Land Use and Land Cover Classification using a Human Group based Particle Swarm Optimization Algorithm with a LSTM classifier on hybrid-pre-processing Remote Sensing Images

T. Kowsalya¹, S.L. Ullo², C. Zarro², K. L. Hemalatha³, and B. D. Parameshachari⁴

Abstract—Land use and land cover (LULC) classification using remote sensing imagery plays a vital role in many environment modeling and land use inventories. In this study, a hybrid feature optimization algorithm along with a deep learning classifier is proposed to improve performance of LULC classification, helping to predict wildlife habitat, deteriorating environmental quality, haphazard, etc. LULC classification is assessed using Sat 4, Sat 6 and Eurosat datasets. After the selection of remote sensing images, normalization and histogram equalization methods are used to improve the quality of the images. Then, a hybrid optimization is accomplished by using the Local Gabor Binary Pattern Histogram Sequence (LGBPHS), the Histogram of Oriented Gradient (HOG) and Haralick texture features, for the feature extraction from the selected images. The benefits of this hybrid optimization are a high discriminative power and invariance to color and grayscale images. Next, a Human Group based Particle Swarm Optimization (PSO) algorithm is applied to select the optimal features, whose benefits are fast convergence rate and easy to implement. After selecting the optimal feature values, a Long Short Term Memory (LSTM) network is utilized to classify the LULC classes. Experimental results showed that the Human Group based PSO algorithm with a LSTM classifier effectively well differentiates the land use and land cover classes in terms of classification accuracy, recall and precision. A minimum of 0.01% and a maximum of 2.56% improvement in accuracy is achieved compared to the existing models GoogleNet, VGG, AlexNet, ConvNet, when the proposed method is applied.

Index Terms—feature extraction optimization; Haralick texture feature; hybrid image pre-processing; histogram of oriented gradient; Human Group Optimization; land use and land cover classification; local Gabor binary pattern histogram sequence; Long Short Term Memory network; Particle Swarm Optimization.

I. INTRODUCTION

In recent years, land use and land cover classification using remote sensing imagery plays an important role in many applications like land use planning (growth trends, suburban sprawl, policy regulations and incentives), agricultural practice (conservation easements, riparian zone buffers, cropping patterns and nutrient management), forest management (harvesting, health, resource-inventory, reforestation and stand-quality) and biological resource (fragmentation, habitat quality and wetlands) [1-3]. In addition, the land use and land cover assessments are very necessary in sustaining, monitoring and planning the usage of natural resources [4-5]. The land use and land cover classification has a direct impact on atmospheric, soil erosion and water where it is indirectly connected to global environment problems [6-7]. The remote sensing imagery delivers up-to date and large scale information on surface condition. Present remote sensing images has two major concerns, those are noise associated with the image and maintaining the large volume of data [8-9]. Several methodologies have been developed by the researchers to address those issues on land use and land cover classification. Some of the methodologies are adaptive reflectance fusion model [10], maximum likelihood classifier [11], decision tree [12], deep convolutional neural network [13], Deep Neural Network (DNN) [14], etc. The conventional techniques used in land use and land cover classification are extremely affected by the environmental changes like destruction of essential wetlands, uncontrolled urban development, haphazard, loss of prime agricultural lands, deteriorating environmental quality, etc. and also due to the factors like cloud cover and regional fog error.

The study presented in this article has proposed a new algorithm, a Human Group based Particle Swarm Optimization (PSO) algorithm, with a LSTM classifier, to address the above discussed issues and improve the land use and land cover classification, in agriculture and urban environment, especially in those cases not related to human habitants. Initially, the remote sensing images are retrieved from Sat 4, Sat 6 and Eurosat datasets [15-17]. After the selection of remote sensing images, normalization and histogram equalization methods are
applied to improve the visual quality of the objects. The undertaken pre-processing techniques effectively improve the contrast of the images and enhance the edges in each region of the image. After normalizing the images, feature extraction is carried out by Local Gabor Binary Pattern Histogram Sequence (LGBPPhS), Histogram of Oriented Gradient (HOG) and Haralick texture features [18-21]. The LGBPPhS is utilized as a two-dimension spatial image gradient measurement to emphasize the high spatial frequency regions based on the image edges. In addition, it is utilized to identify the absolute gradient scales at each point in a remote sensing image. Next, HOG and Haralick texture features are applied to extract the texture and color feature vectors from the image pixels. As, the HOG feature descriptor operates on local cells, so it is invariant to photometric and geometric transformations, that helps in attaining better classification. The textural properties are calculated by Haralick texture features in order to understand the edge details about the image content. Then, the Human Group based PSO algorithm is used to select the optimal feature vectors that significantly reduces the “curse of dimensionality” issue. The obtained optimal feature vectors are given as the input to the LSTM classifier to establish the land use and land cover classes. In the result section, the performance of the proposed Human Group based PSO with LSTM is evaluated in terms of recall, precision and classification accuracy and compared with other existing models: GoogleNet, VGG, AlexNet and ConvNet.

This research paper is organized as follows. Section 2 presents several existing research papers on the topic “land use and land cover classification”, when HOG, LGBPPhS, Machine Learning (ML), Object Based Image Analysis (OBIA), Bag-Of-Visual Words (BOVW) and Scale-Invariant Feature Transform (SIFT) methodologies are used. In Section 3, the proposed model is briefly explained with mathematical expressions. Experimental analysis of the proposed model is then presented in the Section 4. Conclusions of this study are drawn in Section 5.

II. LITERATURE SURVEY

Xiao et al. [22] developed a new rotationally invariant feature descriptor to identify cars and aircraft in the remote-sensing images. The rotationally invariant HOG feature descriptor used elliptic Fourier transform, orientation normalization and feature space mapping to achieve better performance in object detection from remote sensing images. Rahmani and Behrad [23] developed a new model for ship detection in the remote sensing images. Initially, the collected images were divided into overlapping blocks and then LGBPPhS feature descriptor was used to extract the features from the images. Support Vector Machine (SVM) and Artificial Neural Network (ANN) were used for classification after feature extraction. However, SVM supports only binary classification, which is adaptable for multiclass classification.

Kadavi and Lee [24] used SVM and ANN classifiers to evaluate the multi-spectral data from mount Fourpeaked, mount Kanaga, mount Augustine and mount Pavlof. In this study, a Landsat-8 imagery dataset was used to evaluate efficiency and effectiveness of the developed model. The Landsat-8 imagery dataset contains four land cover classes vegetation, snow, water bodies and outcrops (sand, volcanic rock, etc.). Simulation results showed that the SVM classifier attained better performance in land use and land cover classification compared to ANN classifier. For mountain Kanaga, the SVM classifier achieved maximum classification accuracy, which was 9.1% superior to ANN classifier. The developed model was only suitable for minimum class classification not for maximum class classification and the developed model showed poor performance in some conditions like cloud cover and regional fog error. Pencue-Fierro et al. [25] presented a new hybrid framework for multi-region, multi-sensor and multi-temporal satellite image classification. In this study, land cover classification was assessed for Cauca river region, located in the south-west part of Colombia. After image collection, Coordination of Information on the Environment (CORINE) land cover approach was used for extracting the feature vectors from the input image. Next, the extracted features were given as the input to a supervised classifier SVM to classify the land cover classes like urban-area, paramo, snow, clouds, bare soil, grassland, planted forest, permanent-crops, natural forest, water-bodies and transitory crops. However, the computational complexity was higher in the developed hybrid framework compared to the other methods.

Phiri et al. [26] evaluated moderate resolution atmospheric transmission, atmospheric correction, cosine topographic correction and dark object subtraction on a heterogeneous landscape in Zambia. In this study, Landsat OLI-8 with 30 and 15 m spatial resolution images were tested using a combination of random forest classifier [27] and Object Based Image Analysis (OBIA) [28]. The developed method significantly improved land cover classification along with topographic corrections and pansharpening atmosphere. The developed framework (random forest and OBIA) effectively classified eight land-cover classes water bodies, grass land, secondary-forests, dry-agriculture, primary forests, irrigated crops, settlements and plantation-forests. However, this study did not concentrate on the feature extraction that may degrade the performance of land cover classification.

Zhao et al. [29] implemented a new framework for land use classification using UCMerced land-use dataset and simulated dataset. After collecting the satellite data, Bag-Of-Visual Words (BOVW) and Scale-Invariant Feature Transform (SIFT) [30] methodologies were used for extracting the feature vectors from the collected data. In addition, concentric circle based spatial rotation invariant representation was used to describe the spatial information of data. A concentric circle structured multi scale BOVW was used for land use classification. Performance of the developed method was analyzed in terms of average classification accuracy. However, the developed method fails to achieve better land use classification in the large datasets due to “curse of dimensionality” issue.

Nogueira et al. [31] used Convolutional Neural Network (CNN) in different scenarios like feature extraction, fine tuning and full training for land cover classification. The developed model’s performance was investigated on three remote sensing datasets Brazilian coffee scene, UCMerced land use and remote sensing 19. The results indicated that the developed model
attained better performance in land cover classification compared to the existing algorithms. Helber et al. [15] developed a new patch based land use and land cover classification technique using Eurosat dataset. The undertaken dataset had 13 spectral bands and 10 classes with a total of 27,000 geo-referenced and labeled images. This study explained how CNN was used to detect the land use and land cover changes that helped in improving the geographical maps. However, using middle and lower level descriptors, the CNN model leads to poor classification performance because it supports only higher level descriptors. Unnikrishnan et al. [16] developed a new deep learning model for three different networks VGG, AlexNet and ConvNet where Sat-4 and Sat-6 datasets were used to analyze the performance of the developed model. This model includes information on Red and Near Infrared bands, with reduced number of filters, which were tested and trained to classify the images into different classes. The developed model was compared with other networks in terms of trainable parameters, recall and classification accuracy. Papadomanolaki et al. [17] developed a deep learning model based on CNN for precise land cover classification. Performance of the developed model was compared with the existing networks AlexNet-small, AlexNet and VGG in terms of accuracy and precision on Sat-4 and Sat-6 datasets. However, the CNN has two major concerns computationally high cost and more data requirement to achieve precise classification.

As already highlighted, a Human Group based PSO with a LSTM classifier is proposed in this study to address the above discussed issues and improve the land use and land cover classification, as it will be shown and discussed in the last sections.

III. METHOD

Land use and land cover which are present on the surface of the earth are known as the elements or features, including the natural wilderness or environments like settlements, semi natural habitats like pastures, managed woods, arable fields, etc. [32-33]. The land cover features refer to the changes in biodiversity, erosion, modification and conversion of vegetation, soil-quality, sedimentation and land productivity [34-35]. The awareness about land use and land cover classification is very essential to address the concerns of destruction of central wet-lands, wildlife habitat, deteriorating environmental quality, haphazard, loss of prime agricultural lands and uncontrolled development [36]. At this end, a Human Group based PSO with a LSTM classifier is proposed, where the complete workflow is graphically presented in figure 1, highlighting also the pre-processing steps with the optimization of feature extraction included.

![Image](image.png)

**Fig. 1.** Work flow of the complete Human Group based PSO with LSTM, and the pre-processing steps including the feature extraction.
A. Image collection

In this study, Sat 4, Sat 6 and Eurosat databases are utilized for experimental analysis to differentiate the things that are not related to human habitants in both urban and agriculture environments. Sat 4 database comprises of 500,000 airborne images with four broad land cover classes like tree, barren land, grass land and a class with all land cover classes, except, tree, barren land and grass land [37]. The size of each remote sensing image in Sat 4 database is 28 × 28. Sat 6 database comprises of 40,500 airborne images with the size of 28 × 28 and it contains six land cover classes grassland, water bodies, buildings, barren land, roads and trees [16-17]. The sample image of Sat 4 and Sat 6 dataset is presented in figure 2.

In Eurosat database, the satellite images have been captured from European cities, which distributed in over thirty-four countries. A database is generated with 27,000 labeled and geo referenced image patches, where the size of the image patch is 64 × 64. The Eurosat database includes 10 different classes, where each class contains 2,000-3,000 images. The land use and land cover classes in this database are permanent crop, annual crop, pastures, river, sea &lake, forest, herbaceous vegetation, industrial building, highway and residential building [15]. In addition, Eurosat images includes 13 bands like aerosols, blue, green, red, red edge 1, red edge 2, red edge 3, near infrared, red edge 4, water vapor, cirrus, shortwave infrared 1 and shortwave infrared 1. A sample image of Eurosat database is presented in figure 3.

B. Image pre-processing

After collecting the satellite images, normalization and histogram equalization methods are undertaken to improve the quality of the images. Image normalization is also called as contrast stretching that changes the range of pixel values which helps in improving the visual quality of the collected satellite images. General formulas of normalization techniques are presented in equation (1) and (2).

\[ I_{\text{out}} = \left( I_{\text{in}} - \text{Min} \right) \frac{\text{newMax} - \text{newMin}}{\text{Max} - \text{Min}} + \text{newMin} \]  

(1)

where, original satellite image is indicated as \( I_{\text{in}} \), minimum and maximum intensity values are represented as Min and Max respectively, which ranges from 0 to 255, the image after the min-max normalization is indicated with \( I_{\text{out}} \), and the new minimum and maximum values are indicated with newMin and newMax. The common case of a min-max normalization to a new image ranging from 0 to 1, results into the well-known simplified version of the equation (1). Another image normalization can be accomplished through the non-linear approach which follows sigmoid function operation, as presented in the following equation (2), where in this case the \( I_{\text{out}} \) is given by:

\[ I_{\text{out}} = (\text{newMax} - \text{newMin}) \frac{1}{1+e^{-\alpha (I_{\text{in}}-\beta)}} + \text{newMin} \]  

(2)

where, \( \alpha \) is denoted as width of the pixel intensity value and \( \beta \) is indicated as pixel intensity value, where the range is centered. Lastly, the histogram equalization technique adjusts the contrast of the images using the histogram values. In the image enhancement, histogram equalization is the best technique, which delivers better image quality without losing the image information [38-39].

C. Feature extraction

After normalization and histogram equalization of the collected satellite images, feature extraction is carried out by using a hybrid optimization procedure, based on the joint use of HOG, LGBP, and Haralick texture features, namely correlation, contrast, energy, homogeneity, inverse d Once derived, the feature vectors are employed for experimental analysis to differentiate the objects that are not related to human habitation in both urban agriculture environments.

**HOG:** In satellite image, the HOG feature descriptor significantly captures the gradient and edge structure of the objects. Though, the HOG feature descriptor operates on the localized cells, which upholds invariance to photometric and geometric transformations except object orientation. This action helps in finding the changes appears in the large spatial regions. Here, a simple gradient operator \( K \) is applied to determine the gradient value. The gradient of the image is given by equation (3), where \( x, y \) represents a generic point in the image and the image frames are denoted as \( u \).

\[ L_x = K \ast u(x,y) \quad \text{and} \quad L_y = K^T \ast u(x,y) \]  

(3)
The magnitude of the gradients and edge orientation of the point \(x, y\) is calculated by following the respective conditions (Eq.4 and Eq.5),

\[
L(x, y) = \sqrt{L_x(x, y)^2 + L_y(x, y)^2}
\]

\[
\theta(x, y) = \tan^{-1} L_y(x, y) / L_x(x, y)
\]

For improving the invariance in illumination and noise, a normalization process is performed after the calculation of histogram values. The normalization is helpful for contrast and measurement of local histogram. In HOG four different normalizations are used such as L2-norm, L2-Hys, L1-Sqrt and L1-norm. Among these normalizations, L2-norm gives better performance in object detection. The blocks of normalization in HOG is given by Eq. (6),

\[
L_{2-norm} : f = \frac{q}{\sqrt{||q||^2 + \epsilon^2}}
\]

Where, \(\epsilon\) is the small positive value, only when an empty cell is taken into account, \(f\) is a feature extracted value, \(q\) is the non-normalized vector in histogram blocks, and \(||q||^2\) represents the 2-norm of HOG normalization.

**LGBPHS:** Initially, the pre-processed satellite images are transformed to obtain multiple Gabor Magnitude Pictures (GMP) using multi-orientation and multi scale Gabor filters. Then, each GMP is converted into Local GMP (LGMP) that is further categorized into non-overlapping rectangular regions with specific histogram and size [49]. The LGMP histogram of all the LGMO maps are combined to form final histogram sequences.

**Haralick texture features:** The Haralick features are 2\textsuperscript{nd} order statistics that reflects the overall average degree of correlation between the pixels in different aspects like contrast, energy, inverse difference moment, entropy, homogeneity, correlation and angular second moment [40]. The texture features are calculated from the texture information that are presented in the Grey-Level Co-occurrence Matrix (GLCM) [46]. In order to develop a number of spatial indices, Haralick uses the GLCM, because it contains the two neighbouring pixels' relative frequencies by a distance on the image. Haralick developed the vast number of textural features with original 14 features that are described in [47], but only seven features are widely used due to its importance values for remote sensing images. Therefore, in this study, those seven commonly used features are considered as extracted features and this features showed better performance in [48]. A set of seven different GLCM indicators is described in the following equations (7 to 13):

\[
Energy = \sum_{\gamma, \delta} \varphi(y, \delta)^2
\]

\[
Entropy = \sum_{\gamma, \delta} \varphi(y, \delta) \log_2 \varphi(y, \delta), or \ 0 \ if \ \varphi(y, \delta) = 0
\]

\[
Correlation = \sum_{\gamma, \delta} \frac{(y-\mu)(\delta-\mu)\varphi(y, \delta)}{\sigma^2}
\]

\[
Angular \ Second \ Moment = \sum_{\gamma, \mu} (\varphi(y, \delta))^2
\]

\[
Inverse \ Difference \ Moment = \sum_{\gamma, \delta} \frac{1}{1+(\gamma-\delta)^2} \varphi(y, \delta)
\]

\[
Contrast = \sum_{\gamma, \delta} \frac{1}{\gamma - \delta} \left\{ \sum_{\delta = 1}^{N} \sum_{\gamma = 1}^{N} \varphi(y, \delta) \right\}
\]

\[
Homogeneity = \sum_{\gamma, \delta} \frac{\varphi(y, \delta)}{1+(\gamma-\delta)^2}
\]

Where, matrix cell index is depicted as \((y, \delta)\), frequency value of the pair of index is represented as \(\varphi(y, \delta)\), mean and standard deviation of the row sums is illustrated as \(\mu_{\gamma}\) and \(\sigma_{\gamma}\), average of means weighted pixel is described as \(\mu = \sum_{\gamma, \delta} y \cdot \varphi(y, \delta) = \sum_{\gamma, \delta} \delta \cdot \varphi(y, \delta)\), variance of means weighted pixel is defined as \(\sigma = \sum_{\gamma, \delta} (\gamma - \mu)^2 \cdot \varphi(y, \delta) = \sum_{\gamma, \delta} (\delta - \mu)^2 \cdot \varphi(y, \delta)\), and \(N\) illustrates the total number of distinct gray levels in the images.

The variable importance analysis is carried out by the GLCM classification results, where high importance of the variable is represented by the high values of GLCM. From the experimental analysis in [48], the author P. Kupidura, proves that the Haralick’s seven selected features have the highest significance among the 14 original features, by calculating the importance of these features. Therefore, the classification results proved that the Haralick features have the highest resolutions, which are the best features rather than others for satellite image classification.

**Feature selection**

Feature selection is carried out by using the Human Group based PSO algorithm after extracting the feature vectors. Generally, PSO is a population based searching algorithm that mimics behavior of birds. In order to generate new positions of every particle, equation (14) is used to update the velocity \(v_i\) and position \(p_i\) of the particles.

\[
v_i(n + 1) = w \cdot v_i(n) + r_1 \cdot c_1 \cdot (b_l(n) - p_i(n)) + r_2 \cdot c_2 \cdot (g_b(n) - p_i(n))
\]

\[
p_i(n + 1) = p_i(n) + v_i(n + 1)
\]

where, \(n\) is represented as the iteration, \(r_1\) and \(r_2\) are denoted as random numbers between \([0, 1]\), \(w\) is denoted as inertia weight, \(b_l\) is indicated as the best position, \(b_l(n)\) is stated as local best position and \(g_b(n)\) is indicated as global best position of the particle. In PSO, HGO algorithm is utilized initially to influence the particles and then adaptive uniform mutation is utilized to improve the convergence rate and makes the implementation simple.

**Fitness function and encoding of particle:** Initially, HGO is used to transform discrete multi-label into continuous label. The undertaken algorithm finds the extracted feature vectors based
on decision $d_i$, where the vectors of the particles position is presented as $p_i(n) = (p_{i1}, p_{i2}, \ldots, p_{iD})$.

**Adaptive uniform mutation:** The adaptive uniform mutation is utilized to increase the ability of the feature selection algorithm in exploration. In this operator, a non-linear function $p_m$ is used to control the range and decision of the mutation on each particle $p_i$. At every iteration, $p_m$ is updated using equation (15).

$$p_m = 0.5 \times e^{(-10x\sqrt{N}/N)} + 0.01$$

(15)

where, $N$ is indicated as maximum iteration, $n$ is denoted as number of iteration and the $p_m$ value tends to decrease when the number of iterations increases. The mutation randomly picks the $k$ elements from the particle, if the $p_m$ value is higher than the random number between [0,1]. Then, the mutation value of the elements within the search space is reinitialized, where $k$ is an integer value which is used for controlling the mutation range [41-42]. Mathematically, $k$ value is represented in equation (16), as:

$$k = \max\{1, [D \times p_m]\}$$

(16)

The flow chart related to the Human Group based PSO algorithm is given in figure 4, with the further description of the steps below.

**Step 1:** Initialize the particles swarm, a) set the number of iterations $N$, swarm size $T_s$ and archive size $T_a$; b) initialize the particles location, c) estimate the objective of every particles, d) save non-dominated solution into the archive.

**Step 2:** Pareto domination relationship is used to update the personal best position of the particles. If new position $p_i(n+1)$ is better than old personal best position $l_b_i (n)$, set $l_b_i (n+1) = p_i(n+1)$. or else unchanged the personal best position of the particles, where $l_b_i$ is represented as best position and $l_b_i (n)$ is presented as local best position.

**Step 3:** Based on the diversity of solution, select the global best position from the archive. At first, crowding distance value is calculated and then binary tournament is used to select the global best position of the particle $gb_i(n)$.

**Step 4:** Then, initialize the decision value $d_i$ based on $gb_i(n)$. Every decision $d_i$ of the feature vector $d$ is a binary value $d_i = \pm 1$, $i = 1, 2, \ldots, T$. Every feature vector $d$ is related with the fitness value $V(d)$ that is considered as the weighted sum of $T$ stochastic contributions $W_j(d_j, d_j', d_j^k)$. However, these contributions depends on the value of decision $d_j$ and other $S$ decisions $d_j^k, i = 1, 2, \ldots, S$. The fitness function is mathematically presented in equation (17):

$$V(d) = \frac{1}{T} \sum_{j=1}^{T} W_j(d_j, d_j', d_j^k, \ldots, d_j^k)$$

(17)

where, the integer index $S = 0, 1, 2, \ldots, T - 1$ corresponds to the number of interacting decision values. The knowledge level of the $m^{th}$ member is determined by the parameter $P \in [0,1]$, which is the probability of each member that knows the contribution of the decision.

On the basis of the knowledge level, every member $m$ computes own perceived fitness using equation (18):

$$V_m(d) = \frac{\sum_{j=1}^{S} \bar{d}_{mj} W_j(d_j, d_j', d_j^k, \ldots, d_j^k)}{\sum_{j=1}^{S} \bar{d}_{mj}}$$

(18)

where, $\bar{d}$ is denoted as the matrix, whose elements $\bar{d}_{mj}$ considers the value one with probability $P$ and 0 with probability $1 - P$.

**Step 5:** Based on the decision value $d_i$, equation (19) is used to update the velocity $v_i$ and position $p_i$ of the particles.

$$v_i(n+1) = w \times v_i(n) + r_1 \times V_m(d) \times (l_b_i(n) - p_i(n)) + r_2 \times V_m(d) \times (gb_i(n) - p_i(n))$$

(19)

**Step 6:** Perform uniform mutation using the equations (15) and (16).

**Step 7:** Update the external archive using crowding distance methodology.

**Step 8:** Analyze the termination condition, if the proposed algorithm attains the maximum iteration stop the condition, or else return to step 2. Hence, the worst particles (feature vectors) are eliminated based on the fitness function $V_m(d)$ of HGO algorithm. In all three datasets, approximately 70%-80% of the feature vectors are selected from the total extracted features. After selecting the optimal features, classification is then carried out using the LSTM classifier. Table 1 states the extracted and the selected features after applying the Human Group based PSO algorithm.

**Step 1:** Initialize the particles swarm, a) set the number of iterations $N$, swarm size $T_s$ and archive size $T_a$; b) initialize the particles location, c) estimate the objective of every particles, d) save non-dominated solution into the archive.

**Step 2:** Pareto domination relationship is used to update the personal best position of the particles. If new position $p_i(n+1)$ is better than old personal best position $l_b_i (n)$, set $l_b_i (n+1) = p_i(n+1)$. or else unchanged the personal best position of the particles, where $l_b_i$ is represented as best position and $l_b_i (n)$ is presented as local best position.
TABLE I.
SELECTED FEATURE VECTORS AFTER APPLYING THE FEATURE SELECTION ALGORITHM

| Datasets     | Extracted features | Selected features |
|--------------|--------------------|-------------------|
| Sat 4        | $38 \times 5000$   | $38 \times 3671$  |
| Sat 6        | $50 \times 8700$   | $50 \times 6290$  |
| Eurosat      | $55 \times 9000$   | $55 \times 7098$  |

E. Classification

The LSTM classifier has the default behavior of remembering data information for a long time period. In land use and land cover classification, a huge number of remote sensing images are needed to be proceeded for attaining better results. By considering this aspect, LSTM classifier is the best choice for land use and land cover classification [50-51]. Generally, the LSTM classifier is composed of a series of LSTM units, where the temporal quasi periodic features for extracting the long term and short term dependencies are stored. Hence, the structure of the LSTM classifier is denoted in figure 5 and the LSTM unit is graphically stated in figure 6.

The LSTM classifier contains an input gate $i_n$, a forget gate $f_n$, a cell $c_n$ and an output gate $o_n$, which are mathematically expressed in the equations (20), (21), (22) and (23).

$$i_n = \sigma(W_{ih}h_{n-1} + W_{ia}a_t + b_i)$$ (20)
$$f_n = \sigma(W_{fh}h_{n-1} + W_{fa}a_t + b_f)$$ (21)
$$c_n = f_n \times c_{n-1} + i_n \times \tanh(W_{eh}h_{n-1} + W_{ea}a_n + b_e)$$ (22)
$$o_n = \sigma(W_{oh}h_{n-1} + W_{oa}a_n + b_o)$$ (23)

where, $a_n = A[n, \cdot] \in \mathbb{R}^d$ is represented as the quasi periodic feature in different frequency bands at the time step. Work coefficients are denoted as $W$ and $b$ and the hyperbolic tangent and sigmoid activation functions are indicated as $\tanh(\cdot)$ and $\sigma(\cdot)$. The output of the prior LSTM unit is stated as $h_{n-1}$ [43]. The output of the LSTM unit is mathematically denoted in equation (24).

$$h_n = o_n \times \tanh(c_n)$$ (24)

As shown in figure 5, $h_n$ contains the information of the prior time steps by $c_n$ and $o_n$. On the basis of dependency relation, the cell state $[c_n]_{n = 1, 2, \ldots N}$ learns the memory information of the temporal quasi-periodic features for a long and short period of time during the training process. At last, the extracted features are denoted by the output of last LSTM unit $h_N$.

Fig. 5. Structure of the LSTM classifier

IV. RESULT AND DISCUSSION

The proposed model is simulated using MATLAB 2019 in a PC with 128 GB RAM, i9 Intel core processor, Windows 10 operating system (64-bit) and 3 TB hard disk. Performance of the proposed model is compared with a few benchmark models: GoogleNet [15], 2 band VGG [16], hyper parameter tuned VGG [16], 2 band AlexNet [16], hyper parameter tuned AlexNet [16], 2 band ConvNet [16], hyper parameter tuned ConvNet [16], AlexNet [17], ConvNet [17] and VGG [17], in order to find out its effectiveness. Specifically, the performance of the proposed model is evaluated on the selected datasets in terms of precision, recall and accuracy parameters. The mathematical expressions of accuracy, recall and precision are represented in the following equations (25), (26) and (27):

$$\text{Accuracy} = \frac{TP+TN}{FN+TP+TN+FP} \times 100$$ (25)
$$\text{Recall} = \frac{TP}{TP+FN} \times 100$$ (26)
$$\text{Precision} = \frac{TP}{TP+FP} \times 100$$ (27)

where, true negative is denoted as $TN$, false negative is represented as $FN$, true positive as $TP$ and false positive as $FP$.

A. Quantitative investigation on Sat 4 database

Sat 4 database is used to evaluate the performance of the proposed model to classify four land cover classes: tree, barren land, grass land and a class with all land cover classes, except tree, barren land and grass land. In this case, the performance evaluation is validated by using 500,000 satellite images with 70% of the data used for training and 30% for testing. Tables 3 and 4 represent the performance evaluation of the proposed model with different classifiers; DNN, Multi Support Vector Machine (MSVM) and LSTM in terms of classification accuracy, recall and precision. Two different case studies are considered in the experiments. The tables 2 and 3 point out that the LSTM classifier achieves better classification performance in land use and land cover classification on various classes by means of precision, recall and classification accuracy. Tables 4 and 5 illustrate that the LSTM classifier improves the accuracy.
in land use and land cover classification on various classes up to 1% compared to DNN and LSTM classifiers. Table 6 shows the performance of various neural network with proposed LSTM for overall Sat 4 database in terms of classification accuracy. Compared to other classifiers, the LSTM has the ability to remember data information for a long period of time, where this behavior helps to attain better performance in land use and land cover classification. Performance analysis of the proposed model with different classifiers on Sat 4 dataset is represented in figure 7.

HGO and human group based PSO, by pointing out that the LSTM classifier with Human Group based PSO achieves better performance in land use and land cover classification in terms of precision, classification accuracy and recall. The proposed model; human group based PSO with LSTM showed a maximum of 6.025% and a minimum of 1.66% improvement in land use and land cover classification, if compared to LSTM, PSO with LSTM and HGO with LSTM. The figure 8 shows the performance analysis of the proposed model when different optimization techniques are applied on Sat 4 dataset.

| Classes     | Human group based PSO with DNN | Human group based PSO with MSVM | Human group based PSO with LSTM |
|-------------|--------------------------------|---------------------------------|---------------------------------|
|             | Precision (%)                   | Recall (%)                      | Precision (%)                   | Recall (%)                      |
| Barren land | 99.07                          | 99.12                           | 99.65                           | 99.79                           |
| Trees       | 99.54                          | 99.65                           | 99.65                           | 99.98                           |
| Grasslands  | 99.60                          | 99.87                           | 99.80                           | 99.95                           |
| Others      | 99.61                          | 99.90                           | 99.87                           | 99.98                           |
| Overall     | 99.45                          | 99.63                           | 99.58                           | 99.77                           |

| Classes     | Human group based PSO with DNN | Human group based PSO with MSVM | Human group based PSO with LSTM |
|-------------|--------------------------------|---------------------------------|---------------------------------|
|             | Precision (%)                   | Recall (%)                      | Precision (%)                   | Recall (%)                      |
| Barren land | 94.65                          | 94.92                           | 98.74                           | 98.16                           |
| Trees       | 93                             | 95                              | 96.56                           | 97.55                           |
| Grasslands  | 94.90                          | 96.10                           | 97.88                           | 97.82                           |
| Others      | 93.70                          | 94                              | 98.63                           | 98.87                           |
| Overall     | 94.06                          | 95.005                          | 97.95                           | 98.10                           |

| Classes     | HGO with LSTM                  | Human group based PSO with LSTM |
|-------------|--------------------------------|---------------------------------|
|             | Precision (%)                   | Recall (%)                      | Precision (%)                   | Recall (%)                      |
| Barren land | 98.62                          | 98.70                           | 99.90                           | 99.98                           |
| Trees       | 98.69                          | 98.73                           | 99.98                           | 99.97                           |
| Grasslands  | 98.93                          | 98.98                           | 99.97                           | 99.95                           |
| Others      | 98.69                          | 98.92                           | 99.98                           | 99.97                           |
| Overall     | 98.65                          | 98.83                           | 99.95                           | 99.96                           |

The tables 4 and 5 present the performance evaluation of the proposed model with different optimization techniques like PSO,
1) Case Study of Proposed LSTM Method with Existing Techniques on Sat 4 Database

In this subsection, AlexNet [16], ConvNet [16] and VGG [16] are selected for implementing the PSO and HGO techniques. The reason for choosing these techniques is that they are the most widely used neural network architecture for the classification of land use and land cover on satellite images. The selected existing techniques are implemented with HGO and PSO after the max pooling layer of each existing technique. For instance, ConvNet has the output of 4096 features in the max pooling layer and implemented the PSO and HGO as filtering technique that provides only 1000 features as output of fully ConvNet. Table 6 shows the validated results of proposed LSTM, AlexNet, ConvNet and VGG with PSO and HGO on Sat 4 database in terms of overall accuracy.

From the analysis, the results stated that the neural networks and proposed LSTM with PSO and HGO achieved better performance in terms of accuracy on Sat 4 dataset.

B. Quantitative investigation on Sat 6 database

Sat 6 database is used to evaluate the performance of the proposed model to classify six land cover classes: grassland, water bodies, buildings, barren land, roads and trees. In this case, the performance analysis is carried out by using 40,500 satellite images with 70% of them for training and 30% for testing. Performance of the proposed model is analyzed with different classification techniques DNN, MSVM, LSTM and optimization techniques PSO, HGO and human group based PSO in terms of classification accuracy, recall and precision. The tables 7 and 8 point out that the LSTM classifier achieves better performance in land use and land cover classification, if compared to other classification techniques. The tables 9 and 10 present the performance analysis of the proposed model with different optimization techniques applied on various classes from Sat 6 database. Table 11 describes the case study of LSTM, AlexNet, VGGNet and ConvNet with PSO and HGO on whole Sat 6 dataset in terms of overall classification accuracy. In this database, LSTM classifier attained 99.94% of precision, 99.97% of recall and 99.99% of accuracy. Performance analysis of the proposed model with different classifiers on Sat 6 dataset is then presented in figure 9.
Fig. 9. Graphical investigation of the proposed model with different classifiers on Sat 6 dataset

The tables 7 and 8 indicate that the human group based PSO algorithm with LSTM classifier attains better performance in land use and land cover classification in terms of recall, precision and classification accuracy. The proposed model; human group based PSO with LSTM shows maximum of 7.17% and minimum of 2.8% improvement in land use and land cover classification compared to LSTM, PSO with LSTM and HGO with LSTM. The performance investigation of the proposed model with different optimization techniques on Sat 6 database is presented in figure 10.

1) Case Study for Proposed LSTM Method with Existing Techniques on Sat 6 database

In this subsection, the techniques namely LSTM, AlexNet, VGG and ConvNet are implemented with PSO and HGO on Sat 6 database. For example, eight layers are presented in the AlexNet; first five layers are convolution layers followed by max-pooling layers and the remaining three are fully connected layers. The output of second fully connected layer is 4096 features. Here, the PSO and HGO are implemented to minimize the features. Therefore, the final output of AlexNet is 1000 features. Likewise, the other neural networks are implemented with PSO and HGO after the max-pooling layers. Table 11 presents the validated results on Sat 6 database in terms of overall accuracy.
C. Quantitative investigation on Eurosat database

In this section, Eurosat dataset is used to evaluate the performance of the proposed model to classify 12 land use and land cover classes. These are permanent crop, annual crop, pastures, river, sea &lake, forest, herbaceous vegetation, industrial building, highway and residential building. In this scenario, the performance analysis is accomplished for 27,000 satellite images with 70% of the data used for training and 30% for testing with two case studies. Initially, Table 12 presents the performance value of the proposed model for different classes of land use and land cover classification in terms of accuracy, recall and precision, with some existing classifiers DNN, MSVM, LSTM and the optimization techniques PSO, HGO and Human Group based PSO. The accuracy, recall and precision of the LSTM classifier with Human Group based PSO is 97.40%, 98.70% and 97.80%, respectively. The LSTM classifier with Human Group based PSO shows an improvement in land use and land cover classification. Performance analysis of the proposed model on Eurosat dataset is presented in figure 11.

Table XI

| Methodology                  | Dataset | Overall Accuracy (%) |
|------------------------------|---------|----------------------|
| AlexNet + PSO                | Sat 6   | 99.88±0.03           |
| AlexNet + HGO               | Sat 6   | 99.89±0.02           |
| AlexNet + PSO + HGO         | Sat 6   | 99.91±0.01           |
| ConvNet + PSO               | Sat 6   | 99.86±0.03           |
| ConvNet + HGO               | Sat 6   | 99.84±0.02           |
| ConvNet + PSO + HGO         | Sat 6   | 99.90±0.01           |
| VGGNet + PSO                | Sat 6   | 99.92±0.02           |
| VGGNet + HGO                | Sat 6   | 99.93±0.01           |
| Proposed LSTM + PSO         | Sat 6   | 99.98±0.02           |
| Proposed LSTM + HGO         | Sat 6   | 99.98±0.02           |
| Proposed LSTM + PSO + HGO   | Sat 6   | 99.98±0.01           |

Table XII

| Classification | Optimization techniques | Precision (%) | Recall (%) | Accuracy (%) |
|----------------|-------------------------|---------------|------------|--------------|
| DNN            | PSO                     | 87.89         | 90         | 88.2         |
|                | HGO                     | 90            | 92.02      | 90           |
| MSVM           | PSO                     | 87            | 88.39      | 87.03        |
|                | HGO                     | 92.04         | 95         | 90.85        |
|                | HGO + PSO               | 94.90         | 96.50      | 92.90        |
| LSTM           | PSO                     | 92            | 93.98      | 95           |
|                | HGO                     | 94.50         | 94         | 96.90        |
|                | HGO + PSO               | 97.80         | 98.70      | 97.40        |

1) Case Study of implementing PSO and HGO on Proposed Method

In this subsection, GoogleNet [15] is implemented with optimization techniques namely PSO and HGO and selected only 1000 features. The other techniques like AlexNet [16], VGG [16] and ConvNet [16] are worked only on the Sat 4 and Sat 6 database. Hence, these techniques in [16] are not considered in the case study of Eurosat database. While comparing with AlexNet and ConvNet, the GoogleNet uses techniques namely 1×1 convolutions in the middle of the architecture and global average pooling. In addition, the inception module is different than other architectures. The 1×1, 3×3, 5×5 convolution are presented in the inception module and global average pooling is operated in a parallel way and the input and output are stacked together for generating the final output. Table 13 shows the comparative analysis of LSTM and GoogleNet [15] with PSO and HGO on whole Eurosat dataset.

Table XIII

| Methodology                  | Dataset | Overall Accuracy (%) |
|------------------------------|---------|----------------------|
| GoogleNet + PSO              | Eurosat | 96.18±0.3            |
| GoogleNet + HGO             | Eurosat | 96.20±0.2            |
| GoogleNet + PSO + HGO       | Eurosat | 96.40±0.2            |
| Proposed LSTM + PSO         | Eurosat | 97.37±0.03           |
| Proposed LSTM + HGO         | Eurosat | 97.39±0.02           |
| Proposed LSTM+ PSO + HGO    | Eurosat | 97.42±0.01           |

D. Comparative analysis

The comparative analysis between the proposed and existing models is represented in table 11. Analyzing recent works from the literature, based on similar data, it was found that Helber et al. [15] developed a new patch based land use and land cover classification technique using Eurosat database. This work explained how CNN was used to detect the land use and land cover changes which helped in improving the geographical maps. Unnikrishnan et al. [16] implemented a novel deep learning method for three different networks VGG, AlexNet and ConvNet, and Sat 4 and Sat 6 datasets were used to analyze the performance of the developed model. Papadomanolaki et al. [17] designed a deep learning model based on a CNN for accurate land cover classification, by including 2 band information (red
and near infrared) with a reduced number of filters, which were tested and trained to classify the images into different classes. The model proposed in this manuscript was compared with earlier models in terms of precision, recall and accuracy.

The table 14 illustrates that the proposed model achieves a minimum of 0.01% and a maximum of 2.56% improvement in accuracy on Sat 4, Sat 6 and Eurosat datasets. In this study, human group based PSO algorithm is combined with LSTM classifier in order to gain better performance in land use and land cover classification. The proposed Human Group based PSO algorithm significantly reduces the “curse of dimensionality” issue and this helps the LSTM classifier to achieve a better performance in the classification.

| Methodology | Dataset | Overall Accuracy (%) |
|-------------|---------|----------------------|
| GoogleNet [15] | Eurosat | 96.69 |
| 2 band AlexNet [16] | Sat 4 | 99.66 |
| 2 band AlexNet [16] | Sat 6 | 99.08 |
| Hyper parameter tuned AlexNet [16] | Sat 4 | 98.45 |
| Hyper parameter tuned ConvNet [16] | Sat 4 | 99.03 |
| 2 band ConvNet [16] | Sat 4 | 98.45 |
| Hyper parameter tuned ConvNet [16] | Sat 6 | 97.43 |
| Hyper parameter tuned VGG [16] | Sat 4 | 99.10 |
| Hyper parameter tuned VGG [16] | Sat 6 | 99.10 |
| AlexNet [17] | Sat 4 | 99.98 |
| ConvNet [17] | Sat 6 | 99.92 |
| VGG [17] | Sat 4 | 99.99 |
| Proposed model | Sat 4 | 97.40 |
| Proposed model | Sat 6 | 99.99 |

### V. CONCLUSIONS

Objective of this study has been to propose a hybrid feature optimization algorithm along with a deep learning classifier to improve performance of LULC classification, for urban and agriculture environment. The proposed model helped to analyze the changes in land productivity, soil-quality, biodiversity, for instance, which provide a clear idea about environmental quality, wildlife habitat, human habitant, loss of prime agricultural lands, uncontrolled development, etc. In this study, an optimization procedure based on the combination of LGBP/H, HOG and Haralick texture features were first utilized to extract the feature vectors of the objects from the normalized remote sensing images. The Human Group based PSO algorithm was then applied to select the optimal feature vectors, that helped in further improving the performance of classification. The optimal selected features were given as the input to a LSTM classifier. The proposed model achieved a better performance when compared to the existing models in LULC classification in terms of recall, accuracy and precision. The simulation result showed that the proposed model achieved a minimum of 0.01% and a maximum of 2.56% enhancement in classification accuracy on Sat 4, Sat 6 and Eurosat databases. In the future work, an optimization based clustering approach will be included in the proposed model to verify if the classification method can be further improved.

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T. Kowsalya received B.E. Degree in Electronics and Communication Engineering in VLB Janaki Ammal College of Engineering and Technology, Coimbatore in the year 1996 and she received M.E Degree in Communication Systems in Government College of Technology, Coimbatore in the year 2005. She has also completed Ph.D Degree in Anna University, Chennai in the year 2018. She worked in various institutions as Associate professor. She is having 22 years of teaching Experience. Currently she is working as Associate Professor in Muthayammal Engineering College, Raspipuram, Namakkal (Dt), Tamilnadu, India. Her research interests are Low Power VLSI and Signal Processing.
S. L. Ullo (Senior Member, IEEE) graduated with laude in Electronic Engineering at the Faculty of Engineering, of Federico II University, Naples. She received the M.Sc. degree from the Massachusetts Institute of Technology (MIT) Sloan Business School of Boston, USA, in June 1992. Since 2004 she is a researcher with the University of Sannio di Benevento, where she teaches Signal theory and elaboration, and Telecommunication networks, courses for the degree in Electronic Engineering and the Optical and radar remote sensing as Ph.D. course. She has authored 72 research papers in reputed journals and conferences. She is part of the Telecommunications and Remote Sensing group and her research interests mainly deal with signal processing, remote sensing, image and satellite data analysis, machine learning applied to satellite data, ESA Copernicus mission, cognitive radars, sensor networks, telecommunications networks, and smart grids. She is an Industry Liaison for the IEEE IT Joint ComSoc / VTS Chapter. She is a member of the Academic Senate at University of Sannio, and the National Referent for the FIDAPA BPW Italy Sciences and Technologie Task Force. Awarded in 1990 with the Marisa Bellisario prize from the homonymous foundation, and with the Marisa Bellisario scholarship from Italet SpA company. She has been with Italet, since September 1992. She served as a Chief of some production lines at the Santa Maria Capua Vetere factory (CE), until January 2000. She won a public competition and started working at the Center for Data Processing (CED) in the Municipality of Benevento, from January 2000 to January 2004. In February 2004, she won a researcher contest at the Faculty of Engineering, University of Sannio, Benevento.

C. Zarro (Student Member IEEE), graduated at the University of Sannio at the 1st level in Electronic Engineering for Automation and Telecommunications in March 2015 with the thesis entitled "Braking control of a model railway". In July 2019 she obtained the title of Master's Degree with a final grade 110/110 in Electronic Engineering for Automation and Telecommunications of the University of Sannio with the thesis entitled "Extraction of features on urban area from imagesworldview-2 and from LiDAR data through object-oriented classification techniques. Case Study: Lioni (av) ". She has received the 2019 IEEE GRS-Geoscience and Remote Sensing award for her thesis work. From April to June 2018 she worked as a trainee at the company Mapsat Euromediterranean remote sensing S.R.L., with headquarters in Benevento, which has been involved in remote sensing services for years. During these months she carried out activities related to satellite sensing for earth observation with a particular interest in data analysis for the object-oriented classification of images related to the urban area. Subsequently, she worked for several months as a designer at the Electa integrated design company SRL, having as her main responsibility the analysis of electromagnetic compatibility for the design of radio base stations. Winner of a scholarship, she is currently enrolled at the University of Sannio in the second year of the PhD course with Industrial Characterization in "Information Technologies for Engineering". Her main research activity relates to the development of innovative methodologies for the extraction of features on urban areas, from remote sensing data, for environmental sustainability applications in the field of risk analysis and management, territorial planning and local development.

Hemalatha K.L working as Professor and HOD in the Department of Information Science and Engineering, Sri Krishna Institute of Technology has rich experience in Academia and research for more than 7 years. She has completed PhD (Computer Science), SJCIT, Chikballapur under VTU and BE (Computer Science), SRSIT, Bangalore under VTU. Recently she has received “Best Professor in Information Science and Engineering Studies” from Dewang Mehta National Education Awards, 2019 and “Young Achiever’s Award”, from Institute of Scholars, 2019. Also, she was awarded “Women Achiever’s Award” from Institution of Engineers, India, Karnataka State Centre, Bangalore during International Women’s Day Celebration on March 8th, 2019. She has published more than 30 National/International publications in reputed journals. She serves as an editorial board member for the Journal International Journal of Research and Science Innovation (IJRSI) and acted as a reviewer for International Journal of Medical Engineering and Informatics - Inderscience, International Journal of Advanced Intelligence Paradigms – Inderscience, Journal of Super Computing - Springer, International journal of Information Technology-Springer and International Journal of Engineering and Technology-Scopus.

Parameshachari B D currently working as a Professor and Head in the Department of Telecommunication Engineering at GSSSIETW, Mysuru. Also he is the Mysore Region Coordinator for IEEE Bangalore Section. He is the Senior Member of IEEE. He was worked as a Senior Lecturer in the Department of ECE at JSS Academy of Technical Education, Mauritius. He has total Research & Teaching experience of around 16 Years. Obtained B.E degree in Electronics and Communication Engineering and M. Tech degree in Digital communication engineering from Visvesvaraya Technological University, Belagavi, India and Completed Ph.D in Electronics and Communication Engineering from Jain University, Bengaluru. Received Young Scientist Awards from Aufau International Awards and Venus International Research Awards-VIRA for the Initiatives,
Discoveries, and Developments in the discipline of Image Processing.
He is the Outstanding Reviewer - Elsevier Signal Processing, Achieved Since June 2017 (This recognition has been awarded for only top 10th percentile of reviewers for the Elsevier Journal). Invited Speaker for 2019 the 4th International Conference on Multimedia and Image Processing (ICMIP 2019) held in University of Malaya, Malaysia during January 19-21, 2019. Regional Chair for 10th International Conference on Information and Communications Technology Convergence 2019 (ICTC 2019) held on 16-18 October 2019 in Jeju Island, Korea. Published/presented 75 papers in International Journals /International Conferences. (Few papers indexed by Scopus) and having 142 Citations, 6 h-index and i10-index of 5 to his credit. Completed the Project under Institution of Engineers (India) R&D Grant-in-aid Scheme.