



Optimal trained ensemble of classification model for satellite image classification

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Abstract

Satellite image classification is the most significant remote sensing method for computerized analysis and pattern detection of satellite data. This method relies on the image's diversity structures and necessitates a thorough validation of the training data using the chosen classification algorithm. The classifying of remotely sensed images refers to the process of classifying pixels into a fixed set of distinct classes based on their data values. The pixel is categorized into that class if it complies with a specific set of requirements. A new SIC scheme is suggested in this work, where, Contrast limited adaptive histogram equalization (CLAHE) is deployed for pre-processing the image. Further, statistical features, Vegetation Indices (VI) and Improved Hybrid Vegetation Index (IHVI) are extracted from the preprocessed image. Then, we deploy 2 phase classification process for classifying the image. In the first phase, Bi-Directional Gated Recurrent Unit (BI-GRU), Convolutional Neural Network (CNN) and Deep Max Out (DMO) are used. In 2nd phase, optimized RNN is used for determining the final classification result. Also, the training of the model is done by the new Chaotic Opposition Behavior Improvised Coot Algorithm (COBI-CA) optimization via tuning the optimal weights. The COOT method has been enhanced and is now the suggested algorithm. Lastly, we conduct an analysis to compare the suggested Satellite Image Classification (SIC) model's performance to the traditional approaches in terms of statistical analysis, precision, accuracy, and error measure. In comparison to other conventional methods, the accuracy of the suggested model is 97%.

Keywords Satellite image · Statistical features · CLAHE · Improved HVI · COBI-CAalgorithm

1 Introduction

Due to the massive number of images that are produced by satellites, it is crucial to know about them [1–3]. Due to its use in a variety of fields, including agriculture, safety (in the defense), urban growth, the detection of natural disasters, medical diagnostics, and the detection of deforestation, satellite imageries are of immense relevance. Because of the enormity of satellite images, satellite imagery analysis is an extremely difficult task [4–7]. Additionally, the satellite imageries exhibit relatively low interclass variation and considerable

intra-class variety. The pre-processing methods that work fine for lab environment collection do not have much effectiveness for satellite images since they are obtained in the field [8–12].

Researchers have put a lot of effort into comprehending satellite images and have proposed a variety of feature extraction techniques. These techniques can be divided into low-level Local Binary Pattern (LBP), Shift Invariant Feature Transform (SIFT), mid-level Bag of Visual Words (BOVW) model, Probabilistic Latent Semantic Analysis (PLSA), and high-level Convolutional Neural Network (CNN), Restricted Boltzmann Machine (RBM), Deep Belief Networks (DBN), and stacked Auto encoder (AE). Among the methods discussed above, CNN is the most widely used since it extracts the spatial characteristics by combining a variety of layers [13–15].

The DNN “VGG16, Alex Net, Google Net, and VGG-19” are the most often utilized ones. The researchers have suggested networks like Sat CNN, Modified Sesame Network (MSN), and D-DSML for classifying satellite images [16–18]. E2e learning and Transfer Learning (TL) are the two main methods for applying the Deep Neural Networks (DNNs) for satellite image interpretation. E2e learning involves training and modeling a framework from the very initial layer all the way to the end. On the other hand, TL requires less calculation time since just a small number of prior layers are learned in this model. Researchers have investigated both satellite image analysis methods and have attained better results. There are several image interpolation approaches available now as the image processing methods are being advanced [19–22]. These interpolation approaches include a wide range of mathematical expressions, which results in a variety of interpolation artifacts and ambiguity in categorization. Due to their accuracy and ease of use, statistical parameters are frequently employed in satellite image processing techniques. These statistical parameter-based methods can only be used in limited areas and take a lot of time. The noise in the satellite photos is caused by weather-related phenomena and photographic equipment faults. When classifying scenes, high-resolution satellite photos give rise to a number of problems, including the following: Two things happen: (1) items in similar types of scenes have varied orientations and scales; (2) upgraded photographs contain more details, yet low-level features in low-resolution images are insufficient to capture distinct image data. Therefore, assessing the uncertainty brought on by imagery scaling algorithms becomes imperative. This paper proposes a satellite image classification model with the following contributions.

- Derives IHVI features along with other existing features.
- Deploys 2-phase classification. In the initial phase, BI-GRU, CNN and DMO are deployed. In 2nd phase, optimized RNN is used for classifying the image.
- COBI-CA training algorithm is introduced for tuning the optimal weights of RNN.
- Section 2 reviews sextant SIC methods. The description of the new SIC is in Section 3 and Section 4 discusses improved features. Section 5 explained phase classification and Section 6 explained the COBI-CA algorithm. The results are in 7 and 8 sections.

2 Literature review

2.1 Related works

In 2021, Rathee et al. [23] developed CNN and looked at the resizing approach that affected the performance of the Deep Learning (DL) and computed the uncertainty of

classification. The developed classification model is a multi-label categorization issue with 6 potential labels for demonstrating land covered. Finally, the model's performance is assessed on efficiency and uncertainty. This study makes two contributions: first, it proposes a general model that would aid other appliances, and subsequently, it assesses the degree of uncertainty in the categorization task by modifying the image scaling approach.

Bindhu et al. [24]. presented the cellular automata method in 2022. Parallelepiped and Machine Learning (ML) classifiers are used for pixel-based classification, whereas Soft-max Regression (SR) classifiers are used for texture-oriented categorization. The efficiency of these classifiers is increased by integrating ACA, and the effectiveness is then assessed. This comprehensive categorization technique is carried out to comprehend Kerala's Land Cover and Land Use (LC-LU).

Hu et al. [25] developed the Coordinate Partial Adversarial Domain Adaptation (CPADA) e2e unsupervised classification algorithm in 2020 for the categorization of satellite imageries. Our system transferred pertinent examples in the widespread classes to improve performances and ignored inappropriate information in the specific classes to decrease harmful transfers. This is made possible by a new coordinate loss. Our CPADA outperforms extant results for the job of classifying unsupervised satellite images, according to experiments.

The presentation of a three-step, reliable approach is developed by Jayanthi et al. [26]. The first stage entails gathering Hyper spectral Satellite Images (HIS) and their pre-processing, the second separates the images into blocks for arrangement, and the last stage concentrates on categorization depending upon hyper graph structure utilizing DL methodology. A novel approach using LIC and DNN classification is used to analyze satellite images. The use of samples and previous awareness of imaging sets in remote sensing appliances requires greater computing time.

For image fusion in 2020, Swathika et al. [27] employed the Versatile Unsupervised Vector Zone (VUVZ) approach. The generated photos have been classified by collecting data and evaluating the classification accuracy of each image using the IPB rule for supervised categorization. The findings demonstrate that the satellite-identified spectrum anomalies are closely connected to the recognized oil wells and that the nano discharge maps can generate fresh, higher-class data to lower the risk of exploration.

The 3D2D CNN scheme was modified in 2021 by Bandyopadhyay et al. [28] for extracting representative data from a different group of LU-LC utilizing various areas in a multi-stack pattern. The suggested technique aimed to improve the extraction of various representative features while also reducing the number of bands required for learning samples and classification. To determine the effectiveness and robustness of the suggested model, the experiments are conducted utilizing publicly accessible HSI datasets, with a particular concentration on smaller datasets.

Three image fusion techniques were utilized in 2022 by Shakya et al. [29]: pyramid-based fusion techniques, pyramid-based fusion techniques combined with CNN, as well as a mixture of Multiple Distinct Pyramid Decomposition (MMDPD) techniques used simultaneously with CNN. An improved 2D-CNN oriented DL evaluated the effectiveness of the compound images for fusing metrics, higher resolution, and total categorization accuracy. The 2DCNN-oriented DL classification utilized in this work has a number of hyper parameters that were optimized using the Bayesian technique.

The categorization and evaluation of compound land features using fusion images derived by fusing 2 hyperspectral and MS datasets was reported by Vibhute et al. in 2020 [30]. Fusion was done using satellite images with high spatial-spectral resolution, several

instruments, and many time periods. The datasets were subjected to the implementation of 3-pixel fusion-oriented schemes: Color Normalized Spectral Sharpening (CNSS), Principal Component Spectral Sharpening Transform (PCSST), and Gram-Schmidt Transform (GST). Using the classification findings, three fusion algorithms' performance assessments were conducted. Five different types of images were utilized for classification, and the Support Vector Machine (SVM) and Gaussian Maximum Likelihood Classification (GMLC) methods were employed.

A better deep learning model for region-based real-time satellite image classification in application-specific settings is deployed by Reena et al. [31]. Large-scale temporal data is collected by ELSET using Google Earth Engine, and outliers are removed from the datasets using segmentation model filters tailored to the needs of the application. By combining these techniques, it is possible to identify layered regions in images with moderate complexity and great precision.

The PAELM for classifying satellite images is deployed by Hamid et al. [32]. The PAELM technique builds a varied set of extreme learning machine (ELM) classifiers and combines them using the pixel-based LCC accuracy values in order to assign the LCC class of a given pixel to the most highly accurate ELM classifier among the ensemble of ELMs. Three advanced machine learning classifiers—support vector machine, traditional ELM, and extreme gradient boosting—as well as one advanced ensemble classifier were compared to PAELM. Six experimental sites with various geographic contexts across the US were used to validate PAELM. Table 1 shows the review on existing Models.

2.2 Research gaps

- Satellite image categorization is crucial in numerous domains, together with portraying characteristics, land cover categorization, change detection and 3D modeling.
- Understanding and evaluating pertinent information also needs image categorization. Accuracy of Image classification has seen a significant increase due to the quick development of DL techniques.
- The disadvantage of DL techniques for many real-world applications is that they require vast amounts of tagged data.
- Thus, the efficient utilization of image information has emerged as a key area of study.
- There are ways to deal with problems with satellite image categorization, both unsupervised and supervised.
- With the use of DL techniques, we can raise the accuracy of earlier approaches to a respectable level.
- However, in the categorization of satellite images problem, there is a lack of labeled data, which makes supervised learning difficult to use in real-world situations.
- Employing unsupervised image classification methods is a much more practical approach. To improve classification accuracy, unsupervised classification techniques must first identify the probabilistic distribution of data compliant, then assess and evaluate early results.
- These classification techniques, however, have a large processing cost and merely provide a distribution of data with unclear labels.

Table 1 Advantages and disadvantages of proposed model

Author	Methods	Features	Challenges
Rathee et al. [23]	CNN	The classification accuracy is high	The computational time is high
Bindhu et al. [24]	Softmax regression	The efficiency has been improved	Need to consider the imbalance problems
Hu et al. [25]	Coordinate partial adversarial domain adaptation	The loss occurrence is eliminated	During training inaccurate cross-class classification
Jayanthi et al. [26]	Markov chain model for clustering	Consumes less space and the complexity of the time is also reduced	Need to consider the large dataset
Swathika et al. [27]	Linear iterative clustering	Reduces the false classification Ratio	Need to consider the feature sets
Bandyopadhyay et al. [28]	3D-2D CNN Hybrid model	Improves the flexibility of the system	Need to concentrate on noise challenges
Shakya et al. [29]	Deep Learning	The performance of the system has been improved	Need to concentrate the loss functions
Vibhute et al. [30]	Support Vector Machine	The system reliability is good	Need to consider the tuning parameter

3 Description of the new SIC technique

A novel SIC was developed for the pre-processing Contrast limited adaptive histogram equalization (CLAHE) is applied to the input image Ima that is implied as Ima_{pr} . Additionally, the pre-processed image is used to extract statistical features, Vegetation Indices (VI), and Improved Hybrid Vegetation Index (IHVI). Next, we use a two-phase classification procedure to categorize the picture. Convolutional neural networks (CNN), Deep Max Out (DMO), and Bi-Directional Gated Recurrent Units (BI-GRU) are utilized in the initial phase. The final classification outcome is determined in the second phase using an optimized RNN. Additionally, the model is trained by optimizing the ideal weights using the novel Chaotic Opposition Behavior Improvised Coot Algorithm (COBI-CA). Then, statistical features, VI and IHVI features are taken from Ima_{pr} and implied by Ft . Then, we deploy 2 phase classification. In the initial phase, BI-GRU, CNN and DMO are deployed. In 2nd phase, optimized RNN is used for SIC. In RNN, the weights are selected via the COBI-CA algorithm. The suggested method framework is diagrammatically exposed in Fig. 1.

3.1 Pre-processing

CLAHE (<https://www.geeksforgeeks.org/clahe-histogram-equalization-opencv/>): CLAHE is applied to the image with size (472×546×3). It is an AHE variation that addresses the issue of excessive contrast amplification. Instead of the full image, CLAHE works on discrete areas known as tiles. Once the fake borders are eliminated, the surrounding tiles are blended using bilinear interpolation. The CLAHE is deployed to progress the contrast of images.

The CLAHE applied output is implied as Ima_{pr} .

4 Derivation of novel features

The process of mining out characteristics is essential for huge datasets and helps minimize the loss of important data. The statistical features, VI, and enhanced hybrid VI features are drawn from Ima_{pr} .

4.1 VI features

NDVI [14]: In the environmental study; NDVI is amongst the most repeatedly deployed VI. It is assessed based on NIR (*nir*) and red (*red*) light reflecting assessment as presented in Eq. (1), wherein, *nir* and *red* implied quantity of light reflected by rising vegetation and recorded by satellite sensor.

$$VI_1 = \left(\frac{(nir - red)}{(nir + red)} \right) \quad (1)$$

NDI [16]: *NDI* is assessed on the basis of thermal and optimal bands. In Eq. (2), *NDI* is assessed, wherein, *ba* refers to band.

$$VI_2 = \frac{ba_1 - ba_2}{ba_1 + ba_2} \quad (2)$$

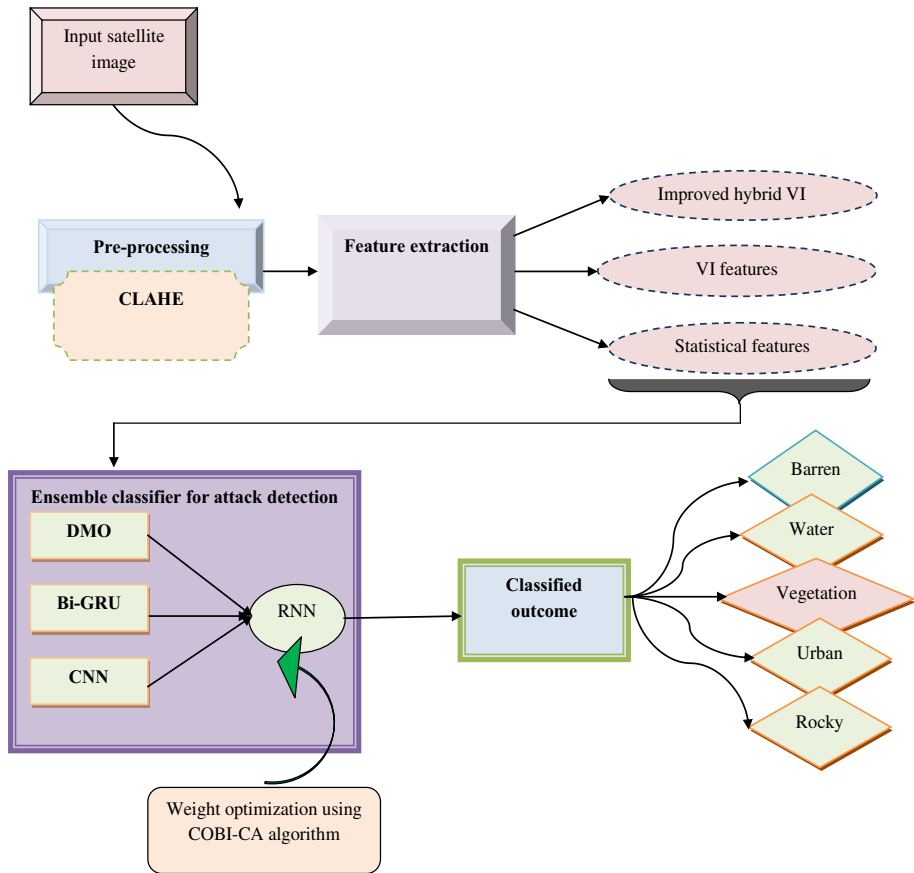


Fig. 1 Diagrammatic depiction of SICscheme

EVI [17]: It is required to meet access to crop growth inconsistency under both sparse and dense vegetation cover situations. In Eq. (3), *EVI* is assessed.

$$VI_3 = 2.5 * \frac{(nir - red)}{(nir + 6 * red - 7.5 * blue + 1)} \quad (3)$$

RVI [17]: It is assessed by the proportion of NIR and RED bands.

$$VI_4 = \frac{red}{nir} \quad (4)$$

Every VI feature is referred by *VI*.

4.2 Statistical features

These features consist of moment (SF_1), mean (SF_2), entropy (SF_3) and SD (SF_4). The statistical features are implied as *SF*.

4.3 Improved hybrid VI features

It is the mixture of statistical model function with VI [33, 34]. Here, the statistical features are $(SF_1) \rightarrow$ moment, $(SF_2) \rightarrow$ mean $(SF_3) \rightarrow$ entropy $(SF_4) \rightarrow$ SD. The arithmetic mean is taken for all the statistical features.

Consider the VI as NDVI (VI_1) , NDI VI_2 , EVI VI_3 and RVI VI_4 . The weighted geometric mean is taken for all the VI features.

Here, HVI can be determined as shown in Eq. (5).

$$HVI = W_1 F_1 + W_2 F_2 \quad (5)$$

F_1 refers to the arithmetic mean of (SF_1) (SF_2) (SF_3) and (SF_4) .

F_2 refers to the weighted geometric mean of (VI_1) (VI_2) (VI_3) and (VI_4) .

The arithmetic mean is assessed as shown in Eq. (6).

$$AM = \frac{1}{n} \sum_{i=1}^n a_i \quad (6)$$

WGM is assessed as shown in Eq. (7).

$$WGM = \exp \left(\frac{\sum_{i=1}^n w_i \ln y_i}{\sum_{i=1}^n w_i} \right) \quad (7)$$

Here, w_1 and w_2 are generated using dis_1 and dis_2 . dis_1 refers to the distance between F_1 and target. dis_2 refers to the distance between F_2 and the target.

If $dis_1 < dis_2$:

$$W_1 = 1 - dis_1$$

$$W_2 = dis_1$$

Else;

$$W_1 = -dis_2$$

$$W_2 = 1 - dis_2$$

Using this W_1 and W_2 , we get IHVI indices.

The whole features derived are referred as $Ft = VI + SF + IHVI$.

4.3.1 Phase classification for satellite image classification

The derived Ft is further given to EC for categorization. So as to create a novel classifier that performs better than its constitutive classifiers, EC combines some fundamental classifiers [35]. Here, we deploy 2 phase classification. In the initial phase, BI-GRU, CNN and DMO are deployed. In 2nd phase, optimized RNN is used for SIC.

4.4 Bi-GRU

It [36] is a kind of RNN that helps in the processing of data from subsequent and earlier time steps to produce projections regarding the current condition. By denoting the sigmoid function, hidden vectors, and input states as σ , hi_t and v_t accordingly, Eq. (8–11) illustrates the BI-GRU computation. Here, r_t implied reset data WG implied weighting factor and t implied time interval. The Bi-GRU output is $Bi - GRU^{out}$.

$$F_t = \sigma(WG_F * [hi_{t-1}, v_t]) \quad (8)$$

$$r_t = \sigma(WG_r * [hi_{t-1}, v_t]) \quad (9)$$

$$hi_t = \tanh(WG * [r_t hi_{t-1}, v_t]) \quad (10)$$

$$hi_t = (1 - F_t)C_{t-1} + F_t hi_t \quad (11)$$

4.5 CNN

The CNN features [37] are revealed in Eq. (12).

$$D_{r,t,w}^l = \varpi_w^l PA_{r,t}^l + B_w^l \quad (12)$$

In Eq. (12), “ ϖ_w^l ” $\rightarrow$ weight that is optimally tuned using IBS-BOA model, $B_w^l \rightarrow$ bias of w^l filter linked to l^{th} layer. At the centre location (r,t) of l^{th} layer, the patch input is indicated as $PA_{r,t}^l$. The activation value $(act_{r,t,w}^l)$ related to convolutional features $D_{r,t,w}^l$ is exposed by Eq. (13).

$$act_{r,t,w}^l = act(D_{r,t,w}^l) \quad (13)$$

Pooling layer: Eq. (14) demonstrates the computation of $H_{r,t,w}^l$. CNN loss PL is exposed by Eq. (15), wherein, θ suggests a term associated with W_w^l and B_w^l . The output, the labels and h^{th} input feature is represented as $F^{(h)}$, $H^{(h)}$ and $PA^{(h)}$ and $nn_{r,t}$ represents (r, t) near neighboring position. The output from CNN is represented as CNN^{out} .

$$H_{r,t,w}^l = pool(act_{m,h,w}^l), \forall(m, h) \in nn_{r,t} \quad (14)$$

$$PL = \frac{1}{wn} \sum_{h=1}^{wn} l(\theta, H^{(h)}, F^{(h)}) \quad (15)$$

4.6 DMO

A DMO [38] consists of many progressively linked max-out layers with hidden units that are split into non-overlapping groups. Each layer generates hidden activations by using the

max-out function and the resulting trainable activation functions. The input for the activation functions of the DMN is the minutiae points, as given in Eq. (16) - (20).

$$c_{s,t}^1 = \max_{t \in [1, h_1]} MP^T k_{\dots st} + d_{st} \quad (16)$$

$$c_{s,t}^2 = \max_{t \in [1, h_2]} \left(c_{s,t}^1 \right)^T k_{\dots st} + d_{st} \quad (17)$$

$$c_{s,t}^e = \max_{t \in [1, h_e]} \left(c_{s,t}^{e-1} \right)^T k_{\dots st} + d_{st} \quad (18)$$

$$c_{s,t}^f = \max_{t \in [1, h_f]} \left(c_{s,t}^{f-1} \right)^T k_{\dots st} + d_{st} \quad (19)$$

$$b_s = \max_{t \in [1, h_f]} c_{s,t}^f \quad (20)$$

Here, hidden unit count at e^{th} layer is referred by h_e , layer's weight and bias is referred by k_{st} and d_{st} . The whole count of DMN layers is referred by f and max out layer's output is referred by b_s . The DMO output is represented as DMO^{out} .

The outputs from the initial phase *IC* (Bi-GRU, CNN and DMO) are combined as in Eq. (21) and given as input to 2nd phase (optimized RNN).

$$IC = Bi - GRU^{out} + CNN^{out} + DMO^{out} \quad (21)$$

4.7 Optimized RNN

RNN [39] included neurons with 3 layers. The inward layer integrated N input units with vectors like $\{\dots, T_{t-1}, T_t, T_{t+1}, \dots\}$, where in $T_t = (T_1, T_2, \dots, T_N)$. All input unit are associated with each hidden unit that are linked by weight ω_{lh} . The hidden layers comprise M hidden units $y_t = (y_1, y_2, \dots, y_M)$, which are associated via recurring links offered by weight ω_{hh} , as depicted in Eq. (22), in which a_y and $f_h(\bullet)$ suggests bias and activation of hidden units and t suggests time.

$$y_t = f_h(\omega_{lh} T_t \omega_{hh} y_{t-1} + a_y) \quad (22)$$

The output layers included q units implied as $x_t = (x_1, x_2, \dots, x_p)$ and exposed in Eq. (23), wherein, $f_o(\bullet)$ and a_o symbolize bias and activating term, ω_{ho} implied weight that is tuned via COBI-CA algorithm.

$$x_t = f_o(\omega_{ho} y_t + a_o) \quad (23)$$

The RNN output gives the final output on SIC, i.e. it determines if the soil is barren, rocky, urban, vegetation and water. The EC is depicted in Fig. 2.

The RNN weights implied as (ω) are elected via COBI-CA optimally. The objective *Obj* is shown in Eq. (24). The chromosome length is set as 100.

$$Obj = Min(Error) \quad (24)$$

5 Weight optimization of RNN via COBI-CA algorithm

5.1 Proposed COBI-CA training algorithm

The CA [40] algorithm offers wide-ranging benefits, nevertheless, exceptional modifications are required consequently, and COBI-CA is formed. Usually, conservative optimization techniques [16, 19, 20] are capable of self-enhancements [17, 18, 21, 22, 41] that ensures optimal outcome better results. The advantages of the proposed model are it provides the better convergence and could solve local optima problem.

The coots can move among levels in two different methods. The primary one concerns followers of Coot. The 2nd is to raise coot followers to positions of leadership. The number of coot followers is suggested as M_{po} . In this work, chaotic OBL-based opposite solutions are generated as shown in Eq. (25). Here, r is generated using a sinus map as shown in Eq. (26).

$$p_{new} = low_i + r * (ub_i - lb_i), i = 1, 2 \dots N \quad (25)$$

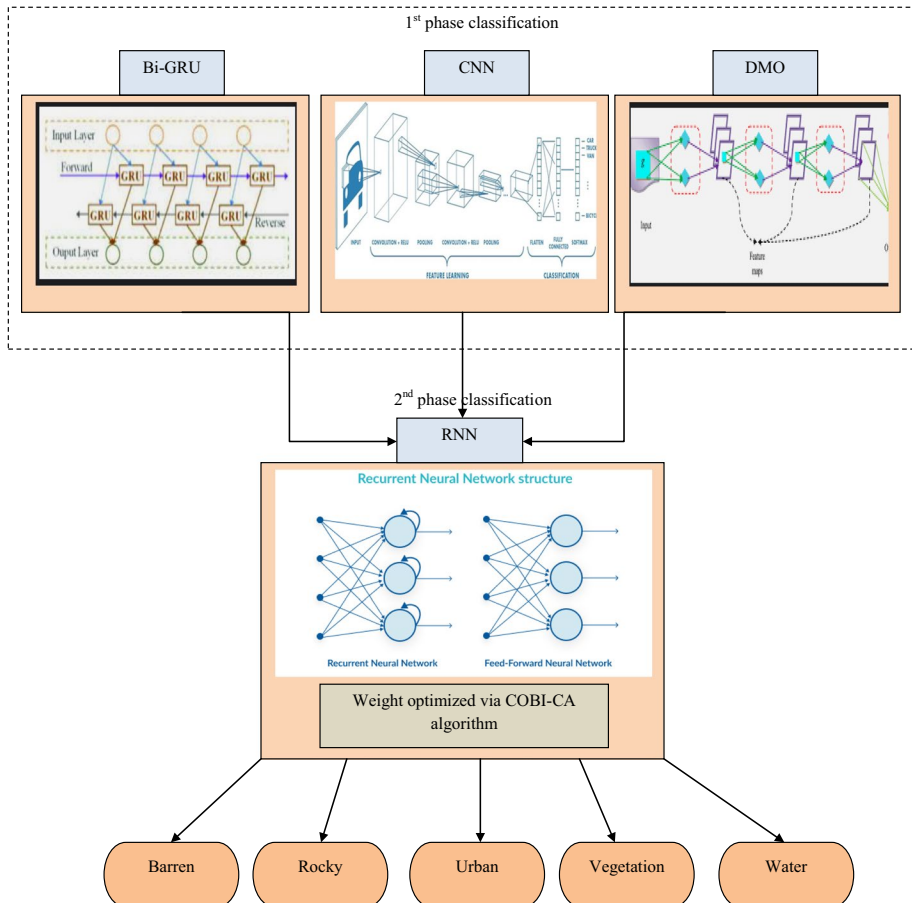


Fig. 2 The suggested ensemble classification

$$X_{n+1} = 2.3 * (X_n)^{2 * \sin(\pi X_n)} \quad (26)$$

Equation (27) and (28) are the beginning locations of leader (pos_{lea}) and follower (pos_{ct0}), wherein, up and $lp \rightarrow$ Upper and lower limits.

$$pos_{ct0} = lp + .(up - lp)ra_{ct} \quad (27)$$

$$pos_{lea} = lp + .(up - lp)ra_{lea} \quad (28)$$

Equation (29) shows the evaluation of the new location of coot.

$$pos_{coot}(i) = pos_{coot}(i) + Ar2_{coot} \times (Q - pos_{coot}(i)) \quad (29)$$

$$A = 1 - L \times \frac{1}{L_{\max}} \quad (30)$$

Chain Movement: Eq. (31) shows this stage.

$$pos_{coot}(i) = 0.5 \times (pos_{coot}(i - 1) + pos_{coot}(i)) \quad (31)$$

The $coot(i)$ have to update their position as per the leaders k . Equation (32) shows the subsequent position of coot depending upon the elected leader.

$$pos_{coot}(i) = \cos(2\pi r)2.r1_{coot} [-pos_{coot}(i) + pos_{lea}(k)] + pos_{lea}(k) \quad (32)$$

The positions of leaders are improved as specified in Eq. (33), wherein gbe_{pos} shows the finest global location and B is computed in Eq. (34).

$$pos_{lea}(i) = B.r3_{lea} \times \cos(2\pi r)[gbe_{pos} - pos_{lea}(i)] + gbe_{pos} \quad (33)$$

$$B = 2 - L \times \left(\frac{1}{L_{\max}} \right) \quad (34)$$

As per the COBI-CA, the position of leader is updated on the basis of levy flight (LF) as exposed in Eq. (35).

$$pos_{lea}(i) = B.r3_{lea} \times \cos(2\pi r)[gbe_{pos} - pos_{lea}(i)] + gbe_{pos} + LF \quad (35)$$

Heuristic crossover is moreover performed to create offspring. Primarily, consider 2 parents β^{g1} and β^{g1} and presume that 1st parent (β^{g1}) has lesser value on every allele. After that, the offspring (β^s) is formed as exposed in Eq. (36). Table 2 represents the optimization parameters of the suggested model.

$$\beta_i^s = \alpha \cdot (\beta_i^{g1} - \beta_i^{g2}) + \beta_i^{g1} \quad (36)$$

Table 2 Parameters of optimization

Method	Parameters
Proposed Model	problem_size = 5, batch_size = 10, verbose = True, epoch = 50, pop_size = 100, A = 5, Speed = 1, T1 = 3, e = 4, c1 = 2, c2 = 6, c3 = 2, c4 = 0.5, acc_upper = 0.9, acc_lower = 0.1,Max_iter = 50,dim = 10

6 Results and discussion

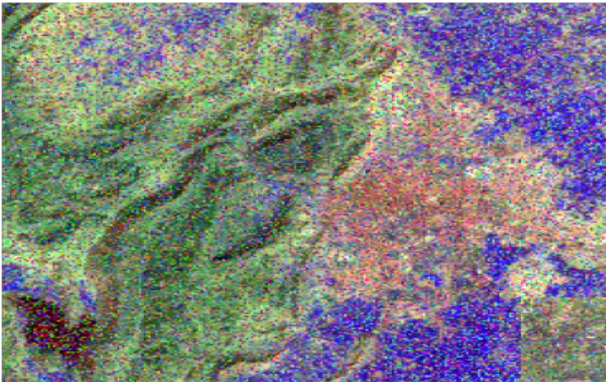
6.1 Simulation procedure

This suggested SIC was implemented using Python, and results related to the simulation were recorded. On several criteria, the applicability of the COBI-CA model was compared to that of the classic schemes, AO, POA, HBA, HGSO, and CA, CNN + NN [42], and Simple CNN [43]. The sample images for SIC are depicted in Figs. 3 and 4.

6.2 Dataset description

An image of the Rajasthani region of Alwar using multiple sensors, resolutions, and spectral types. A satellite image is obtained for each of the seven bands. Red, Green, Radarsat-1 (RS1), Radarsat-2 (RS2), Near Infrared (NIR), Middle Infrared (MIR), and

Fig. 3 Predicted image



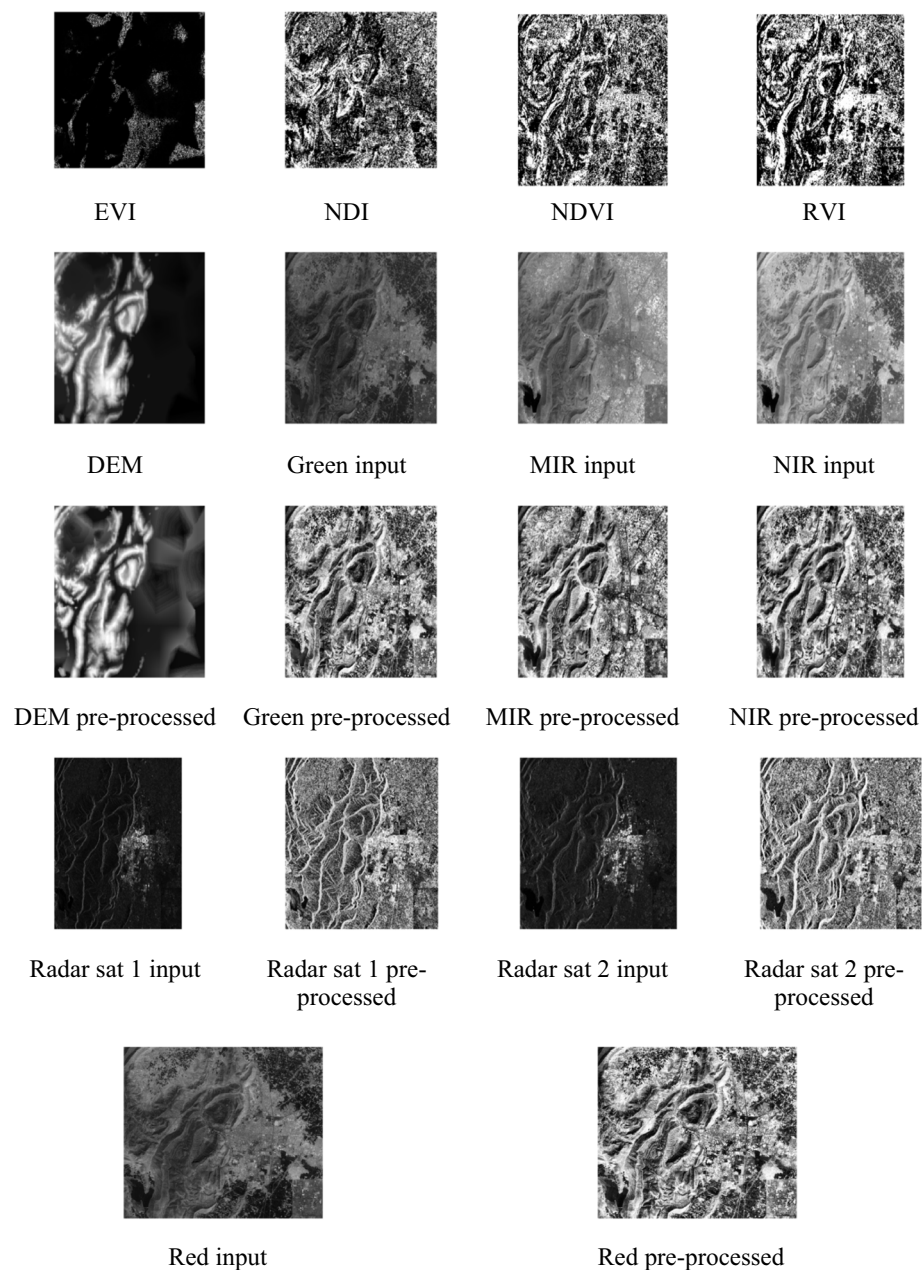


Fig. 4 Sample images for 7 bands

Digital Elevation Model (DEM) are these bands. Every feature habitat starts out with training pixels belonging to that class. On these pixels, the feature habitat's HSI is computed. After that, every species in the universal habitat is moved to a feature habitat, and the HSI is recalculated to determine which species are suitable in the new

feature environment. After migrating, a species is absorbed into (and hence belongs to) the feature habitat with the least amount of variation in its HSI. "With rocky" denotes HSI recalculation following the species' migration to this habitat, whereas "pure rocky" denotes HSI computed in rocky habitat using training pixels. Because there is not much of a difference between the two HSI values, the species will migrate to "rocky" habitat. These images, which were obtained with the LISS-III sensor and have a ground resolution of 23.5 m, were given to us by the DTRL (Remote Sensing) Lab, DRDO, Delhi.

6.3 Analysis of proposed and conventional methods for satellite image classification

Figures 5 and 6 display the assessment of COBI-CA for SIC over AO, POA, HBA, HGSO, and CA. For different LPs, the COBI-CA was examined. Here, COBI-CA has produced values for each measure that are the most satisfying. In Fig. 5(a), we can see that the accuracy value employing the COBI-CA approach at the 90th LP is fairly high, coming in at around 97%. At the 90th LP, the accuracy of the other techniques—AO, POA, HBA, HGSO, and CA—was 95%, 93%, 95%, 93%, and 94%, in that order. The hybrid improved features and COBI-CA-assisted EC implemented for SIC are to blame for the superior outcomes when employing COBI-CA.

The F measure must also be higher for the system to work well. Table 3 displays a higher F measure of 96% when COBI-CA is at the 90th LP. The high F measures established by AO, POA, HBA, HGSO, and CA, on the other hand, are 94%, 93%, 94%, 93%, and 94%, respectively. The FNR for COBI-CA is less than 0.032% at LP=80, which is better than AO, POA, HBA, HGSO, and CA. At the 60th LP, the NPV achieved by the COBI-CA is 91%, while at the 90th LP, it is 97%. Therefore, the COBI-CA has established higher positive values, proving that the scheme can efficiently classify SIC. The preprocessed image is used to extract statistical features, Vegetation Indices (VI), and Improved Hybrid Vegetation Index (IHVI). Next, we use a two-phase classification procedure to categorize the picture. Convolutional neural networks (CNN), Deep Max Out (DMO), and Bi-Directional Gated Recurrent Units (BI-GRU) are utilized in the initial phase. The final classification outcome is determined in the second phase using an optimized RNN. Additionally, the model is trained by optimizing the ideal weights using the novel Chaotic Opposition Behavior Improvised Coot Algorithm (COBI-CA). The COOT method has been enhanced and is now the suggested algorithm.

6.4 Analysis on prior studies over the COBI-CA

Table 4 summarizes the analysis of the prior study (CPUBES) over COBI-CA. By utilizing the CPUBES approach, the model's accuracy is 0.935935; by using the COBI-CA approach, it is 0.947542. Moreover, the precision using the CPUBES method is 0.84726, while, the precision using COBI-CA is 0.953307. The F-measure using the CPUBES method is 0.888089, while, F-measure using COBI-CA is 0.958393. The MCC using the CPUBES method is 0.837107, while, MCC using COBI-CA is 0.958393. The better results using COBI-CA are owing to the hybrid improved features and COBI-CA-aided EC deployed for SIC.

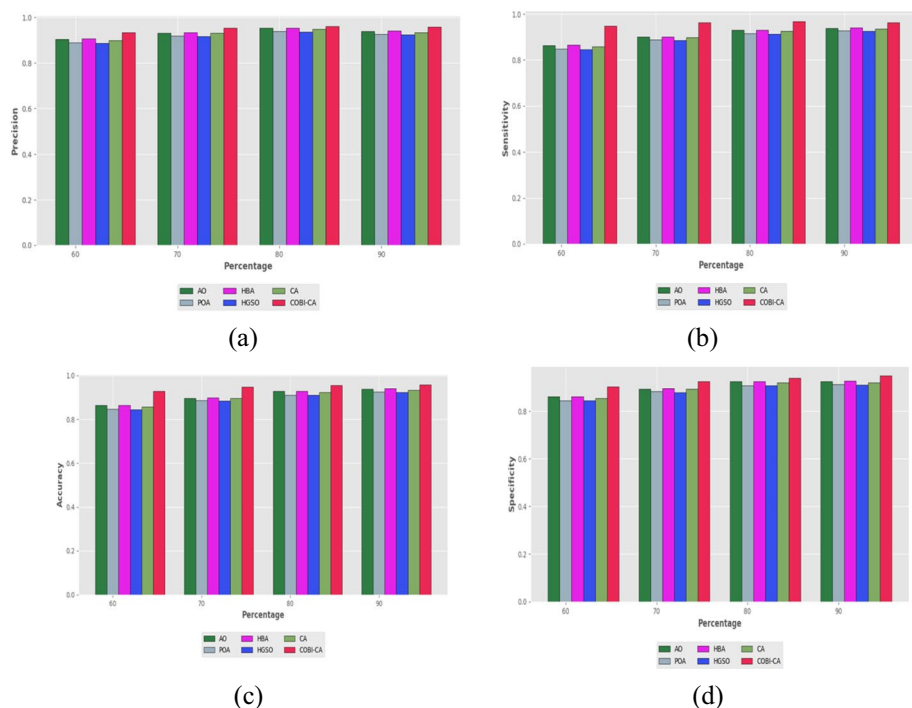


Fig. 5 Assessment of COBI-CA over existing methods for **a** Precision **b** Sensitivity **c** Accuracy **d** Specificity

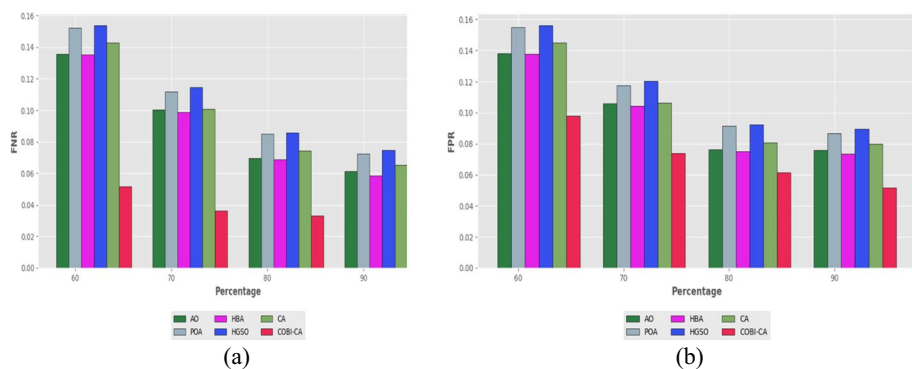


Fig. 6 Examination of COBI-CA over traditional methods for **a** FNR **b** FPR

6.5 Statistical analysis of error

Table 5 shows the examination of error via the COBI-CA technique over AO, POA, HBA, HGSO and CA. The COBI-CA model gained the negligible error of 0.006106 for standard deviation, while AO, POA, HBA, HGSO and CA have recorded considerably high error of 0.021737, 0.009266, 0.015821, 0.014134 and 0.025709. The minimal scenario using the COBI-CA model is 1.052657, while, AO, POA, HBA, HGSO and CA gained less minimal values of 1.075889, 1.072989, 1.059774, 1.062213 and 1.057091.

Table 3 Evaluation of COBI-CA over traditional methods

MCC						
LPs	AO	POA	HBA	HGSO	CA	COBI-CA
60	66.71263	64.87286	66.61795	64.62852	65.35344	81.18372
70	74.45348	73.64611	74.57526	73.08055	74.40937	86.12844
80	82.34105	80.76741	82.41741	80.6202	81.45829	89.48327
90	88.24182	87.51666	88.61273	86.9761	88.28311	92.79328
NPV						
60	81.30154	79.61021	81.31372	79.47283	80.52503	91.92969
70	85.34417	84.25374	85.47751	83.91919	85.30583	93.96144
80	89.40805	87.86237	89.51237	87.7711	88.85011	94.8564
90	91.75696	90.7757	92.04938	90.42322	91.49491	95.31669
F—measure						
60	88.42264	86.75901	88.45482	86.64118	87.75112	94.11604
70	91.54761	90.36753	91.68456	90.10638	91.51108	95.83931
80	94.12999	92.59743	94.24743	92.53229	93.72218	96.31555
90	94.47823	93.32767	94.71919	93.09991	94.01222	96.09697

Table 4 Analysis of prior studies

	CPUBES	COBI-CA
FPR	0.062915	0.073885
F-measure	0.888089	0.958393
Accuracy	0.935935	0.947542
NPV	0.950514	0.939614
Sensitivity	0.933103	0.963535
Precision	0.84726	0.953307
MCC	0.837107	0.861284
Specificity	0.937085	0.926115
FNR	0.066897	0.036465

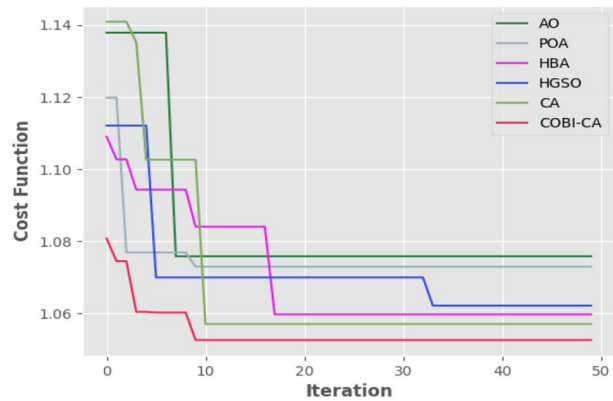
Table 5 Statistical analysis of error

Methods	Mean	Standard Deviation	Max	Median	Min
AO	1.084572	0.021737	1.137905	1.075889	1.075889
POA	1.075416	0.009266	1.119855	1.072989	1.072989
HBA	1.070522	0.015821	1.109083	1.059774	1.059774
HGSO	1.071574	0.014134	1.112145	1.070012	1.062213
CA	1.069154	0.025709	1.140946	1.057091	1.057091
COBI-CA	1.055018	0.006106	1.08082	1.052657	1.052657

Table 6 Comparison of EC over other classifiers

	KNN	CNN	BI-GRU	DMO	RNN	CNN + NN [42]	Simple CNN [43]	2-phase classifier	SVM
F—measure	0.8372	0.8825	0.8970	0.9249	0.9149	0.8827	0.8837	0.9583	0.9180
Sensitivity	0.8368	0.8630	0.8966	0.9245	0.9145	0.8633	0.8644	0.9635	0.8977
NPV	0.8375	0.9031	0.8973	0.9252	0.9153	0.9032	0.9042	0.9396	0.9084
Accuracy	0.8376	0.9030	0.8973	0.9253	0.9153	0.9031	0.9041	0.9475	0.9062
FPR	0.1618	0.0677	0.1020	0.0740	0.0840	0.0676	0.0669	0.0738	0.1920
MCC	0.8351	0.8006	0.8947	0.9226	0.9126	0.8010	0.8028	0.8612	0.8847
Specificity	0.8381	0.9322	0.8979	0.9259	0.9159	0.9323	0.9330	0.9261	0.8968
FNR	0.1631	0.1369	0.1033	0.0754	0.0854	0.1366	0.1355	0.0364	0.1633
Precision	0.8376	0.9029	0.8974	0.9253	0.9154	0.9031	0.9039	0.9533	0.9163

Fig. 7 Convergence Analysis of COBI-CA versus other optimizers



6.6 Classifier assessment: proposed 2-phase classifier and other classifiers

In Table 6, the classifier evaluation of the COBI-CA contrasted to KNN, CNN [31], SVM [32], Bi-GRU, DMO, RNN, CNN+NN [42] and simple CNN [43]. Primarily, the NPV of COBI-CA is 0.939614, which is moderately superior to others. On the other hand, the NPV of KNN is 0.837569, CNN is 0.903154, SVM is 0.9084, Bi-GRU is 0.8973, DMO is 0.9252, RNN is 0.9153, CNN+NN [42] is 0.903287 and simple CNN [43] is 0.904292. In addition, a less FNR of 0.03646 is achieved by the COBI-CA, while, KNN, CNN, SVM, Bi-GRU, DMO, RNN, CNN+NN [42] and simple CNN [43] has acquired quite higher FNR of 0.1631, 0.1369, 0.1633, 0.1033, 0.0754, 0.0854, 0.1366 and 0.1355. Therefore, the better results using COBI-CA is owing to the hybrid improved features and COBI-CA-aided EC deployed for SIC.

6.7 Convergence analysis

Figure 7 presents the cost evaluation of COBI-CA for SIC over AO, POA, HBA, HGSO, and CA. On scrutinizing Fig. 7, COBI-CA has got a less cost of (1.053) from iterations 10–50. Alternatively, a lower cost of 1.06 is resulted by COBI-CA from 3 – 8th iterations. The cost is lessened for the increase in iterations. Here, AO has shown a high cost of 1.075 at the 7th to 50th iterations. The better results by means of COBI-CA are owing to the hybrid improved features and COBI-CA-aided EC deployed for SIC.

7 Conclusion

A new SIC scheme was suggested, where, CLAHE was deployed for pre-processing. Further, statistical features, VI and IHVI features were also extracted. Then, we deployed 2 phase classification. In the initial phase, BI-GRU, CNN and DMO were deployed. In 2nd phase, optimized RNN was used for SIC. In RNN, the weights were selected via the COBI-CA algorithm. Predominantly, the NPV of COBI-CA was 0.939614, which was comparatively superior to others. Python was the software tool considered here. On the other hand, the NPV of KNN was 0.837569, CNN was 0.903154, Bi-GRU was 0.897322, DMO was 0.925277, RNN was 0.915305, CNN+NN was 0.903287 and simple CNN was 0.904292. Furthermore, the FNR of 0.036465 is obtained by the COBI-CA, but the FNRs of 0.1631, 0.1369, 0.1033,

0.0754, 0.0854, 0.1366, and 0.1355 are moderately higher for KNN, CNN, Bi-GRU, DMO, RNN, CNN+NN, and plain CNN. The limitation of the proposed model is Label issues are occurred. The advantage of the proposed model is classification accuracy has been improved. In future, large dataset can be considered. Moreover, the label issues can be solved.

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Data availability The data is available in <https://github.com/ujjwalli/GACMIS>.

Declarations

Ethical approval Not applicable.

Informed consent Not applicable.

Conflict of interest The authors declare no conflict of interest.

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