test image is acquired and it is subjected to weighted shape size spectra for feature extraction in testing phase. Here, matching is performed by centroid to identify cluster information, and new cluster vector is generated. Along with this, the performance of the developed approach is evaluated using three metrics, like accuracy, specificity and sensitivity. Hence, the developed technique achieved better accuracy, sensitivity and specificity of 96.21%, 95.22% and 96.20% for 128×128 image size.

Keywords: Image Classification, Deep Learning, Clustering, Sunflower Optimization Algorithm, Fuzzy Local Information C-Means Clustering.

1. Introduction

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Image classification is a major task in security surveillance of large amount of image dataset. Normally, image classification is a task of classifying number of images to different categories using accessible training image. The huge number of images is available in public, such as video datasets, web pages, photo collections and so on [11]. Humans have capacity to classify the images easily than the computers. [12]. The large group of images is easily accessible from web pages to huge video datasets. Here, data retrieval and data indexing is a most important challenge in image classification. The main aim of image processing is to acquire high image quality and high processing speed. The noise may be affect the image, and the noise should be predicted effectively using image denoising technique. The image denoising technique combines the Non-Local Means (NLM) and sparse representation for reducing the Gaussian noise and random valued impulse noise [13]. The digital revolution over the world provides a beam for improvement of techniques for efficient acquirement of images based on several sources. Consequently, various methods are created for efficient storage of the digital images. In more amounts of images, the effectual technologies are essential to identify appropriate images from huge data [14]. Besides, image classification plays a significant task in socio-economic and environmental applications [29]. Additionally, image classification is an essential element of pattern recognition applications, remote sensing and image analysis. Moreover, image classification is major tool for object identification and digital images analysis.

The most important procedure included in image classification is identification of appropriate classification system, collection of training and testing images and classification algorithm. Image classification is performed for extracting important information from an image. The principal intention of image classification is to identify, predict and classify the features in images with respect to class type and so on [15] [9]. Image classification is generally classified into unsupervised and supervised or non-parametric and parametric or per field and pixel field, and soft or hard classification. Generally, supervised classification process is separated into two stages, namely training stage and classification stage [9].Most of the classification techniques are employed using per-pixel information where every pixel is categorized into land cover classes and one group are equally exclusive. Image classification is mostly used in image processing domain, such as video classification, pedestrian tracking, and image quality assessment. The major challenge is fine-grained image classification in computer vision, and it is employed to search appropriate object in huge class of image. Meanwhile, the movement is dissimilar in same class and movement is similar in various sub-classes [16]. The development of automatic approaches to handle large amount of images is very challenging, because the online resources maintains essential source in daily lives. Furthermore, automatic indexing and organization of images is most significant problem in image classification. The deep learning approach has obtained massive popularity in various image classification methods.

Commonly, the Convolutional Neural Networks (CNNs) is very significant in visual recognition tasks, like image classification [18] [1], biological image segmentation [19] [1] and traffic sign recognition [20] [1]. The image classification approaches are categorized into supervised or unsupervised, parametric and non-parametric and hard or soft classifiers [17]. Moreover, most of the image classification approaches uses edge-based methods, statistical-based schemes, Support vector machine (SVM), data mining, feature extraction and neural networks [30]. Additionally, the above mentioned techniques are used for image classification and image identification of related images [14]. The Deep Artificial Neural Network (Deep ANN) is utilized in various existing methods for performing image classification process. The Deep ANN has major attention in machine learning-based challenges in several domain, namely computer vision, social network analysis and machine translation [17]. Moreover, the Deep Neural Network (DNN) has high variance, and low bias because of high capability and flexibility. The techniques, such as Dropout [21] [10], Stochastic depth [22] [10] and Batch Normalization [23] [10] are employed for joining and avoiding degradation and over-fitting problems in image classification. Besides, residual learning [24] [10], Visual Geometry Group (VGG) [25] [10] and Inception [26] [10] are devised for training process of DNN in image classification. Furthermore, seven CNNs are developed for image classification [19]. Apart from this, Multiple Deep CNN is introduced for image localization and classification process. Top-down attention model is also devised based on control gates, region proposal and sequential process in image classification process [10].

The major intention of this research work is to devise an effective image classification approach, named exp RSFO-based DCNN. This method is mainly developed based on two phases, namely training phase and testing phase. The weighted shape size pattern spectra, clustering information-based feature vector, and then image classification is processed in training stage. Initially, input training images are subjected to weighted shape size pattern spectra for analysing the patterns and extracting features. Here, a weighted shape size pattern spectrum is designed by adapting weight shape decomposition and gray scale decomposition. Consequently, clustering process is performed by FLICM approach [31] for clustering the extracted features. After the clustering process, cluster information-based feature vector is executed for grouping the features and cluster information. Finally, image classification is carried out using DCNN classifier [32], which is trained by developed exp RSFO algorithm. Besides, the exp RSFO technique is newly devised by integrating EWMA [35] and RSFO technique. On the other hand, weighted shape size pattern is performed for test images and the extracted features are matched with centroid for finding cluster information. Moreover, new feature vector is generated and it is fed to DCNN classifier for image classification. At last, the classified output is obtained from testing and training phase.

The major contribution of this research paper are enlisted as follows,

- **Proposed exp RSFO-based DCNN approach for image classification:** In this paper, exp RSFO-based DCNN technique is devised for image classification. Moreover, the developed exp RSFO algorithm is the combination of RSFO technique and EWMA scheme. In addition, FLICM process is also utilized for clustering process.

The remaining sections of the paper are arranged as follows: Section 2 elaborates the existing image classification techniques with various challenges and it is considered as the inspiration for this research. The developed exp RSFO-based DCNN approach is explained in section 3, and section 4 displays the output of devised image classification model. Finally, section 5 concludes the research work and provides the future extension idea.

2. Motivation

This section demonstrates the review of existing image classification approaches along with disadvantages, and it provides the motivation for devising a novel image classification method.

2.1 Literature Survey

In this section, existing image classification process is described with their disadvantages. Yanan Sun *et al.* [1] developed Deep CNN technique for image classification process. Initially, the efficient variable length gene encoding scheme was modelled for representing various building blocks. After that, new representation approach was introduced for effectual initializing of connection weights in Deep CNN. The novel fitness estimation technique is developed for speeding up heuristic search with low computational resource. This approach effectively reduces the classification error rate, but this method not included fitness evaluation approaches for effective classification. Jiaqi Zhang *et al.* [2] introduced Deep self-paced residual network for image classification. Initially, 2-dimensional wavelet was employed for obtaining sparse representation and multi scale features. Moreover, self paced learning Deep residual network classifier was introduced for extracting respective characteristics of two satellites. After that, feature level fusion was performed through cascading two feature vectors. This method achieved high classification accuracy, even though the processing speed of this method is low. Jaehwan Lee *et al.* [3] modelled new sparse coding approach for image classification. In this method, input images are transformed to overlapped patches for better classification performance. After the transformation, patch wise weight allocated and obtained optimal weight by single sparse representation. Besides, two step update method was devised to obtain optimal weight. This method obtained better image classification accuracy, but this method not considered label information and other classifiers to estimate the performance. Guoming Gao and Yanfeng Gu [4] devised unsupervised tensorized principal component alignment technique for solving band irregularity, spectral drift and spatial deformation. In this technique, local spatial spectral patch was employed to obtain multi dimensional alignment. Consequently, Mahalanobis distance was used for computing tensor subspace size and moderating computational difficulty. This technique is appropriate in every multi modal circumstances, however this method not operated efficiently inconsistent order data.

Guoqing Li *et al.* [5]developed diagonal kernel CNN for image classification process. The developed method has less parameters and high local receptive fields, which improves the performance of system. Moreover, standard convolutional layers were replaced by various combination of diagonal kernel. This developed method achieved better accuracy and it has less parameter for less accuracy loss. However, this method failed to calculate diagonal kernel with more experiments on various tasks, like semantic segmentation and object detection. Yongsheng Liu *et al.* [6] introduced weakly supervised learning of deep CNN for image classification. Here, graph convolutional network classifier was employed for capturing semantic label co-occurrence in the image. Then, initialization approach was developed for label embedding, and it enables smoother optimization for interrelationship learning. This method utilizes matrix factorization for learning initial label dependency from labels. This technique achieved good classification accuracy, but still this method is not effective for high level computer vision tasks. Guanqun Wei *et al.* [7] devised Center-aligned Domain Adaptation Network (CenterDA) for image classification. This method considered association in information for obtaining discrimination of inter class domain data and compactness of intra class domain data. After that, common class center is introduced for target domain, and source domain with similar class label. The global domain discrepancy of intra class data was computed among target and source domain by center alignment. Furthermore, the intra class domain data was accurately semantic aligned in compacted depiction. Besides, this method effectively reduces semantic misalignment issues. Although, uncertainty analysis was not performed in this technique for selecting accurate labelled target samples. Youngmin Parka *et al.* [8] modelled CNN based Extreme Learning

Machine (ELM) for image classification. This approach was a layer wise training model, and it employs semi-supervised filters and random convolutional filters for improving the performance. In every semi supervised layer, the classifier efficiently solves convex optimization issue using non-linear random projection. This method operates with less human interaction, and it is faster, even though this method not utilized unsupervised learning for stacking, part information and scalable online learning scheme.

2.1. Challenges

The challenges confronted by image classification techniques are described as follows:

- Genetic algorithms [1] are developed for initializing the connection weight in Deep CNN for image classification. Although, this method not considered evolutionary approaches for addressing time dependent data, like video and voice data.
- In [3], sparse coding techniques using collection of image patches is introduced for image classification, but this method not devised weight updating method for better classification process.
- Diagonal-kernel CNN is modelled in [5] for image classification process, however this method not developed customized hardware accelerator to achieve improved accelerating performance.
- The GCN scheme is developed in [6] for image classification, even though this method not included re-training techniques and robust re-localization scheme to solve uncertainty and context of objects problem.
- The CNN architecture with ELM training method is devised for image classification in [8]. However, this approach not considered pseudo-labeling, sampling, normalization and patch model for solving computer vision problems.

3. Image classification based on developed Exponential Rider Sun Flower Optimization-based Deep Convolutional Neural Network

This section elaborates the developed expRSFO-based DCNN for classification of image. Generally, this developed classification model contains training phase and testing phase, also it involves three stages, like weighted shape size spectra, clustering and image classification. Initially, input image is taken from certain dataset and it is given to weighted shape size spectra stage in training phase. Here, the most important features are extracted from input image and the weighted shape size spectra is devised by integration of gray scale decomposition and weight shape decomposition model. Once features are extracted, then clustering is performed using FLICM scheme [31] and feature vector is generated using cluster information. After that, DCNN classifier [32] is used for image classification process and the classifier is trained by developed optimization algorithm. The developed expRSFO technique is the combination of RSFO technique and EWMA model [35], whereas RSFO technique is the integration of ROA [33] and SFO technique [36]. On the other hand, testing phase is employed in which the test image is taken, and it is fed to weighted shape size spectra for extracting features. Subsequently, matching process is executed with centroid for finding cluster information. Meanwhile, new feature vector is produced using the cluster information and it is given to classifier. Finally, the final classified output is obtained using testing image and training image. The schematic diagram of developed expRSFO-based DCNN for image classification is portrayed in figure 1.

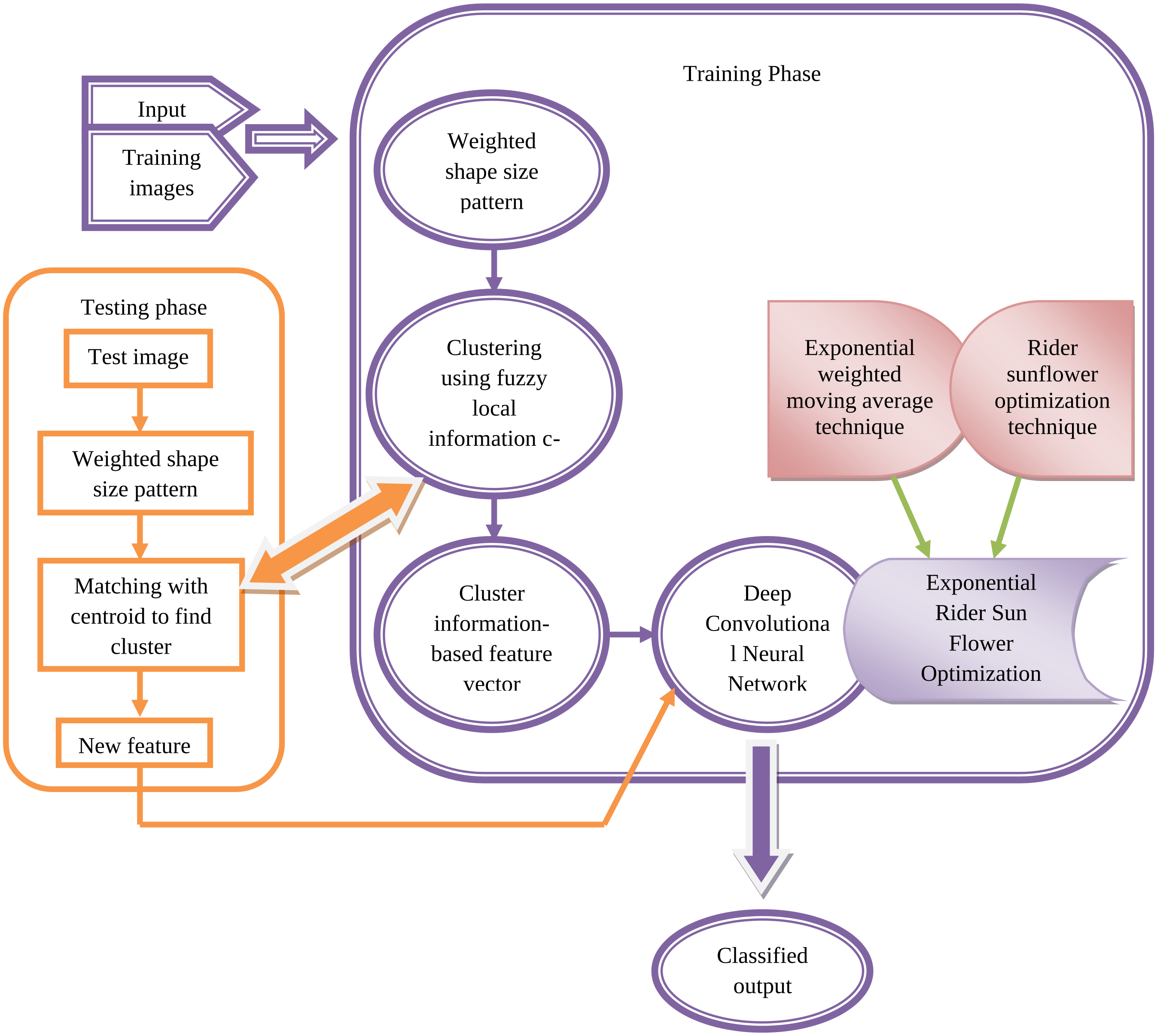


Figure 1. Schematic diagram of developed expRSFO-based DCNN for image classification

3.1 Input image

The training images acquired from several sources are taken as input image for image classification process. Let us consider a training imageand it is denoted as,

$$C = \{Y_1, Y_2, \ldots Y_e, \ldots Y_o\} \quad (1)$$

where, C is the dataset, Y_o represents the total number of images and Y_e indicates the e^{th} image, which is considered as input training image for image classification.

3.2 Weighted Shape-Size Pattern Spectra

After that, the significant features are extracted based on weighted shape size pattern spectra. The weighted shape size pattern spectra are introduced by combining weight shape decomposition [27] and gray scale decomposition [28].

3.2.1 Shape operators

Let us assume the scaling set W through scalar factor $\hat{f} \in XO$, which is indicated as $\hat{f}W$ and it is expressed as,

$$\hat{f}W = \left\{ \bar{e} \in XO^{a} \,\middle|\, \hat{f}\,\bar{e} \in W \right\} \tag{2}$$

Likewise, scaling factor with gray scale image is denoted as,

$$\left(\hat{f}\bar{q}\right)\left(\bar{h}\right) = \bar{q}\left(\hat{f}^{-1}\bar{h}\right) \forall \hat{f}^{-1}\bar{h} \in \hat{D} \tag{3}$$

$$\alpha\left(\hat{f}W\right) = \hat{f}\left(\alpha(W)\right) \text{ or } \lambda\left(\hat{f}\bar{q}\right) = \hat{f}\left(\lambda(\bar{q})\right) \tag{4}$$

where, α is binary operator, and gray scale operator is indicated as λ. The gray scale operator and binary operator are named as scale-invariant, and it is very sensitive to shape rather than size. If an operator is termed as translation invariant, rotation, and scale, then it is shape operator, and if it is idempotent, it is shape filter.

3.2.2 Shape Granulometries

The theory of size granulometries is utilized to define shape granulometries, which are invariant to scale. The shape filter set is defined to size granulometries in order to decrease sensitivity size. The binary shape granulometry is a set of operators α_v with v from completely well-ordered set $\wedge$, which satisfies the following three properties,

$$\alpha_v(W) \subseteq W \tag{5}$$

$$\alpha_v\left(\hat{f}W\right) = \hat{f}\left(\alpha_v(W)\right) \tag{6}$$

$$\alpha_v\left(\alpha_a(W)\right) = \alpha_{\max(v,a)}(W) \tag{7}$$

where, $v, a \in \wedge$ and $\hat{f} < 0$. Hence, shape granulometry includes of operators, which are anti-extensive, idempotent and scale invariant. The granulometries size, translation and rotation are not considered, however expansion of gray level operator is uncomplicated.

3.2.3 Shape Pattern Spectra

The space pattern spectra have the similar process as the size pattern spectra. If v represents shape parameter, W is the binary image, and the shape class of $\bar{h} \in W$ be the least value of v in which $\bar{h} \notin \alpha_v(W)$. The pattern spectra is expressed as,

$$\left(a_{\alpha}(W)\right)\left(\bar{k}\right) = -\left.\frac{\bar{l}\,\sigma\left(\alpha_{v}(W)\right)}{\bar{l}\,v}\right|_{v=\bar{k}} \tag{8}$$

where, shape granulometry is indicated as α_v, and binary image is specified as W. The term σ refers to a measure.

3.2.4 Image Decomposition

The image is decomposed to its constituent elements using shape of gray scale attribute thinning. The gray scale attribute thinning with gray scale decomposition of image is specified by,

$$\alpha_{v}^{\bar{E}}\left(\tau_{\bar{u}}\left(\bar{E}\left(\bar{q}-\alpha_{v}^{\bar{E}}(\bar{q})\right)\right)\right)=\phi \tag{9}$$

The kernel function $\bar{E}$ is introduced in equation (9) for improving the image performance, and $\bar{q}$ is grey scale image. Moreover, image can be reconstructed from pair of grains and it is given by,

$$\bar{q} = y_{\min} + \sum_{y=y_{\min}+1}^{y_{\max}} \sum_{\bar{i}\in \bar{I}_{u}^{q}} \chi\left(\bar{S}_{\bar{i}}^{\varpi_{\bar{u}}(\bar{q})}\right) \tag{10}$$

where, characteristic function is indicated as χ, and the grains is signified as $\bar{S}_{\bar{i}}^{\varpi_{\bar{u}}(\bar{q})}$.The subtraction filter is given by,

$$\bar{R}\left(\bar{q}-\alpha_{v}^{\bar{M}}(\bar{q})\right)=\Pi_{\bar{i}}\exp\left(-\frac{1}{2}\left(\bar{q}-\alpha_{v}^{\bar{M}}(\bar{q})\right)^{\bar{M}}\sum_{\bar{i}}^{-1}\left(\bar{q}-\alpha_{v}^{\bar{M}}(\bar{q})\right)\right) \tag{11}$$

where, $\bar{M}$ denotes logical negation. Moreover, the output of weighted shape size pattern spectra is represented as D_i.

3.3 Clustering using Fuzzy Local Information C-Means Clustering Algorithm

The output of weighted shape size pattern spectra D_i is given to clustering phase for grouping the extracted features. The clustering process is performed using FLICM clustering [31] for the significant extracted features. The FLICM clustering process included the local spatial information and grey level information into its objective function. The FLICM clustering is denoted by,

$$G = \sum_{\bar{s}=1}^{\mathrm{B}} \sum_{\bar{t}=1}^{f} J_{\bar{m}\bar{s}}^{\bar{b}} \left\| P_{\bar{s}} - Q_{\bar{m}} \right\|^{2} + N_{\bar{t}\bar{s}} \tag{12}$$

where, B is the total amount of pixels, $J_{\bar{m}\bar{s}}$ denotes the fuzzy membership of $\bar{s}^{th}$ pixel with regards to $\bar{m}^{th}$ cluster. $P_{\bar{s}}$ signifies the grey scale value of $\bar{s}^{th}$ pixel, $Q_{\bar{m}}$ is the sample value of $\bar{m}^{th}$ cluster $\bar{b}$ is weighting exponent on each fuzzy member and $N_{\bar{t}\bar{s}}$ specifies the fuzzy factor.

The steps of FLICM clustering is illustrates as follows,

Step-1: Locate the fuzzification parameter as $\bar{a}$, number of cluster samples as Q, and stopping circumstance as ϑ.

Step-2: Initialize the fuzzy partition matrix randomly.

Step-3: Fix a loop counter as $l = 0$.

Step-4: Estimate the cluster sample using following equation

$$Q_{\bar{m}} = \frac{\sum_{\bar{s}=1}^{B} J_{\bar{m}\bar{s}}^{\bar{b}} P_{\bar{s}}}{\sum_{\bar{s}=1}^{B} J_{\bar{m}\bar{s}}^{\bar{b}}} \tag{13}$$

Step-5: Calculate membership values using the below equation,

$$J_{\bar{m}\bar{s}} = \frac{1}{\sum_{\bar{c}=1}^{\bar{p}} \left(\frac{\left\| P_{\bar{s}} - Q_{\bar{m}} \right\|^2 + N_{\bar{t}\bar{s}}}{\left\| P_{\bar{s}} - Q_{\bar{m}} \right\|^2 + N_{\bar{t}\bar{s}}} \right)^{\frac{1}{\bar{g}-1}}} \tag{14}$$

Step-6: If $\max\left\{ W^{(\bar{l})} - W^{(\bar{l}+1)} \right\} < \vartheta$, then discontinue the procedure otherwise, locate $\bar{l} = \bar{l} + 1$ and repeat step 4.

The grouped clusters are subjected to cluster information for further classification of image process.

3.4 Cluster information-based new feature vector

The total extracted features are combined and generate a new feature vector for classification process and it is formulated as,

$$F_n = \left\{ F_n^1, F_n^2, \ldots F_n^r \right\} \tag{15}$$

where, the image dimension is represented as $1 \times r$, and total feature dimension is signified as r.

3.5 Image classification using developed Exponential Rider Sun Flower Optimization-based Deep Convolutional Neural Network

In this section, developed exp RSFO-based DCNN technique for image classification is elaborated. Once the new feature vector is produced, then image classification is carried out using developed exp RSFO algorithm. The generated feature vector F_n is fed as the input to DCNN classifier for classification, which is trained using developed exp RSFO algorithm. In addition, the developed optimization algorithm is the combination of RSFO method and EWMA scheme, whereas RSFO technique is the integration of ROA [33] and SFO technique [36]. The EWMA model [35] is employed for identifying small shifts in target processing values. On the other hand, RSFO technique is the combination of SFO technique and ROA. The SFO scheme is a population enabled iterative heuristic global optimization technique for multi-modal issues. The irregular characteristics of sunflowers are used in search space and optimal orientation to the sun is considered for image classification. SFO technique is employed for efficiently search the optimal solution with better accuracy. Furthermore, this technique neglects difficult operations, thus the execution is simple and flexible. The ROA technique mainly consists of rider, follower, attacker and overtaker. ROA mainly depends on new computing technique, named as fictional computing. Moreover, this model fully depends on imaginary ideas and thoughts to decide the winner using success rate of riders. Meanwhile, these RSFO and EWMA model is included together for efficient training of DCNN classifier. The DCNN architecture and the developed optimization technique for training process of classifier is explained as follows.

3.5.1 Structure of Deep Convolutional Neural Network

Generally, DCNN consist of number of convolutional layer, fully connected layer and pooling layer, and every layer is responsible for executing a particular task. The purpose of the convolutional layer is to create feature maps using feature vector A acquired from input data and developed feature maps are sub-sampled based on pooling layer. The major intention of third layer is fully connected layer, and it is used to direct the image classification process. Therefore, convolutional layers are arranged as multilayer loop of kernel weights, input maps and output maps. The quantity of input and output data decreases with consecutive convolutional layers in comparison with first convolutional layer. In addition, the accuracy of image classification depends on quantity of DCNN layers [32]. The DCNN architecture is depicted in figure 2.

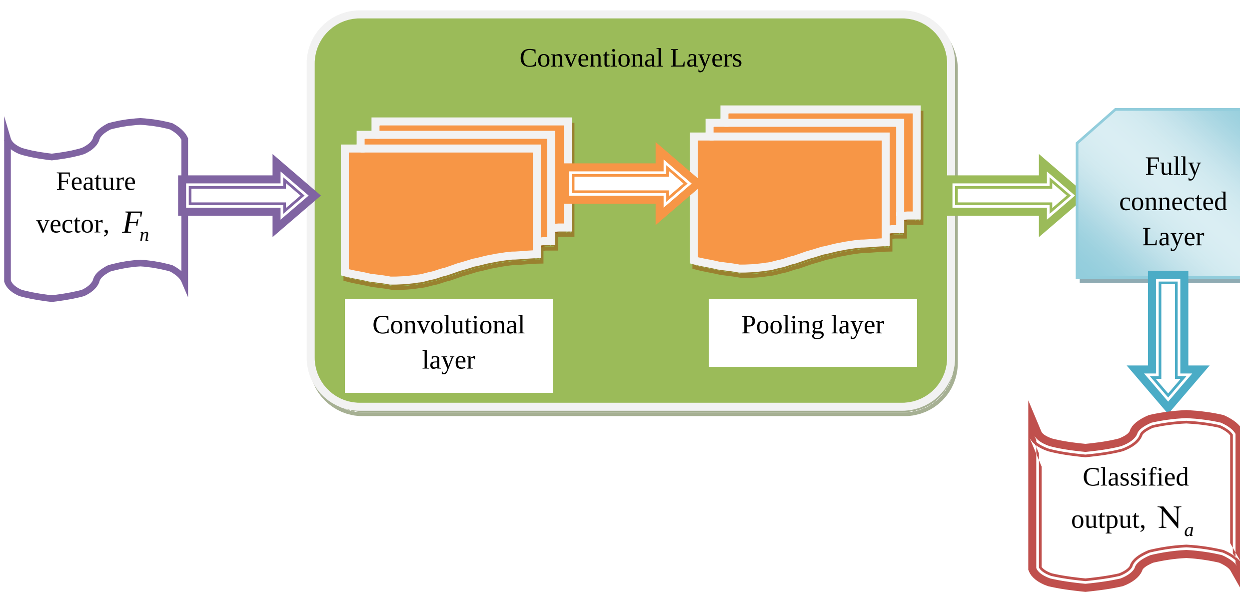


Figure 2. Architecture of DCNN

Convolutional layer:

This layer utilizes the selected features and feature vector obtained from input image for image classification process. The convolutional layer is an interconnection of neurons, which produce the feature map. Furthermore, convolutional neurons from accessible fields connect the neurons using trainable weights. The convolution of input data and trained weights are generated for producing new feature map and the result of convolution is broadcasted by non-linear activation function. The amount of convolutional layer in DCNN is represented as,

$$A = \{A_1, A_2, \ldots A_c, \ldots A_d\} \tag{16}$$

where, d denotes the total amount of convolutional layers, and A_c indicates c^{th} convolutional layer in DCNN. The output of convolutional layer is expressed as,

$$\left(Y_i^c\right)_{x,y} = \left(\mathrm{P}_i^c\right)_{x,y} + \sum_{j=1}^{\mathrm{A}_1^{j-1}} \sum_{k=-d_1^n}^{d_1^n} \sum_{l=-d_2^n}^{d_2^n} \left(\mathrm{T}_{g,h}^c\right)_{k,l} * \left(Y_j^{c-1}\right)_{x+k,y+l} \tag{17}$$

where, $\left(Y_j^{c-1}\right)_{x+k,y+l}$ is the fixed feature maps, A_1^{j-1} signifies total feature maps from previous convolutional layer and $*$ is a convolutional operator. $\left(\mathrm{T}_{g,h}^c\right)_{k,l}$ indicates network weights, which is trained by developed exp RSFO algorithm, and it generates weights of c^{th} convolutional layer.

Pooling layer:

This layer utilizes the activation function to guarantee efficiency and simplicity, when handling huge networks. The output of pooling layer is subjected to feature map, and it is formulated by,

$$Y_i^c = fun\left(Y_i^{c-1}\right) \tag{18}$$

where, $fun(\ )$ specifies the activation function and the pooling layer decreases the difficulty.

Fully connected layers:

In fully connected layer, input is created based on pooling and convolutional layer, and it is fed to high level reasoning. The output of fully connected layer is expressed by,

$$B_i^c = \left(\mathrm{Z}_i^c\right) \text{ with } \mathrm{Z}_i^c = \sum_{j=1}^{\mathrm{A}_1^{j-1}} \sum_{k=d_1^n}^{\mathrm{A}_2^{j-1}} \sum_{l=d_2^n}^{\mathrm{A}_3^{j-1}} \left(\mathrm{X}_{i,j,x,y}^c\right) \cdot \left(Y_i^{c-1}\right)_{x,y} \tag{19}$$

where, $\mathrm{X}_{i,j,x,y}^c$ is the weight connecting (x, y) in j^{th} feature map of layer $c-1$ and i^{th} element in c^{th} layer. The weights are optimally tuned by developed exp RSFO technique, and it is indicated as, $\mathrm{I} \in \mathrm{P}, \mathrm{T}, \mathrm{X}$. The classified output from DCNN classifier is represented as N_a.

3.5.2 Training process of DCNN using Exponential Rider Sun Flower Optimization algorithm

The image classification is carried out using DCNN classifier, which is trained using developed exp RSFO algorithm. The developed exp RSFO technique is devised by including EWMA model and RSFO technique, and RSFO is the combination of ROA and SFO technique. The algorithmic process of developed exp RSFO algorithm is described as below.

a) Population initialization: Let us assume F be the total amount of flowers in biological process of reproduction and it is expressed as,

$$F = \{U, ..., \alpha - 1, \alpha, \alpha + 1, ...V\} \tag{20}$$

where, sunflower between plant group is indicated as α .

b) Fitness function computation: The fitness function is computed for finding the optimal solution for image classification process. The minimum value of objective function represents the better solution, thus solution with minimal error value is selected as better solution. The error value is estimated by,

$$MSE = \frac{1}{\mathrm{K}}\left[\sum_{r=1}^{\mathrm{K}} \mathrm{M}_{target} - \mathrm{N}_a\right] \tag{21}$$

where, M_{target} and N_a are the target and estimated output of classifier.

c) Orient the plant to sun: The plant is adjusted towards the sun to obtain total amount of radiation, and orientation vector signifies sunflower direction towards sun. Hence, orientation vector is formulated as,

$$\vec{\mathrm{E}}_\alpha = \frac{\mathrm{O}^* - \mathrm{O}_\alpha}{\left\|\mathrm{O}^* - \mathrm{O}_\alpha\right\|} \quad ;b = 1,2,...\mathrm{H} \tag{22}$$

where, sunflower direction to the sun is specified as $\vec{\mathrm{E}}_\alpha$.

d) Computation of new plantation: The plants, which are near to sun gets simpler steps to search local refinement, while more distance plants shift usually. The new plantation is formulated as follows.

The updated equation of RSFO algorithm is given as below,

$$F_{m+1}^D = \frac{w_{u,v}}{w_{u,v} - \left\|F^H(H,v) - F_m(u,v)\right\|\left(1+\cos\left(S_{u,v}^m\right)\right)}\left[\begin{array}{l} F_m(u,v)\left(1+\cos\left(S_{u,v}^m\right)\right)\dfrac{\left\|F^H(u,v) - F_m(u,v)\right\|}{w_{u,v}} \\ + F_m(u,v)\left(1+\cos\left(S_{u,v}^m\right)\right) + t_p^q \end{array}\right] \tag{23}$$

Moreover, the updated equation of EWMA is expressed by,

$$F_m^R = \lambda F_m(u,v) + (1-\lambda)F_{m-1}^R(u,v) \tag{24}$$

$$\lambda F_m(u,v) = F_m^R(u,v) - (1-\lambda)F_{m-1}^R(u,v) \tag{25}$$

$$F_m(u,v) = \frac{1}{\lambda}\left[F_m^R(u,v) - (1-\lambda)F_{m-1}^R(u,v)\right] \tag{26}$$

Rearranging equation (23),

$$F_{m+1}^D = \frac{w_{u,v}}{w_{u,v} - \left\|F^H(H,v) - F_m(u,v)\right\|\left(1+\cos\left(S_{u,v}^m\right)\right)}\left[\begin{array}{l} F_m(u,v)\left(1+\cos\left(S_{u,v}^m\right)\right) \\ \left\{\frac{\left\|F^H(H,v) - F_m(u,v)\right\|}{w_{u,v}} + 1\right\} + t_p^q \end{array}\right] \tag{27}$$

Substitute equation (27) in (26),

$$F_{m+1}^D = \frac{w_{u,v}}{w_{u,v} - \left\|F^H(H,v) - F_m(u,v)\right\|\left(1+\cos\left(S_{u,v}^m\right)\right)}\left[\begin{array}{l} \frac{1}{\lambda}\left(F_m^R(u,v) - (1-\lambda)F_{m-1}^R(u,v)\right)\left(1+\cos\left(S_{u,v}^m\right)\right) \\ \left\{\frac{\left\|F^H(H,v) - F_m(u,v)\right\|}{w_{u,v}}\right\} + t_p^q \end{array}\right] \tag{28}$$

where, $w_{u,v} = \eta Z_u\left(\left\|F(u,v) + F(u-1,v)\right\| \times \left\|F(u,v) + F(u-1,v)\right\|\right)$, η is constant and $Z_u\left\|F(u,v) + F(u-1,v)\right\|$ is the probability of pollination. The tuning parameter is indicated as λ and $t_p^q = s_p^q \times \frac{1}{T_{OFF}}$ here, T_{OFF} represents off time.

e) Check feasibility of solution: The feasibility of solution is estimated based on objective function. The newly created solution is better than earlier one, then change the new solution.

f) Termination: Replicate the above process for maximum number of iterations until the best solutions are identified. The pseudo code of developed exp RSFO-based DCNN is illustrated in Algorithm 1.

Algorithm 1. Pseudo code of developed exp RSFO-based DCNN technique

Input: Flower population
Output: Best solution
Start
Initialize the population
Define the best solution
Orient every plants to the sun
While $z < M$; M is maximum number of days
Orientation vector calculation
Eliminate the plants, which are distant from sun
Estimate the sunflower step with direction E
Best plants pollinate the sun
Compute new plantation using equation (28)

Check feasibility of the solution
Return best solution
$m = m + 1$
End while
Stop

3.5.3 Testing phase

The developed exp RSFO-based DCNN obtains the image classification output based on training image. On the other hand, the test image is considered as input in testing phase and the weighted shape size pattern is identified. After that, cluster index is identified by finding distance between cluster centroid of test features. Once the cluster index is attained, then new feature vector is generated. The image classification output is obtained using developed exp RSFO-based DCNN in testing phase. Finally, the output obtained from both training and testing phase produces a final image classification output.

4. Results and Discussion

The results and discussion of developed exp RSFO-based DCNN technique for image classification is illustrated in this section. Moreover, dataset description, experimental setup, experimental results, comparative methods, performance metrics and comparative analysis are described below.

4.1 Experimental setup

The implementation of developed image classification approach is performed in MATLAB in Windows 10 OS with Intel core i-3 processor and 4 GB RAM.

4.2 Dataset description

The developed image classification model is implemented using UK Bench dataset [34]. This database is introduced by Henrik Stewenius and David Nister. Moreover, this dataset includes 10,200 images and every group has four images with 640×480 size.

4.3 Performance metrics

The performance of the developed technique is computed based on three metrics, namely accuracy, specificity and sensitivity.

a) Accuracy: Accuracy is estimated using closeness of developed approach and it is formulated as,

$$Acc = \frac{T^{+} + T^{-}}{T^{+} + F^{+} + T^{-} + F^{-}} \tag{29}$$

b) Sensitivity: Sensitivity is a measure of calculating true positives accurately and it is given by,

$$Sen = \frac{T^{+}}{T^{+} + F^{-}} \tag{30}$$

c) Specificity: Specificity is defined as the probability of true negatives and it is expressed as,

$$Spe = \frac{T^{-}}{T^{-} + F^{+}} \tag{31}$$

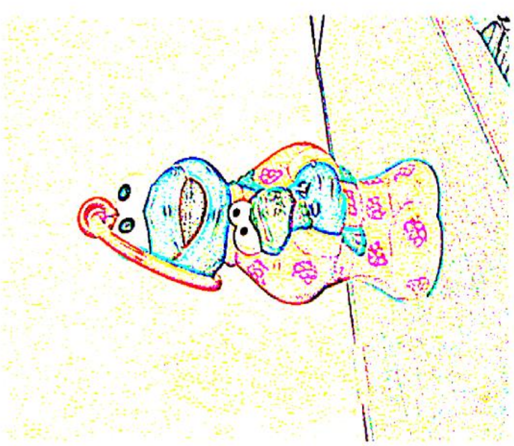
where, true positive is denoted as T^{+}, true negative is termed as T^{-}, false positive is denoted as F^{+} and false negative is indicated as F^{-}.

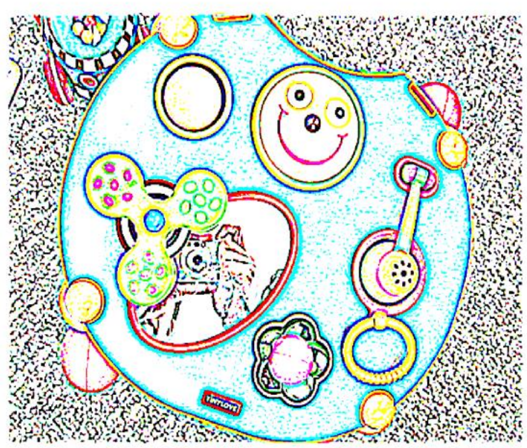
4.4 Experimental Results

In this section, the experimental results of developed exp RSFO-based DCNN for image classification are represented. Here, figure 3 a) and 3 b) denotes the input image 1 and 2, figure 3 c) and 3 d) indicates the decomposed image. In addition, figure 3 e) and 3 f) portrays the histogram representation of input image 1 and 2.

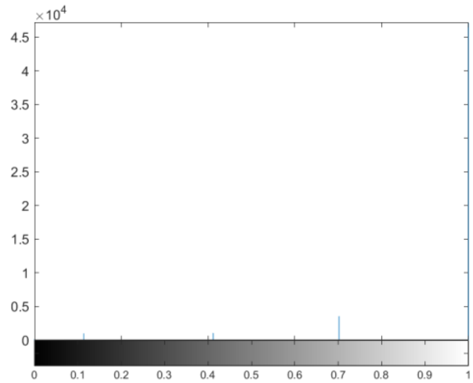
(a)

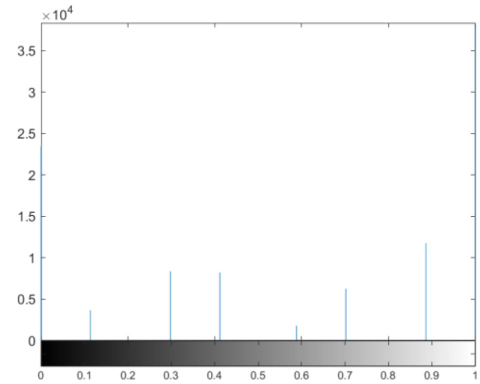
(b)





(c)	(d)





(e)	(f)

Figure 3.Experimental results of a) Input image 1, b) Input image 2, c) Decomposed image of input 1, d) Decomposed image of input image 2, e) Histogram representation of input image 1 and f) Histogram representation of input image 2

4.5 Comparative approaches

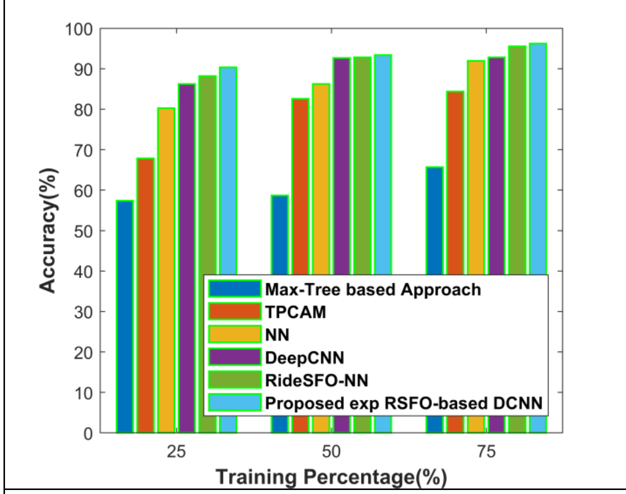
The techniques, like Max-Tree based model [28], TPCAM [4], NN [33], DeepCNN [1] and RideSFO-NN are employed for comparisonwith developed exp RSFO-based DCNN.

4.5.1 Comparative analysis using image size 128×128

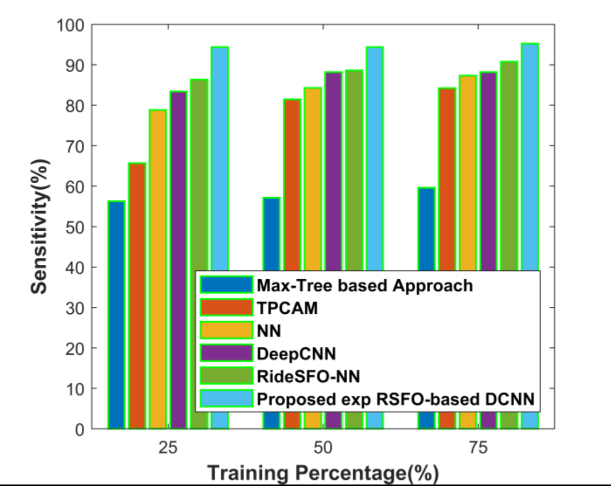
This section elaborates about the comparative analysis of developed exp RSFO-based DCNN using 128×128 image size with respect to training data percentage and K-fold value.

i) Based on training data percentage

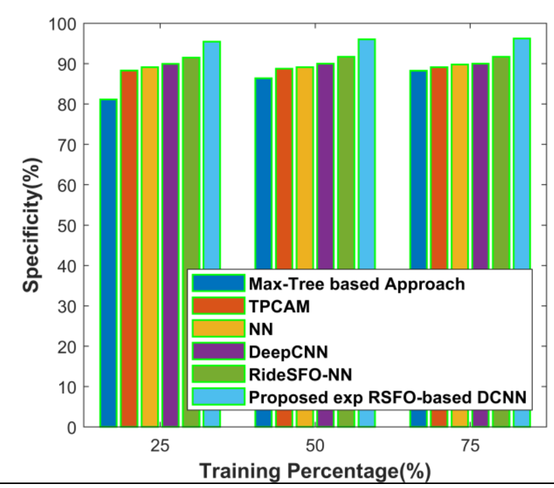
Figure 4 shows the comparative analysis of developed image classification model using 128×128 image size in terms of accuracy, sensitivity and specificity. Figure 4 a) depicts the comparative analysis of accuracy by changing training data percentage. The accuracy value of existing methods, such as Max-Tree based model, TPCAM, NN, DeepCNN and RideSFO-NN are 65.66%, 84.34%, 91.92%, 92.83% and 95.53%, whereas developed method has 96.21% for 75% of training data. In addition, the performance improvement of developed method is 31.75%, 12.33%, 4.46%, 3.52% and 0.71%, when compared with existing image classification techniques.The comparative analysis of sensitivity by changing training data percentage is portrayed in figure 4 b). The developed method has 95.22% of sensitivity, whereas existing techniques, Max-Tree based model, TPCAM, NN, DeepCNN and RideSFO-NN has 59.58%, 84.20%, 87.32%, 88.18% and 90.75% in 75% of training data. The performance improvement of developed image classification technique with Max-Tree based approach is 37.43%, TPCAM is 11.57%, NN is 8.29%, DCNN is 7.38% and RideSFO-NN is 4.69%. Similarly, figure 4c) signifies the comparative analysis of specificity by varying training data percentage. When training data percentage is 75, the existing techniques, such as Max-Tree based model, TPCAM, NN, DeepCNN and RideSFO-NN and developed image classification method has specificity value of 88.24%, 89.11%, 89.78%, 89.97%, 91.70% and 96.20%. Moreover, the performance improvement of developed exp RSFO-based DCNN is 8.27%, 7.36%, 6.67%, 6.48% and 4.67%, while compared with existing approaches.



(a)



(b)



(c)

Figure 4. Comparative analysis of developed method with respect to training percentage using image size 128×128 a) Accuracy, b) Sensitivity and c) Specificity

ii) Based on K-Fold

Figure 5 specifies the comparative analysis of developed exp RSFO-based DCNN technique based on 128×128 image size with respect to accuracy, sensitivity and specificity. The comparative analysis of accuracy by varying K-fold value is shown in figure 5 a). The developed method has 96.35% of accuracy, while existing techniques, Max-Tree based model, TPCAM, NN, DeepCNN and RideSFO-NN has 81.44%, 82.19%, 86.56%, 91.95% and 94.61%, when K-fold value is 10. The performance improvement of exp RSFO-based DCNN approach with Max-Tree based approach is 15.47%, TPCAM is 14.69%, NN is 10.16%, DCNN is 4.57% and RideSFO-NN is 1.81%. Figure 5 b) depicts the comparative analysis of sensitivity by changing K-fold value. The sensitivity value of existing methods, such as Max-Tree based model, TPCAM, NN, DeepCNN and RideSFO-NN are 74.78%, 75.76%, 79.96%, 84.56% and 89.88% also, developed method has 93.62% for K-fold value is 10. Furthermore, the performance improvement of developed image classification method is 20.11%, 19.07%, 14.59%, 9.67% and 3.99%, when compared with existing image classification techniques. Likewise, figure 5 c) shows the comparative analysis of specificity by varying K-fold value. When K-fold value is 10, the existing techniques, such as Max-Tree based model, TPCAM, NN, DeepCNN and RideSFO-NN and developed image classification method has specificity value of 86.51%, 87.36%, 88.20%, 89.05%, 89.90% and 90.74%. The performance improvement of developed exp RSFO-based DCNN is 4.66%, 3.73%, 2.79%, 1.86% and 0.93%, while compared with existing image classification techniques.

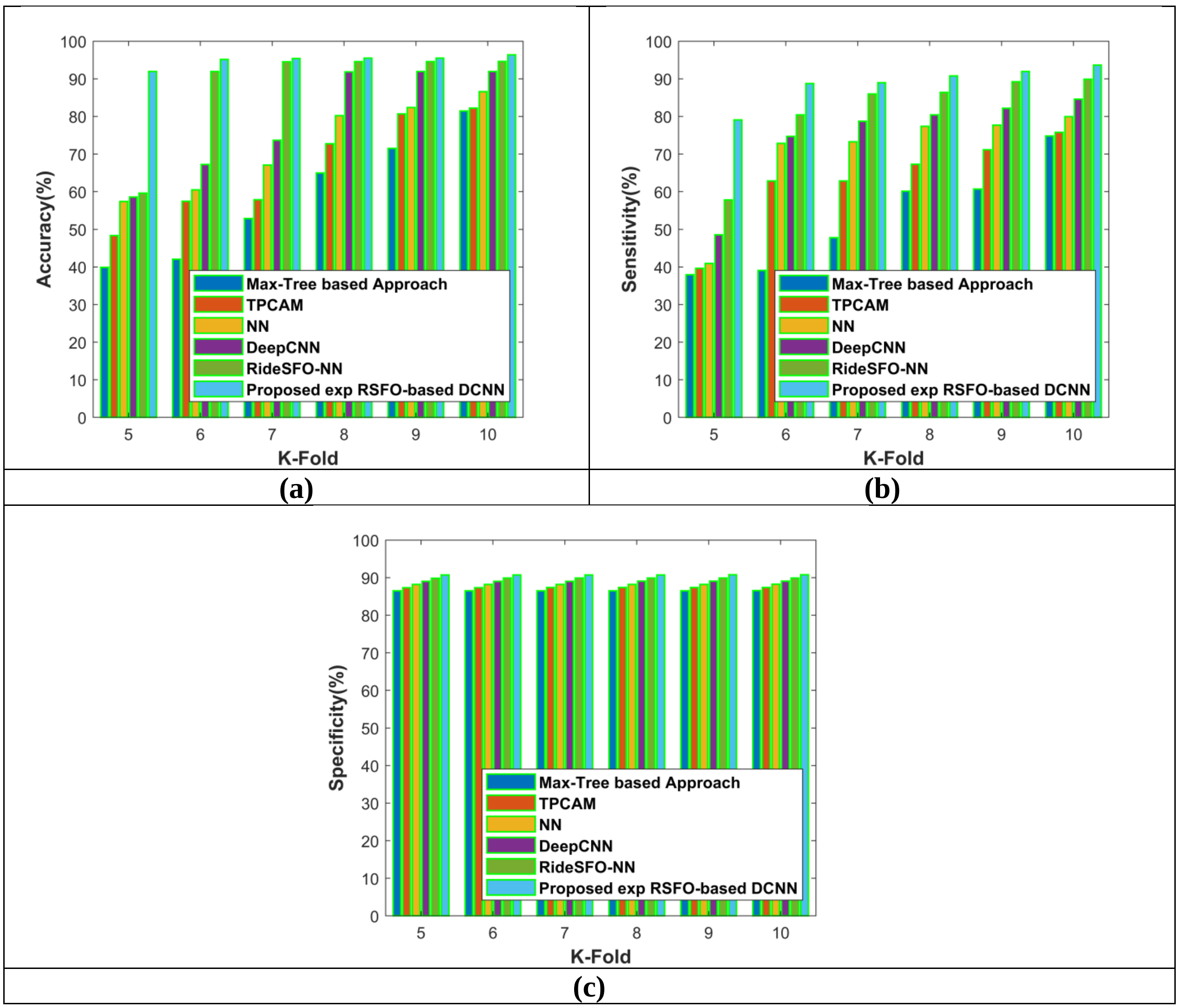


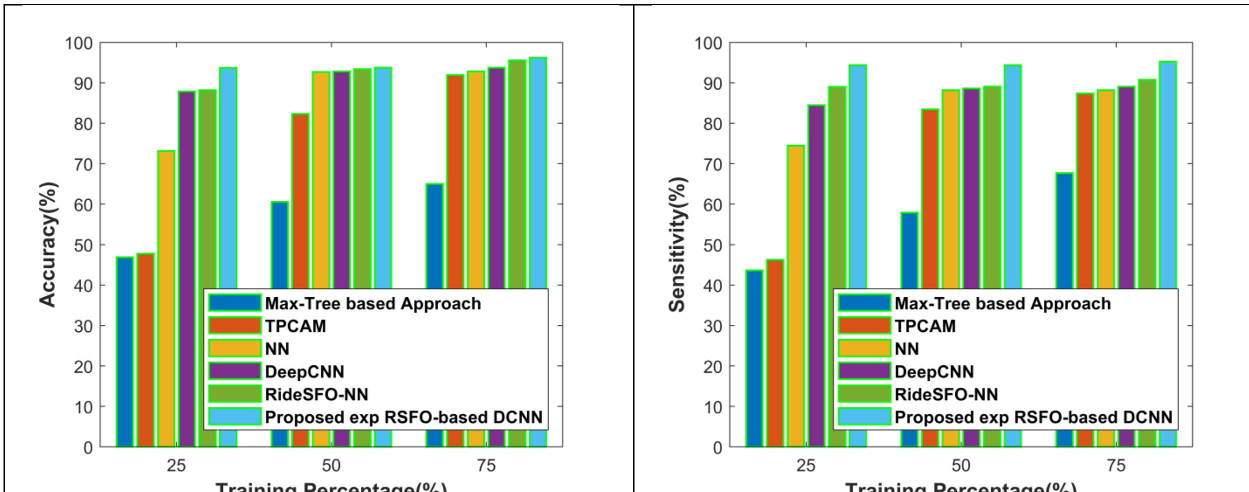
Figure 5. Comparative analysis of developed exp RSFO-based DCNN model using 128×128 image size with respect to K-fold value in terms of a) Accuracy, b) Sensitivity and c) Specificity

4.5.2 Analysis based on image size 256×256

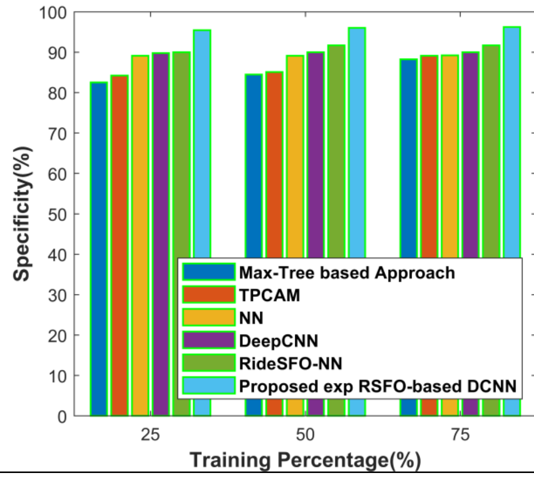
This section describes the comparative analysis of developed exp RSFO-based DCNN based on 256×256 image dimension with respect to training data percentage and K-fold value.

i) Based on training data percentage

Figure 6shows the comparative analysis of developed image classification model using 256×256 image size in terms of accuracy, sensitivity and specificity. Figure 6 a) depicts the comparative analysis of accuracy by changing training data percentage. The accuracy value of existing methods, such as Max-Tree based model, TPCAM, NN, DeepCNN and RideSFO-NN are 64.99%, 91.93%, 92.83%, 93.73% and 95.53%, whereas the developed method has 96.21% for 75% of training data. In addition, the performance improvement of developed method is 32.45%, 4.45%, 3.52%, 2.58% and 0.71%, when compared with existing image classification techniques. The comparative analysis of sensitivity by changing training data percentage is portrayed in figure 6 b). The developed method has 95.22% of sensitivity, whereas existing techniques, Max-Tree based model, TPCAM, NN, DeepCNN and RideSFO-NN has 67.68%, 87.33%, 88.188%, 89.04% and 90.75% in 75% of training data. The performance improvement of developed image classification technique with Max-Tree based approach is 28.91%, TPCAM is 8.28%, NN is 7.38%, DCNN is 6.49% and RideSFO-NN is 4.69%. Similarly, figure 6 c) signifies the comparative analysis of specificity by varying training data percentage. When training data percentage is 75, the existing techniques, such as Max-Tree based model, TPCAM, NN, DeepCNN and RideSFO-NN and developed image classification method has specificity value of 88.25%, 89.11%, 89.23%, 89.98%, 91.70% and 96.20%. Moreover, the performance improvement of developed exp RSFO-based DCNN is8.26%, 7.36%, 7.24%, 6.47% and 4.67%, while compared with existing image classification approaches.



(a)	(b)



(c)

Figure 6. Comparative analysis of developed approach with respect to training percentage using 256×256 image size in terms of a) Accuracy, b) Sensitivity and c) Specificity

ii) Based on K-Fold

Figure 7shows the comparative analysis of developed exp RSFO-based DCNN technique based on 256×256 image size with respect to accuracy, sensitivity and specificity. The comparative analysis of accuracy by varying K-fold value is represented in figure 7 a). The developed method has 96.35% of accuracy, while existing techniques, Max-Tree based model, TPCAM, NN, DeepCNN and RideSFO-NN has79.30%, 82.38%, 88.66%, 91.94% and 94.65%, when K-fold value is 10. The performance improvement of exp RSFO-based DCNN approach with Max-Tree based approach is 17.69%, TPCAM is 14.50%, NN is 7.98%, DCNN is 4.58% and RideSFO-NN is 1.77%. Figure 7 b) depicts the comparative analysis of sensitivity by changing K-fold value. The sensitivity value of existing methods, such as Max-Tree based model, TPCAM, NN, DeepCNN and RideSFO-NN are 75.77%, 77.91%, 87.51%, 89.20% and 92.72% also, developed method has 93.62% for K-fold value is 10. Furthermore, the performance improvement of developed image classification method is 19.06%, 16.78%, 6.52%, 4.71% and 0.96%, when compared with existing image classification techniques. Likewise, figure 7 c) signifies the comparative analysis of specificity by varying K-fold value. When K-fold value is 10, the existing techniques, such as Max-Tree based model, TPCAM, NN, DeepCNN and RideSFO-NN and developed image classification method has specificity value of88.28%, 89.14%, 90%, 90.87%, 91.73% and 92.60%. The performance improvement of developed exp RSFO-based DCNN is 4.66%, 3.73%, 2.79%, 1.86% and 0.93%, while compared with existing image classification techniques.

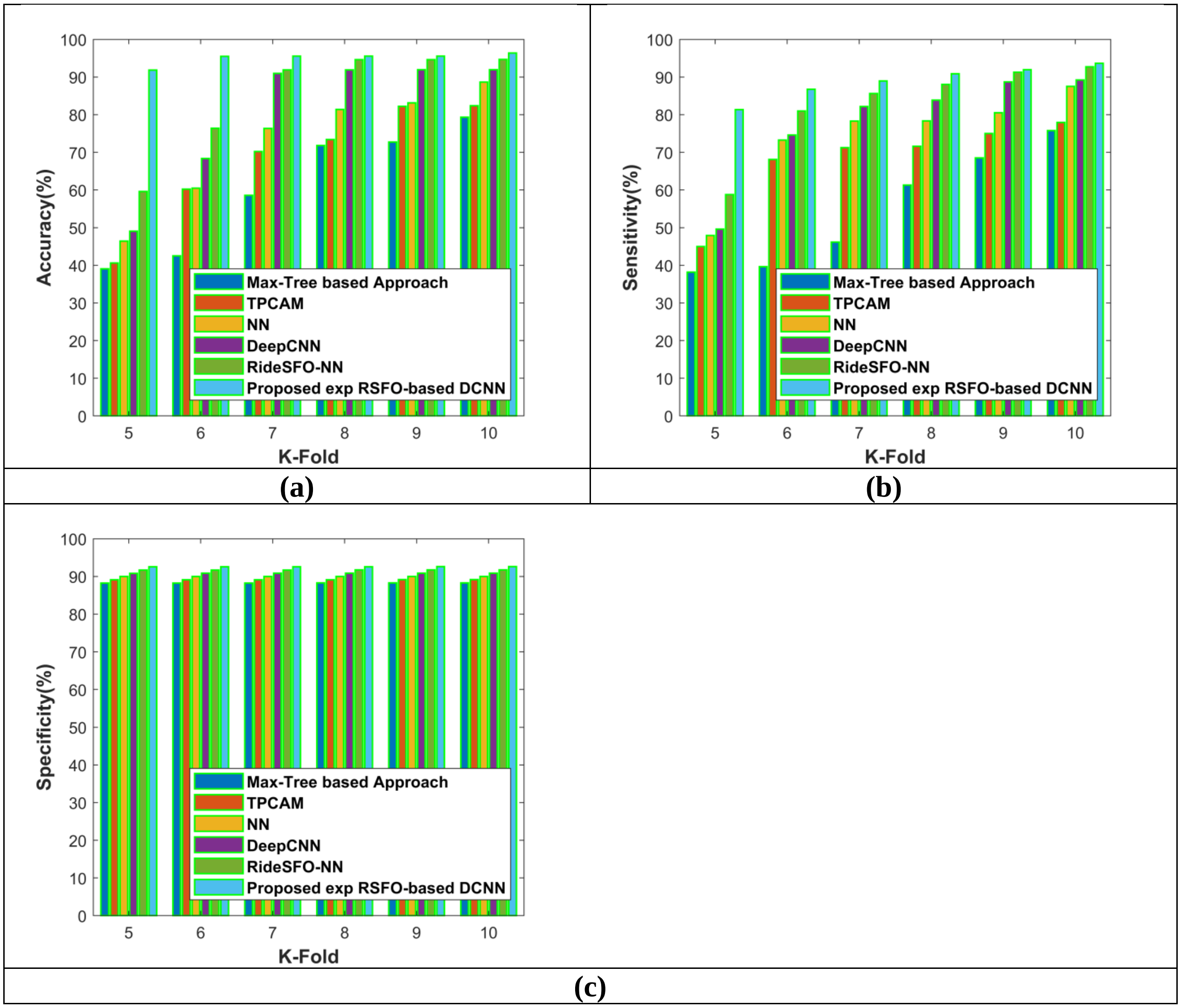


Figure 7. Comparative analysis of developed exp RSFO-based DCNN model using 256×256 image size regards to K-fold value in terms of a) Accuracy, b) Sensitivity and c) Specificity

4.6 Comparative discussion

Table 1 describes the comparative discussion of developed exp RSFO-based DCNN technique by changing training data percentage in terms of accuracy, sensitivity and specificity for 128×128 and 256×256 image size. The developed image classification technique has accuracy of 96.21%, whereas existing methods, like Max-Tree based model, TPCAM, NN, DeepCNN and RideSFO-NN has 65.66%, 84.34%, 91.92%, 92.83% and 95.53%. Similarly, the sensitivity obtained by existing methods, like TPCAM, NN, DeepCNN and RideSFO-NN are 59.58%, 84.20%, 87.32%, 88.18% and 90.75%, while developed technique achieved 95.22%. Moreover, the specificity value of existing techniques are 88.24%, 89.11%, 89.78%, 89.97% and 91.70% and developed exp RSFO-based DCNN obtains 96.20%. Therefore, from the below table it is well-clear, that the developed exp RSFO-based DCNN achieves maximum accuracy, sensitivity and specificity.

Table 1 Comparative analysis based on training data percentage

Image size	Metrics	Max-Tree based model	TPCAM	NN	Deep CNN	RideSFO-NN	Proposed exp RSFO-based DCNN
128×128	Accuracy (%)	65.66	84.34	91.92	92.83	95.53	**96.21**
	Sensitivity (%)	59.58	84.20	87.32	88.18	90.75	**95.22**
	Specificity (%)	88.24	89.11	89.78	89.97	91.70	**96.20**
256×256	Accuracy (%)	64.99	91.93	92.83	93.73	95.53	**96.21**
	Sensitivity (%)	67.68	87.33	88.18	89.04	90.75	**95.22**
	Specificity (%)	88.25	89.11	89.23	89.98	91.70	**96.20**

Table 2 denotes the comparative discussion of developed exp RSFO-based DCNN for image classification by varying K-fold value in terms of accuracy, sensitivity and specificity for 128×128 and 256×256 image size. The developed image classification technique has accuracy of 96.35%, whereas existing methods, like Max-Tree based model, TPCAM, NN, DeepCNN and RideSFO-NN has 81.44%, 82.19%, 86.56%, 91.95% and 94.61% for 128×128 image size. Likewise, the sensitivity obtained by existing methods, like TPCAM, NN, DeepCNN and RideSFO-NN are 74.78%, 75.76%, 79.96%, 84.56% and 89.88%, while developed technique achieved 93.62%. Furthermore, the specificity value of existing techniques are 86.51%, 87.36%, 88.20%, 89.05% and 89.90% and developed exp RSFO-based DCNN obtained 90.74%. Thus, from the below table, it is familiar, that the developed image classification approach achieved better accuracy, sensitivity and specificity for 256×256 image size.

Table 2 Comparative analysis using K-Fold

Image size	Metrics	Max-Tree based model	TPCAM	NN	Deep CNN	RideSFO-NN	Proposed exp RSFO-based DCNN
128×128	Accuracy (%)	81.44	82.19	86.56	91.95	94.61	**96.35**
	Sensitivity (%)	74.78	75.76	79.96	84.56	89.88	**93.62**
	Specificity (%)	86.51	87.36	88.20	89.05	89.90	**90.74**
256×256	Accuracy (%)	79.30	82.38	88.66	91.94	94.65	**96.35**
	Sensitivity (%)	75.77	77.91	87.51	89.20	92.72	**93.62**

	Specificity (%)	88.28	89.14	90	90.87	91.73	**92.60**

5. Conclusion

This paper presents an effective technique, named exp RSFO-based DCNN technique for image classification process. This image classification process includes three stages, namely weighted shape size spectra, clustering and image classification. Originally, the input image is extracted from UK bench database, and it is given to weighted shape size spectra for extracting significant features. Here, weighted shape size spectra model is designed using weight shape decomposition and gray scale decomposition. After that, FLICM scheme is employed for clustering process. Consequently, image classification is performed. Furthermore, DCNN classifier is utilized, which is trained by developed exp RSFO algorithm for classification of image. The developed exp RSFO technique is designed by integrating EWMA model and RSFO algorithm. Here, RSFO method is the inclusion of SFO technique and ROA. Alternatively, test image is taken, and it is fed to weighted shape size spectra to extract the features in testing phase. Moreover, matching is executed with centroid value to find cluster information, and it creates a new vector feature. At last, final classified output is produced based on training and training image. The performance of developed image classification technique is estimated using various performance metrics, like sensitivity, accuracy and specificity. Therefore, developed image classification attains better accuracy of 96.21%, sensitivity of 95.22% and specificity of 96.20% for 128×128 image size. In addition, the future development of this research will be utilization of other classifiers for better performance of image classification.

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