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Clustering based ACO and ABC algorithms for the shadow detection and removal

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Abstract
In this paper, k-means and fuzzy c-means (FCM) algorithms have been used as it is efficient in grouping based on classified data points. Then ant colony optimization (ACO) and artificial bee colony (ABC) algorithms for the detection of critical regions based on the multi-modal parameters were used. It is mainly beneficial for the detection of pixel points on the large search space. These algorithms are used with the combination of k-means and FCM algorithms. We have selected ACO algorithm as it is efficient in the rapid discovery based on feedbacks. In our case we have to recognize the image points in terms of correlated pixels based on the feedbacks and clustering thresholds of the related pixels. So, ACO may be beneficial in this case and also avoids premature convergence. The ABC algorithm has been considered for the fast convergence and efficient in outlier masking. The k-means and fuzzy c-means-ant colony optimization (KFCM-ACO) and k-means and fuzzy c-means-artificial bee colony (KFCM-ABC) algorithms are used to optimize the search process and to find the segmented and associated pixels for shadow detection. The comparison of the approaches clearly depicted that the approaches have less error rates and higher accuracy.

Keywords
K-means, FCM, ACO, ABC, KFCM-ACO, KFCM-ABC.

1.Introduction
Shadow detection and removal is challenging due to different factors like image context, light conditions, complexity etc. [1–3]. So, accruing, detection, convergence and removal in terms of computer vision is a challenging task [4–6]. There are several algorithms were explored in the same direction for the proper detection and removal. Clustering, classification and nature inspired algorithms were used mostly [7, 8]. Main clustering algorithms are k-means, fuzzy c-means (FCM) and hierarchical clustering. These algorithms are beneficial in key grouping and shadow pointing [9–12]. Ant colony optimization (ACO), particle swarm optimization (PSO), teaching learning-based optimization (TLBO), cuckoo search, artificial bee colony (ABC), etc. are the main nature inspired algorithms [13,14]. Classification algorithms mainly used for the same are decision tree (DT), random forest (RF), support vector machine (SVM), logistic regression (LR), naïve Bayes (NB), k-nearest neighbor (KNN), etc. [15–24].

The following problems were identified during the time of the review and analysis. This was annotated based on the analysis and the observations of the complete study. It shows the analytical and explorative way of exploration of the purpose and the study scenarios.
1. There is the need of exploration of surface complexity as it may affect the detection results.
2. There is the need to cover multiple correlated attributes like intensity, shape, brightness, complexity etc. in terms of the overall analysis and complete detection computation.
3. There is the need of clustering mechanism for the selection of key frames for different lighting and ecological conditions. It can be further segmented for better accuracy.

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4. There is the need of combining the aspects of clustering and classification algorithms with optimized parameters for the spectral and geometric features. It may be helpful in the pairwise reason detection.

The objectives of this paper are as follows:
1. To survey and analysis the computer vision approaches for the exploration and correlation investigation of shadow and non-shadow points.
2. To apply data clustering and classification efficiently to provide a hybrid framework based on the combination for the efficient computing to achieve cluster and classified groups with high performance.
3. To allow heterogeneous environment for different computational parameters with multiple correlated attributes for better detection and shadow removal.
4. To design the elaborative shadow aware optimization framework considering texture and depth cue for the complex shadow.

The main motivation of this paper is to apply data clustering and the optimized classification mechanism in the combined way. It efficiently allow heterogeneous environment for shadow detection and removal. This paper contains reviews, discussion on the challenges associated with the detection and removal of shadow from the images. Different combination of methodologies has been applied including clustering, classification and nature inspired algorithm. The selection mechanism has also been discussed with the justification by the approaches used. It has been compared with other optimization techniques along with the clustering and classification mechanism. This approach is also efficient in terms of reallocating the regions which are important for the final coverage.

Rest of the paper is organized in the following sections. Related work was discussed in section 2. Methods and the way of applicability in section 3. Results and its impact were explored in section 4. It also covers study limitations. Concluding remarks was in section 5.

2.Literature review

This section explores the recent related work considering main focus on the approach, applicability, challenges and results. In 2019, Ghewari et al. [25] presented a successive thresholding scheme (STS) which was taken from the Tsai's method using the global thresholding scheme. The ratio map is modified so that accurate gap can be identified between shadow and non-shadow pixels. The Otsu's method was used for the shadow detection based on the thresholding. The shadow model was used and a shadow algorithm was applied to display the final image after removing the shadow. This shadow model was implemented in MATLAB. The method based on proposed model obtained the precision of 0.813, recall of 0.652 and F1-score of 0.562 whereas Otsu's method achieved the precision of 0.662, recall of 0.543 and f1-score of 0.634. In 2019, Hanafy et al. [26] used the image processing and machine learning for the detection of depositions. They used the machine learning approach for determining the depositions. They introduced a four-step system for the Photovoltaic (PV) cleanliness. They applied it on aerial and terrestrial images of Solar Panels. For removing the background, they used the GrabCut algorithm. The classification phase was performed by utilizing the NN, RF, SVN and KNN as the classification algorithms. They achieved the approx. 100 training accuracy, approx. 85.5% as testing accuracy in KNN, approx. 91.70% of training and approx. 90.65% of testing accuracy in NN, whereas RF obtained the approx. 99.90% as training and 93.25% as testing accuracy. The SVM achieved the approx. 97.05 as the training and 97.02 as the testing accuracy. In 2019, Khan et al. [27] presented a methodology to remove the shadow and then machine learning was applied to train the proposed system. They used the Stony Brook University (SBU) dataset. This dataset consisted of 4107 images with the shadows. The images were converted from RGB to YCbCr and CIE L*a*b colorspace. On the basis of threshold value, the images were converted into binary basis for performing the multi-channel binarization so that they can locate the shadows. Further, the Canny's edge detection algorithm was used to detect the edges. Finally, the detected images went through the technique of shadow matting and finally a shadow-free image is obtained which can be deliver through user application. In 2019, Sidorov [28] proposed an architecture named as AngularGAN specific to ColorChecker (CC). They have selected the SFU Grayball as the dataset which consisted of 11,346 images of real-world. The ColorChecker was also selected as another smaller dataset. In CC dataset there are 548 real-images among which they used the 360 images for the training purpose. They have proposed an approach through generative end-to-end algorithm which was based on Generative Adversarial Network. They have discussed the different dataset for Uniform Color Constancy, Multi-Illuminant Color Constancy and for the shadow removal. The angular error was used as the metric for the comparison. The angular error was found to be low in comparing the dataset of each category. In 2019, Zhang et al. [29] proposed a coarse-to-fine framework for the cloud removal in the remote sensing image sequence. They decomposed the cloud image sequence into the low-rank component, group the sparse outliers and sparse noise. Later, the discriminative robust principal component analysis (DRPCA) algorithm was utilized for assigning the aggressive penalizing weights for facilitating the cloud removal and scene restoration. They used the landsat-8 operational land imager (OLI) and Sentinel-2 scenes as their datasets. The images were cropped with the size of 518×518 pixels. The DRPCA received the RMSE of 2.2747, peak-signal-to noise ratio (PSNR) of 40.9925 and structural similarity index (SSIM) of 0.9939 for the image 1 among the three images. The proposed method is prone to false detection as the land cover changes with the large magnitude. Moreover, the data was limited so it not tested on the real image sequence. In 2020, Talavera-Martinez et al. [30] presented an approach which uses the deep learning techniques for the task of hair removal on the dermoscopic images. Their proposed model relies on the encoder and decoder architecture with the convolutional neural network. They introduced a new loss function in the training phase of network, total variation loss and the loss function which was based on structural similarity index metric. They have considered the simulation of skin hair in the hairless images which was extracted from the five publically available datasets like dermquest, PH2, EDRA2002 and ISIC Data Archive. They constructed a dataset of 618 images. This constructed dataset had the combination of 322 images from EDRA2002, 239 images from PH2, 46 images from ISIC, 6 images from dermis and the 5 images from the dermquest dataset. For the experimentation purpose they considered the 70% (433 images) of data for the training and 30% (185 images) for the testing purpose. The proposed architecture was implemented by using the Keras. The result was compared with six state-of-the-art algorithms and it was found that the proposed model is provides good results and effectiveness in terms of both qualitative and quantitative way. In 2020, ji et al. [31] proposed a cascade convolutional neural network which used the integration of cloud detection and the removal framework. Initially, they developed a fully convolutional network (FCN) which was embedded with multiscale aggregation and a channel attention mechanism. Then the second FCN was constructed which contained the mask of detected cloud and its shadow, and the cloudy images as the input. They considered the dataset of Landsat-8 which is also called as WHU dataset of cloud. It consisted of six cloudy and the cloud free image pairs available in different areas. Another dataset considered was of GF-cloud-detection dataset. It consisted of ten GF cloudy images. The WHU cloud dataset by using cloud-detection network (CDN) achieved the accuracy of 98.75 in shadow, 98.62% in Cloud, 98.68% in shadow and cloud both. The CDN used in GF dataset obtained the accuracy of 96.76% in shadow, 97.74% in cloud and 97.25% for both shadow and cloud. In 2020, Guo et al. [32] proposed a three-stage scheme in a cascade manner. In the first stage they trained the shadow detection model on the synthetic data which was generated from the simulated environment with the help of Unity game engine. In the second stage they trained the other model for transferring the style from real world to the synthetic. The final stage used these results as the input for the scheme. Their approach used the conditional variant of generative adversarial network (GAN) that was used as the input for both generator and discriminator. The datasets used for the experiment was Stonybrook University (SBU) and ISTB. The SBU dataset contained the 4089 training pairs and 638 as the testing pairs for the shadow image and the shadow mask. The ISTB database used the 1330 pairs for training and 540 pairs for testing pairs. They benchmarked their method with stackedCGAN, cGAN, scGAN and stackedCNN by using balance error rate (BER). They achieved the BER of 2.89 for shadow on ISTD and 3.45 of shadow in SBU. It was used for training with synthetic data and testing with style transfer for the SBU and ISTD dataset. In 2020, Kim et al. [33] suggested a method for background subtraction for removing the shadow of the moving object. The advised method used the enduring ViBe algorithm and they removed the shadow by using color hue, luminance and texture model. The suggested method was verified with the help of simulation. They used the scale invariant local ternary pattern (SILTP) operator and calculated the hue and texture for each pixel available in the frame video. In 2020, Batchuluun et al. [34] proposed a method based on pruned fully convolutional network (PFCN) for removing the thermal reflection. They used the self-collected databases like Dongguk thermal image database (DTh-DB) and the Dongguk items and vehicles database (DI&V-DB) and other open databases. They collected the database in both indoor and outdoor environments. It was conducted in two-fold cross-validation. They compared the proposed method with traditional methods like

CycleGAN, Mask R-CNN+ Cycle-GAN, FCN_V1, Mask R-CNN-based removal, FCN_V2, SegNet-based removal, PLN. They obtained the higher global accuracy of 99%, precision of 98%, Recall of 93%, F1-score of 95% and Jaccard value of 94% in the proposed method. It was found that there is a need of method required to transform low-resolution to high-resolution thermal images. In 2020, Gad et al. [35] proposed an approach which works with components of RGB having some variations. They applied the Gaussian filter in the input image and the vertical scanning and analysis was performed so, initially they were able to remove the shadow. The final shadow removal image was retrieved after performing the horizontal scanning and analysis. They were able to detect the local minimum and maxima values and calculated the mean value which was used as the knee point value for detecting the drop points. The RGB values were compared for before and after values retrieved from the previous step. They used the 300 images for the analysis and optimization purpose whereas 4085 images were used for the SBU dataset. The proposed approach was compared with other approaches where the proposed approach achieved the accuracy of 96% for shadow and 87% for non-shadow detection. In 2020, Luo et al. [36] presented a convolutional neural network (CNN) which was based on the framework of shadow detection for the aerial remote sensing images. They constructed the aerial Imagery dataset for the shadow detection (AISD) as the publicly available dataset. On the basis of this AISD dataset they proposed a deeply supervised convolutional neural network for the shadow detection (DSSDNet). In the first step they adopted the encoder-decoder residual (EDR) structure for the extraction of multi-level and discriminative shadow features. Secondly, they imposed the deeply supervised progressive fusion (DSPF) on the EDR. The proposed DSSDNet was compared with different state-of-art methods in terms of both qualitative and quantitative analysis. They randomly selected the 463 images as the training set and 51 as the testing set. The achieved the F-score of 91.79% for the proposed method on the testing images. In 2020, Kurbatova and Pavlovskaya [37] proposed an approach which consisted of three phases i.e., pre-processing, then detection of shadow and its removal and finally the road detection. Initially the RGB images were converted into HSV color. In this they calculated the H and V component only where the range of V component lies from 0 to 100 and value of H component lies from 0 to 360. For obtaining the digital Halftone images they ranges selected was from 0 to 255. The 2D Markov chains for contour detection was used for the detection algorithm as the second step. Next, shadow removal step is used between the shadow detection and the road detection steps. The proposed approach was implemented by using the MATLAB. They have used the five state-of-art methods for the comparison. These methods were YCbCr, RGB clor space, linear correction method, color constancy and gamma correction method. The dataset of 49 images were considered for the testing and it was taken from Massachusetts Roads dataset. They found the best results in gamma correction method. In 2020, Wang et al. [38] proposed a technique which used the Support Vector Machine for the detection of shadow based on the color saliency space and the gradient field. It was helpful in the reconstruction of images after optimizing the results obtained from the previous step. They adopted the nonlinear SVM as the classifier to represent the shadow regions on road. The adaptive variable scale region compensation operator was proposed for the removal of shadowed. The minimum variance was used for the derivation of optimal compensation operator between shadow and non-shadow areas. Overall, the proposed framework was divided into two parts one was shadow detection and another one was the shadow removal. The local compensation and variable scale compensation operator were used for the road shadow elimination. The dataset selected for this study was included from different groups. One group belongs to shadow dataset of road scenes, second one is of UCF dataset, third one is from CMU dataset, KITTI road dataset and some data collected from the camera. They normalized the dataset to the resolution of 160×120 for the 580 road images of different light conditions and the road scenes. The proposed technique achieved the accuracy of 83.6% for the road shadows and 93.5% for the non-road shadows. In 2021, Gound and Thepade [39] proposed the fusion of different methods like dark channel prior (DCP), local color correction (LCC) with Adaptive Histogram Equalization (AHE) and Guided Filter (GF). A method for reducing haze from remote sensing images obtained by airborne visible/infrared imaging has been proposed. The output from the spectrometer is of higher quality. The inputted images were taken from Airborne visible/infrared imaging spectrometer (AVIRIS) with the help of aerial photography. They divided the captured images into 47 blocks. It showed that the proposed fusion-based haze removal method has the maximum entropy among the other algorithms examined. The highest average entropy received was 5.6279 for the fusion-based method. In 2021, He et al. [40] proposed a deep neural network

Mask-ShadowNet for the shadow removal. They used the masked adaptive instance normalization (MAdaIN) as the mechanism. The ISTD dataset was considered for the experimentation. The 1870 image triplets were used for the training and 540 image triplets for the testing set. They adopted the RMSE as the measurement. The proposed Mask-ShadowNet achieved the value of 3.92 for the shadow area, 1.85 for the non-shadow area and a value of 2.36 for the whole image. The experiments results showed that the proposed method outperformed among all other methods. In 2021, Hongjuan et al. [41] proposed the multi threshold analysis and a homomorphic filter for the image pre-processing so that they can remove the shadow and can enhance the contrast of engine. They constructed the multi-parameters inspection vision of the system. Based on the multi threshold analysis the shadow elimination method was studied. They designed the Gaussian homomorphic filter to increase the contrast of image. In 2021, Hu et al. [42] proposed an algorithm which considered the difference in various features and the difference in the pixel of background. The inputted the current pixel and its background as the input in generalized learning vector quantization (GLVQ) so that they can classify the current position of pixel. They used the 15 nodes as the competition layer of generalized GLVQ. They applied this algorithm on the real traffic video. The proposed algorithm compared the detection rate and discrimination rate with other algorithms. They found that the proposed algorithm obtained the detection rate of 86.43% and discrimination rate of 84.74%. In 2021, Kim and Kim [43] adopted a non-local self-attention mechanism and modified it so that complexity can be improved. They used the architecture which consisted of three sub-network like encoder, decoder and refinement networks. The encoder consisted of 14 convolutional layers; decoder is used for the refinement of shadow's region. But here the instead of using refinement they have used the self-attention mechanism where they have added modules for self-attention. The proposed network performed the task in 0.01 seconds which is the 47.3% reduction. In 2021, Sahoo and Nanda [44] proposed a scheme based on background modelling and model learning. The spatio-temporal kernel density estimation (ST-KDE) model was used for the background modelling whereas the model learning was performed by the help of fusion feature space. The fusion process took place between the Local Binary Patterns (LBP) features of ST-KDE model and the Gabor features of the original frame. This proposed approach was tested on various videos sequences considered from ISTD, SRD, ATON-CVRR, Lasiesta and CDnet. The seven-performance metrics were considered for this comparison and they were precision, recall, specificity, f-measure, etc. The balance error ratio (BER) and root mean square error (RMSE) were used as two quantitative measures. When the proposed system was compared with other existing methods; it was found that proposed system found to be better results in terms of F-score and precision. In 2021, Sarker et al. [45] proposed a mechanism to find the people and trash from the video. They have applied a technique of shadow removal and after that a subtraction procedure on background was applied. The received binary frames were applied to morphological operation and a clear and noise free image was received which was used for labelling and filtering. The histogram of oriented gradient (HOG) features was used on the training dataset. The result of this was fed to linear-SVM for the detection of human. They have tested the 1000 frames of various resolutions. They have used the 861 positive and 1953 negative samples. Recall, precision and f1-score were used as the performance metrics. The proposed system achieved the accuracy of 87.98%, recall of 89.42% and precision of 86.58%. The average computational time received per frame was 3.92 seconds. In 2021, Trapal et al. [46] focused on the improvement of vision-based drone system. They applied the simple openCV technique for the shadow elimination. The technique used were Dilation, Absdifd, Blurring and Normalization. They applied the single image super resolution (SISR) to the individual frames of video. This technique was tested with a video of 3 seconds having 75 frames. The two methods of SISR i.e., Efficient Sub-Pixel Convolutional Neural Network (ESPCN) and fast super-resolution convolutional neural network (FSRCNN) were used. Both these methods offered the 2x,3x and 4x magnification option. The contour thresholds selected were like this: for default the contour threshold of 50 pixel, for 2x,3x and 4x the contour threshold was 100,150 and 200. The results of drone tracking were performed on the basis of discriminative correlation filter (DCF) with the spatial and channel reliability (CSR-DCF). They considered the data of two drones. The first drone named as target drone (DJI Tello) captured the images and it was observed by another drone named as DJI Mavic. The major challenges found in the review and the analysis are computation time, other parameters need to involve, operational limitations, need of hybrid correlation etc.

3.Methods

In this paper clustering and nature inspired algorithms have been used for the shadow detection and removal. In the first phase image data points are clustered using k-means and FCM algorithm. K-means and FCM algorithms have been used as it is efficient in grouping based on classified data points. The speed of these algorithms is also better in case of different distance points. As in our case we have categorical data based on shadow and non-shadow. So, these algorithms are capable in the initial grouping and pre-processing. It also produced tighter clusters based on different needed iterations. The convergence is also guaranteed. But the major problem with these algorithms is the initial value dependency, size variability and the outlier choosing their own clusters. So, for the proper detection and shadow removal clustering alone is not sufficient. The cluster data should be tuned based on the parameters as well as optimized on variable threshold for the performance improvement. So, we have used nature inspired algorithms like ACO and ABC algorithms for the detection of critical regions based on the multi-modal parameters. It is mainly beneficial for the detection of pixel points on the large search space. These algorithms are used with the combination of k-means and FCM algorithms. We have selected ACO algorithm as it is efficient in rapid discovery based on feedbacks. In our case we have to recognize the image points in terms of correlated pixels based on the feedbacks and clustering thresholds of the related pixels. So ACO may be beneficial in this case and also avoids premature convergence. The ABC algorithm has been considered for the fast convergence and efficient in outlier masking. We have used sampling based on normal distribution for handling the search space limitation of ABC algorithm.

The complete work has been divided in the following parts:

- Dataset

We have used five benchmark functions [47]. These functions are Griewank-function, Rastrigin-function, Rosenbrock-function, Ackley-function, and Schwefel-function.

- Preprocessing

Data preprocessing is an information mining strategy that includes changing raw information into a reasonable structural configuration. Here we have applied a preserving filter. It is used to remove the texture so to efficiently consider the shadow information.

- Feature extraction and selection

Feature extraction is process of reducing the amount of data efficiently and effectively. It is helpful in the reduction of number of resources. It is capable in the reduction of redundant data also for a given analysis. It is helpful in the process speed up in case of object recognition and matching tasks

- Grouping in case of clustering

In the phase image data points are clustered using k-means and FCM algorithm. K-means and FCM algorithms have been used as it is efficient in grouping based on classified data points

K-means algorithm

Step 1: Here we input the pre-processed data.

Step 2: Seed initialization has been performed based on random values.

Step 3: For the weight assignment random function has been used.

Step 4: The centroid distance estimation has been performed through the following equation

$$X(c)=\sum_{j=1}^{k}\sum_{i=1}^{n}||d_i^{(j)} - c_j||^2$$

$d_i - c_j$ indicates the centroid distance based on k

k denotes the cluster number

Total iterations have been denoted by n

Step 5: The above steps will be repeated till the final similarity of the centroid bases on the previous iteration

$$c_i = \left(\frac{1}{n_i}\right)\sum_{j=1}^{n_i} d_i$$

Step 6: Data clusters have been formed based on the above selection.

FCM algorithm have been used and compared based on different attributes.

Fuzzy c-means algorithm:

Step 1: The membership matrix let U has been generated based on the below formula:

$$\sum_{i=1}^{c} u_{ij} = 1, \forall j = 1,\dots,n$$

Step 2: Dissimilarity has been generated next using the below equation:

$$J(U, c_1, c_2, \dots, c_c) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}{}^m d_{ij}{}^2$$

u_{ij} is between 0 and 1;

c_i is the centroid of cluster i;

d_{ij} is the Euclidian distance between i_{th} centroid(c_i) and j_{th} data point;

m ϵ [1, ∞] is a weighting exponent.

Step 3: It should be minimum of dissimilarity function using the below equation:

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}{}^{m} x_j}{\sum_{j=1}^{n} u_{ij}{}^{m}}$$

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}}$$

Step 4: The iteration is then stopped till the epsilon value is lower than the retrieved iteration condition.
Step 5: Finish.

Figure 1 shows the combination of k-means and FCM algorithm. It mainly shows the k-based selection with FCM algorithm. The major benefit of hybridization is to improve the k-based selection for the assignment of same data point in different cluster at a same time. It is capable in the selection of higher fuzzy set. It is further processed with the ACO and ABC algorithm for the better parameter tuning based on the multilevel thresholds.

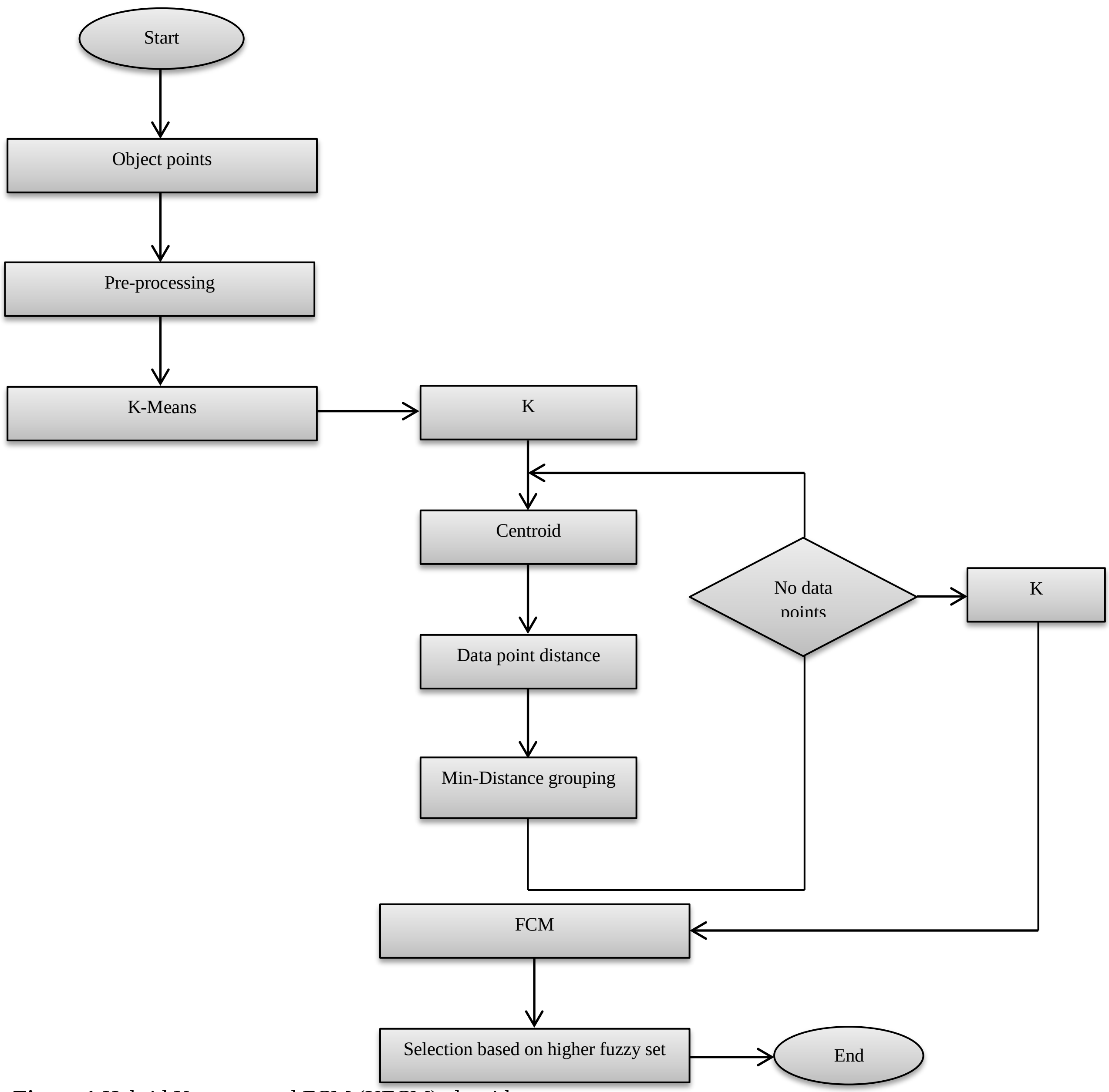

Figure 1 Hybrid K-means and FCM (KFCM) algorithm

- ACO with clustering (k-means and fuzzy c-means-ant colony optimization) (KFCM-ACO)

The combination of k-means and FCM(KFCM) approaches have been applied. The major benefit of this combination is to use the variance with same centroid capability of k-means with the fuzziness of iteration of FCM. It will be helpful in the multiple cluster selection of the data point for the single occurrence. So, the best threshold can be selected for the cluster. These feature points or the data points is then processed with ACO algorithm. Different texture features have been obtained due to the different texture operations. We have developed a systematic and cooperative way to handle the edges and texture with other properties by structuring the colony. It will generate a binary mapping or binary image for comparisons based on the ant pixel. It compares each pixel with the binary ant developed by the colony system. Then HSV color space model has been used for the background generation. It is combined with the texture feature to reduce the region with similar chrominance information. It is helpful to reduce the shadow in much better way due to the binary mapping as well as it is based on the texture and edge features. The complete procedure is shown in *Figure 2*.

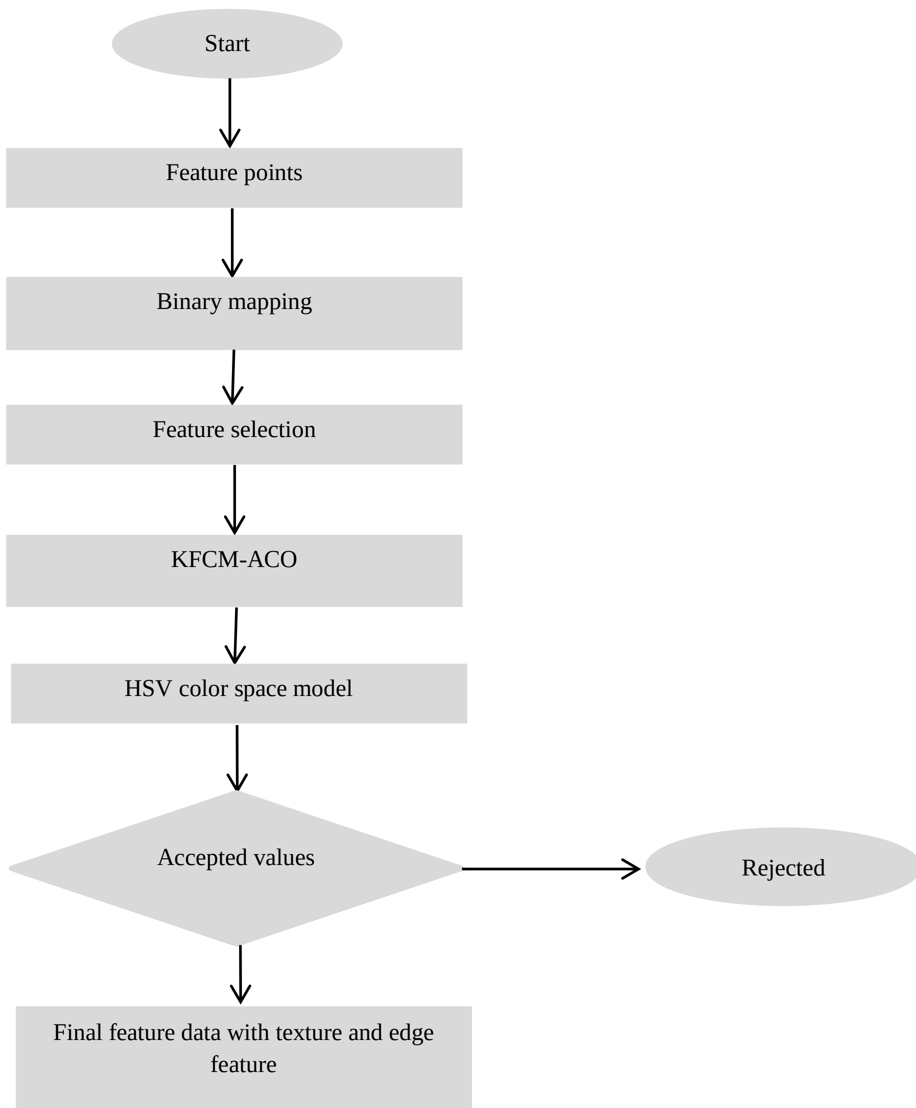

Figure 2 ACO with clustering (KFCM-ACO)

- ABC with clustering (k-means and fuzzy c-means-artificial bee colony) (KFCM-ABC)

Then the optimization of shadow detection and removal using multilevel thresholds and ABC algorithm. It has been applied on the KFCM data.

4.Results and discussion

In this section the results are compared, analyzed and discussed. For the comparison different attribute values are considered along with the changes in different groups and spanning.

The following measures have been used for the performance comparison. Some basic terminology should be discussed first for understanding the performance measures. The terminologies are as follows:
True positive (TP): Correctly predicted the positive class labels
True negative (TN): Correctly predicted the negative class labels
False positive (FP): Not correctly predicted the positive class labels
False negative (FN): Not correctly predicted the negative class labels

Accuracy
It determines the ration of correct outcomes to the complete outcomes (Equation 1).

$$\text{Accuracy} = \frac{TP + TN}{TP+FP+FN+TN} \quad (1)$$

Precision
It determines the ration of correct positive outcomes to the complete positive labels (Equation 2).

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

Recall (Sensitivity)
It determines the ration of correct positive outcomes to the complete case outcomes (Equation 3).

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

F1-score (F-Score / F-Measure)
This shows the measure of accuracy based on the combination of precision and recall. It shows the average or harmonic mean of the same (Equation 4).

$$\text{F1 Score} = \frac{2\times(Recall\times Precision)}{Recall+Precision} \quad (4)$$

Specificity
It determines the ration of correct negative outcomes to the complete non-case outcomes (Equation 5).

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (5)$$

Root Mean Square Error (RMSE)
It shows the square correlation of MSE (Equation 6).

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(\hat{o_i}-o_i)^2}{n}} \quad (6)$$

$\hat{o_i}$ = predicted values
o_i = Values which is observed
n = Complete number of observations

Mean Square Error (MSE)
It represents the original and predicted values differences in terms of differences over the period of time.
Mean Absolute Error (MAE)
It represents the original and predicted values differences in terms absolute difference average (Equation 7).

$$\text{MASE} = \frac{1}{n}\sum_{i=1}^{n} \frac{|f_i-a_i|}{\sum_{j=2}^{n}|a_i-a_{j-1}|} \quad (7)$$

a_i = actual time series
f_i = forecast results

Figure 3 shows the comparison of different performance metrics based on variable split-ratio in case of KFCM-ACO algorithm. *Figure 4* shows the RMSE, MSE, MAE comparison based on variable split ratio in case of KFCM-ACO algorithm. *Figure 5* shows the average accuracy comparison based on variable split ratio in case of KFCM-ACO algorithm. It clearly shows the accuracy level of 94% to 96% variations in case of different aspects and attribute variations. It also depicts that it is capable in classifying the data. Here SR varies from 70%-30%, 75%-25%, 80%-20%, 85%-15% to 90%-10%.

Figure 6 shows the comparison of different performance metrics based on variable split-ratio in case of KFCM-ABC algorithm. *Figure 7* shows the RMSE, MSE, MAE comparison based on variable split ratio in case of KFCM-ABC algorithm. *Figure 8* shows the average accuracy comparison based on variable split ratio in case of KFCM-ACO algorithm. It clearly shows the accuracy level of 95% to 97% variations in case of different aspects and attribute variations. It also depicts that it is capable in classifying the data.

The limitations of this study which can be further implemented at the final stage, instead of a simple median filter, some variants of median filter like weighted median or any other filter may be used which can improve the image quality.

A complete list of abbreviations is shown in *Appendix I.*

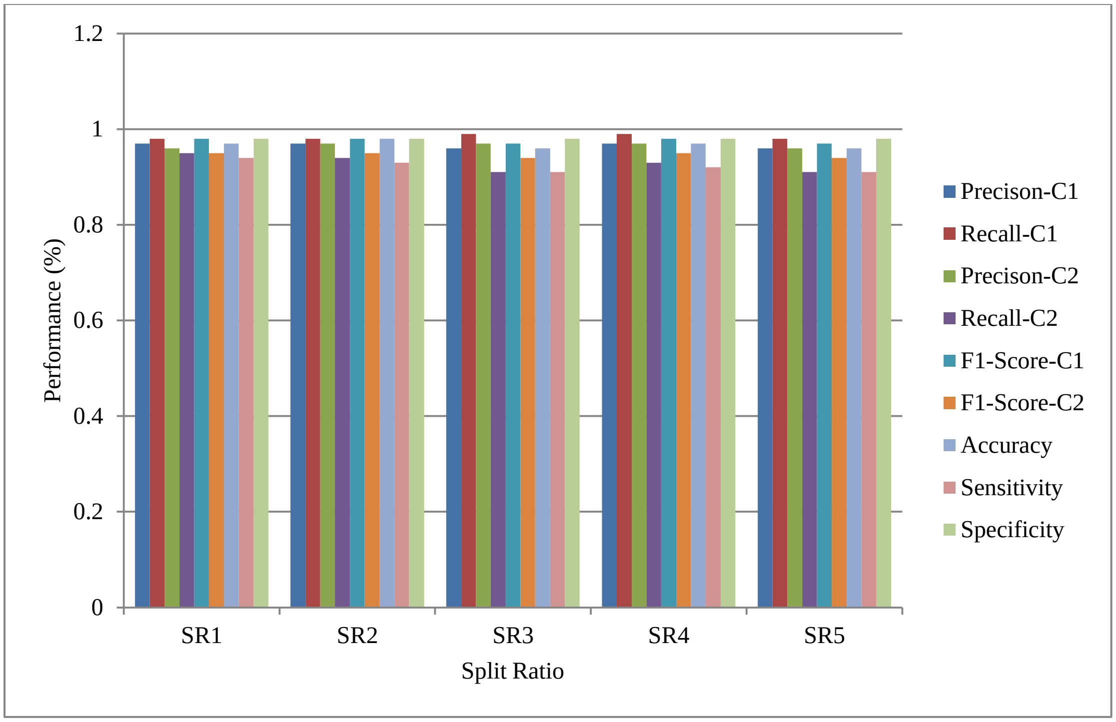

Figure 3 Comparison of different performance metrics based on variable split-ratio in case of KFCM-ACO algorithm

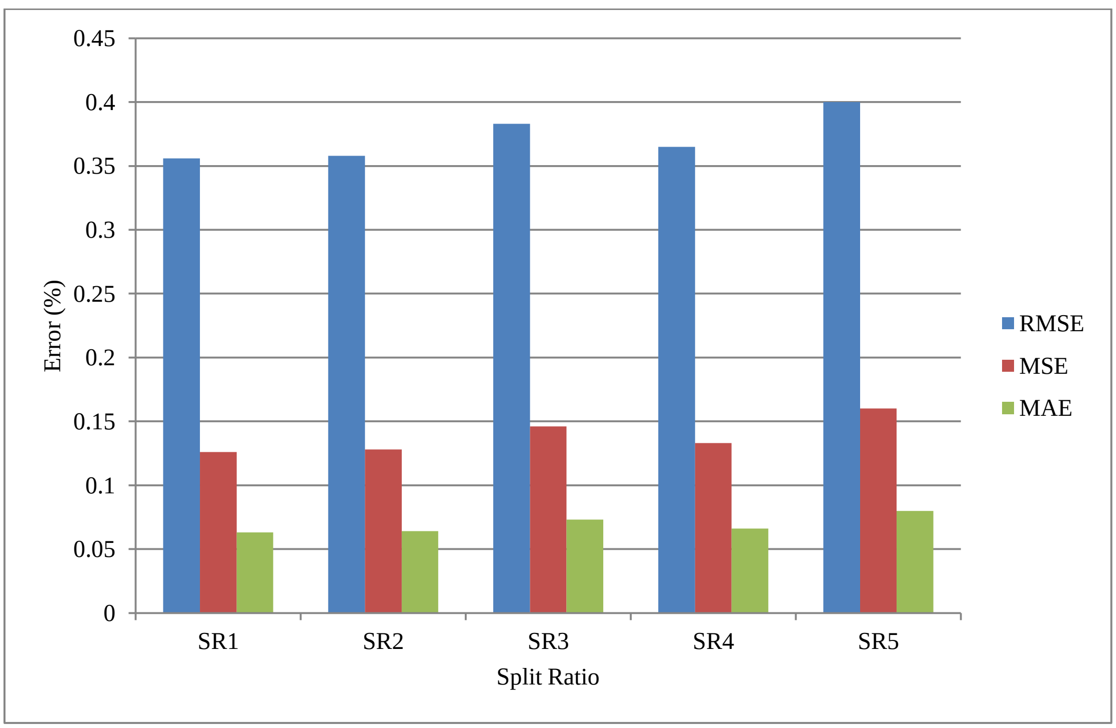

Figure 4 RMSE, MSE, MAE comparison based on variable split ratio in case of KFCM-ACO algorithm

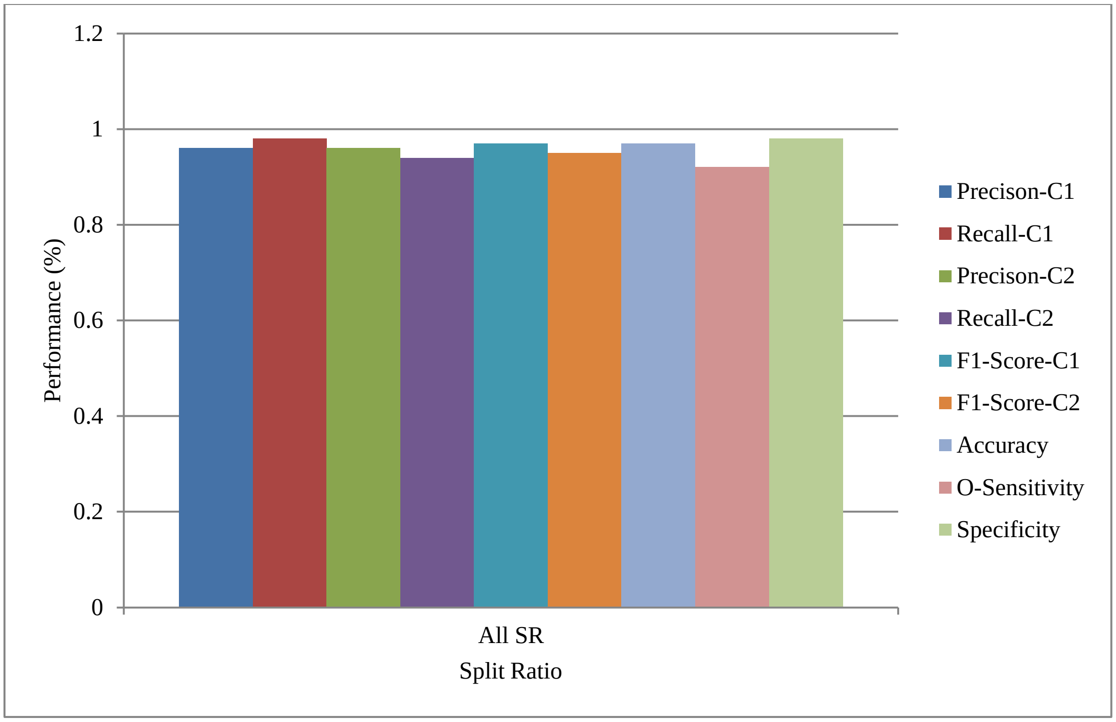

Figure 5 Average accuracy comparison based on variable split ratio in case of KFCM-ACO algorithm

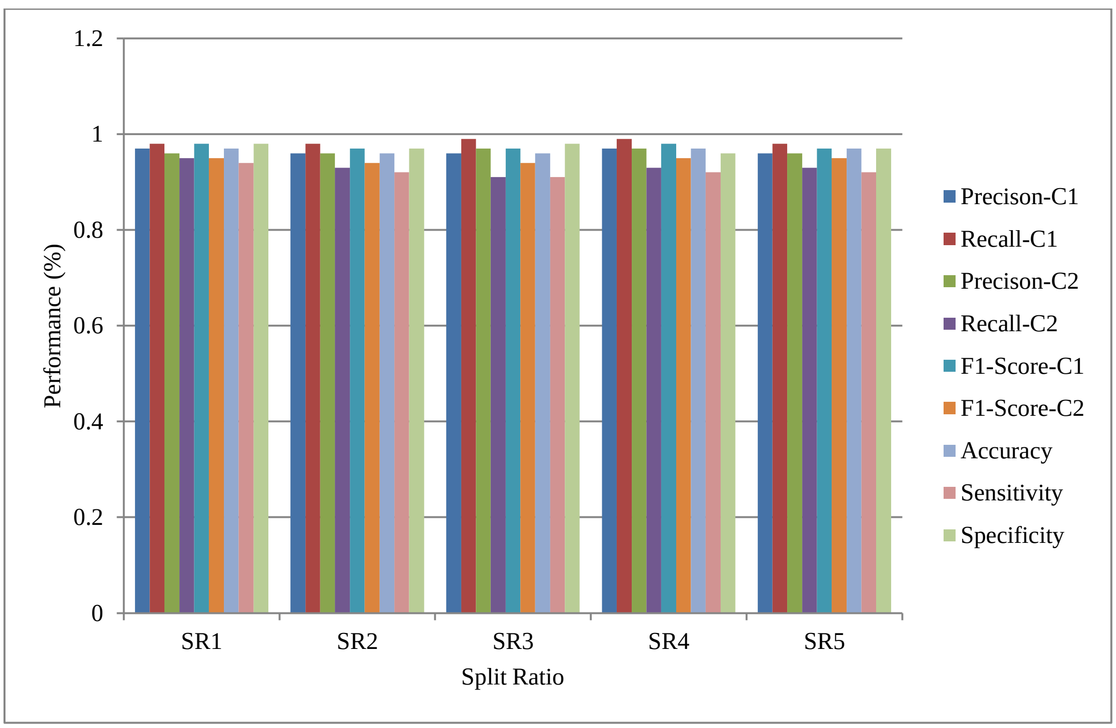

Figure 6 Comparison of different performance metrics based on variable split-ratio in case of KFCM-ABC algorithm

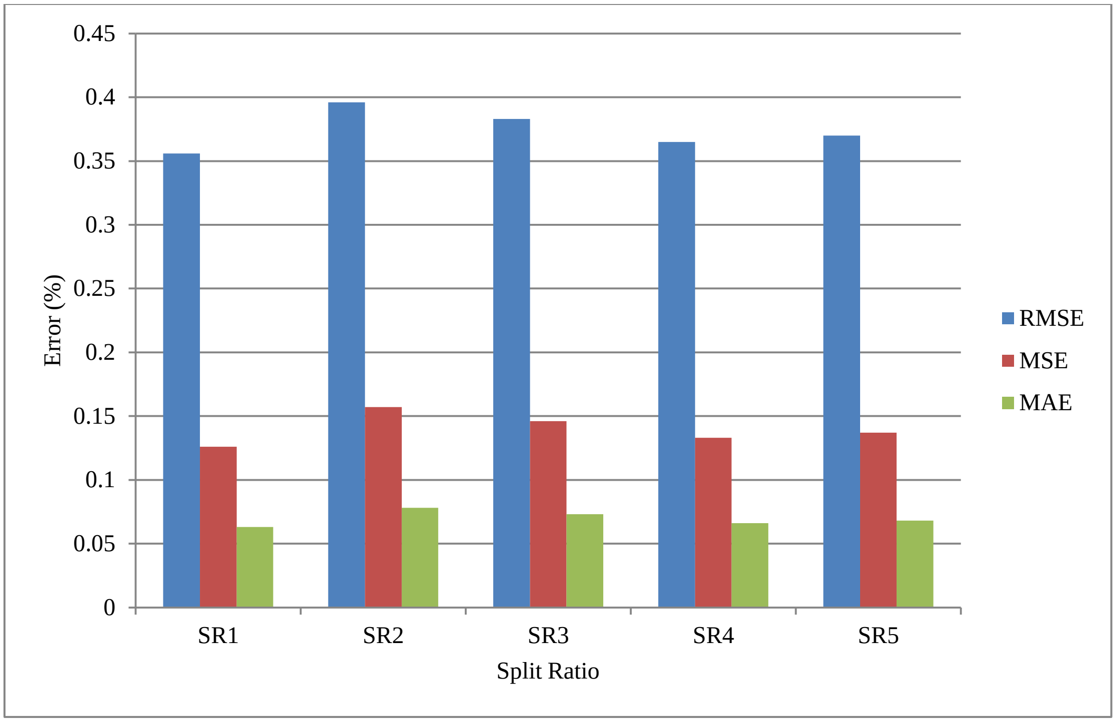

Figure 7 RMSE, MSE, MAE comparison based on variable split ratio in case of KFCM-ABC algorithm

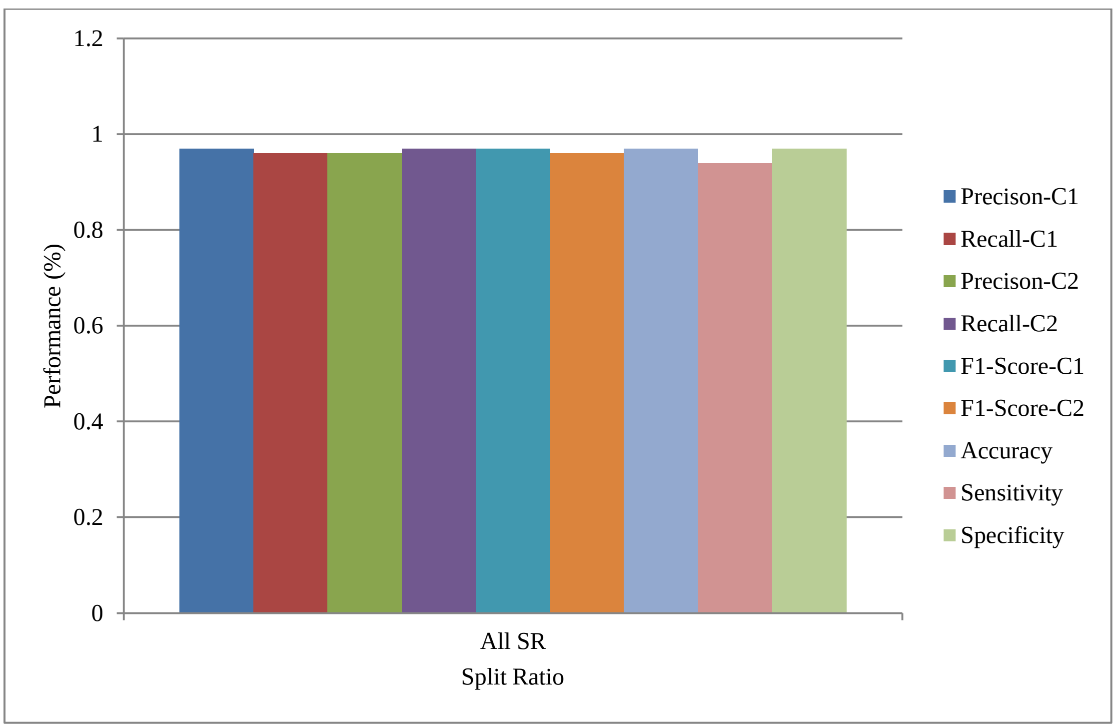

Figure 8 Average accuracy comparison based on variable split ratio in case of KFCM-ACO algorithm

5.Conclusion

The combination of clustering algorithms has been applied. The major benefit of this combination is to use the variance with same centroid capability of k-means with the fuzziness of iteration of FCM. It will be helpful in the multiple cluster selection of the data point for the single occurrence. So, the best threshold can be selected for the cluster. It has been applied with ACO and ABC algorithm. KFCM-ACO and KFCM-ABC using a three-level of thresholds and boundary evaluation method is proposed to detect and remove the shadows under various illumination conditions such as Indoor, Outdoor, Moderate, and Rainy- cases. In this method, intelligent learning methods are used to increase the convergence rate. The concept of masking is used to improve the local boundary. The gradient, curvature evaluation, and edge response help to enhance the overall accuracy. The KFCM-ACO and KFCM-ABC algorithms are used to optimize the search process and to find the segmented and associated pixels for shadow detection. The comparison of the approaches clearly depicted that the approaches have less error rates and higher accuracy. It has been confirmed from the results considering different cases also. New feature extraction and different optimization techniques can be analyzed in the future with various classification techniques.

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Conflicts of interest

The authors have no conflicts of interest to declare.

Author's contribution statement

Rakesh Kumar Das: Conceptualization, investigation, writing –original draft, analysis and interpretation and Study conception. **Madhu Shandilya:** Writing – review and editing and supervision.

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Appendix I

S. No.	Abbreviation	Description
1	ABC	Artificial Bee Colony
2	ACO	Ant Colony Optimization
3	AISD	Aerial Imagery Dataset for The Shadow Detection
4	AHE	Adaptive Histogram Equalization
5	AVIRIS	Airborne Visible/Infrared Imaging Spectrometer
6	BER	Balance Error Rate
7	CC	ColorChecker
8	CDN	Cloud-Detection Network
9	CNN	Convolutional Neural Network
10	DCF	Discriminative Correlation Filter
11	DCP	Dark Channel Prior
12	DT	Decision Tree
13	DTh-DB	Dongguk Thermal Image Database
14	DRPCA	Discriminative Robust Principal Component Analysis
15	DSPF	Deeply Supervised Progressive Fusion
16	EDR	Encoder-Decoder Residual
17	ESPCN	Efficient Sub-Pixel Convolutional Neural Network
18	FCM	Fuzzy c-Means
19	FCN	Convolutional Network
20	FSRCNN	Fast Super-Resolution Convolutional Neural Network
	GLVQ	Generalized Learning Vector Quantization
21	GAN	Generative Adversarial Network
22	GF	Guided Filter
23	HOG	Histogram of Oriented Gradient
24	KFCM-ABC	k-Means And Fuzzy c-Means-Artificial Bee Colony
25	KFCM-ACO	k-Means and Fuzzy c-Means-Ant Colony Optimization
26	KNN	k-Nearest Neighbor
27	LBP	Local Binary Patterns
28	LCC	Local Color Correction
29	LR	Logistic Regression
30	NB	Naïve Bayes
31	OLI	Operational Land Imager
32	PFCN	Pruned Fully Convolutional Network
33	PSO	Particle Swarm Optimization
34	PSNR	Peak-Signal-To Noise Ratio
35	PV	Photovoltaic
36	RF	Random Forest
37	SBU	Stony Brook University
38	SILTP	Scale Invariant Local Ternary Pattern
39	ST-KDE	Spatio-Temporal Kernel Density Estimation
40	SSIM	Structural Similarity Index
41	SISR	Single Image Super Resolution
42	STS	Successive Thresholding Scheme
43	SVM	Support Vector Machine
44	TLBO	Teaching Learning-Based Optimization