Feature selection for urban land cover classification employing genetic algorithm

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ABSTRACT

Feature selection has attained substantial research interest in image processing, computer vision, pattern recognition and so on due to tremendous dimensional reduction in image analysis. This research addresses a genetic algorithm based feature selection strategy for urban land cover classification. The principal purpose of this research is to monitor the land cover alterations in satellite imagery for urban planning. The method is based on object based classification by detecting the object area of a given image with the knowledge of visual information of the object from remote sensing images. The classification system is organized through a multilayer perceptron with genetic algorithm (MLPGA). Experimental results explicitly indicate that this MLPGA based hybrid feature selection procedure performs classification with sensitivity 94%, specificity 90% and precision 89%, respectively. This MLPGA centered hybrid feature selection scheme attains better performance than the counterpart methods in terms of classification accuracy.

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1. INTRODUCTION

Feature selection refers to the process where some important features are selected automatically or manually which contribute maximum to the prediction variable or output in which we are mesmerized. With feature selection, inappropriate and superfluous components from the dataset is discarded, which is an initial phase of object classification. Genetic algorithm (GA) belongs to a class of stochastic search process that employs processes originate in natural biological evolution. It does not provide any single solution but works on sets of chromosomes and establishes the parallel processing to optimize the process [1]-[3]. Since GA provides auspicious implemention in solving a substantial number of optimization problems, this article proposes a robust approach to select features in urban land cover analysis for high resolution images using GA.

On the rapid urbanization and with the proliferation of satellite remote sensing technologies, an enormous amount of high resolution images are now accessible which carry land cover information. With object-based processing and investigation of high-resolution images, enormous topographies are included. The amount of the features extracted from high resolution images are more than the number of pixels, which mostly compromise of statistical analysis like mean, median, mode, normal distribution and so on [4]-[7]. The object-based clustering involves in several topographies concerning spatial, spectral, geometrical, and texture information attained from image interpretation. With number of features contributing in classification continuously produces the “dimension catastrophe” by increasing the search region. Since the number of possible solutions for n features is 2n, which boils down the classification accuracy [8]-[10]. Therefore, reducing and selecting features are becoming indispensable for image identification. The principal objective and mission of selecting the best features are to identify the best feature subclass attaining an improved or related clustering criteria and to decrease the dimensionality of the data.

A fair amount of research works have been cited in literate on urban land use classification employing satellite imagery. Shi *et al.* [11] addressed a feature selection technique employing a hybrid model consisting of GA and Tabu search. They performed Tabu search on genes with upper fitness values so that an upgraded mutation operation was established at the early stage of converging GA and thereby decreased the probability of convergence of GA by employing Tabu Search strategies. Huang *et al.* [12] proposed an optimum feature GA search method. They considered the correlations between the candidate features and classes, as well as among candidate features and the selected features and used the mutual information in fitness function. Yan *et al.* [13] proposed an adaptive evolutionary algorithm for feature selection by identifying the fittest individuals. Although their method improves the convergence speed but nevertheless suffers from diversity in population. Employing Tabu search and organizing correlation feature subset assessment, Danenas *et al.* [14] presented a credit risk estimation algorithm for feature selection. Considering variable neighborhood strategy, Sicilia *et al.* [15] proposed an optimization method in resolving vehicle routing planning in metropolitan zones. Wang *et al.* [16] presented a cooperative co-evolution algorithm as a thriving approach for global optimization. They employed a divide-and-conquer technique for decomposing the high dimensional decision variables with low dimensional modules and then optimize each of these subcomponents with a separate evolutionary algorithm. Although the cooperative co-evolution strategy sounds promising, but the presentation of this approach depends on the selection of the decomposition scheme.

Liu *et al.* [17] described an evolutionary algorithm with wrapper-embedded feature method for selecting features. They integrated the global search idea of GA with embedded regularization approaches to identify features. Silva *et al.* [18] employed GA in hierarchical feature space to select features. They suggested two mutation operators for the management of superfluous features with categorized fashoin. Emary *et al.* [19] presented a wolf optimization with binary grey strategy for choosing features. They aimed to take full advantage of classification accuracy and decrement in number of chosen features and proposed two methods for wolf optimization in the feature selection process. Mafarja *et al.* [20] developed a metaheuristic procedure employing Ant-Lion optimization strategy for selecting features. They outlined the variants for ant-lion optimizer with the arrangement of V-shaped and -shaped diverse mapping functions, each mapping function was dedicated for transforming the continuous search domain to a discrete search space. Zawabaa *et al.* [21] designed a bioinspired system that integrated the Ant-Lion Optimization and Grey Wolf Optimization algorithms for selecting features. This heuristic algorithm performs better in terms of speed and converges towards global optimization by renouncing local minima problem. Anter *et al.* [22] combined chaos theory with fuzzy c-means strategies and proposed a crow search optimization algorithm for determining features. Paul and Das [23] proposed a GA with multi-objective optimization to select features. Rather than only performing feature selection, they applied a synchronized feature selection and weighing strategy and derived an expression for interclass and intra-class distance measures to employ a multi-objective procedure. They presented a fitness function to decrease the features employing a renovation strategy to obtain best features.

The residential expansion and land use transformation in city areas have fashioned an urban sprawl for the last few decades. The urbanization in diverse dimensions and perceptions have motivated the rural and industrial developments, culminating in profound effects on the surrounding environment, agglomeration economies, knowledge spillovers and societal climaxing. Recently, the vibrant expansion of urban zones has triggered a snowballing requirement for automatic analysis of terrestrial information in metropolitan areas. Therefore, finding the metropolitan land cover data from high spatial and spectral resolution remote sensing imagery and clustering to numerous land cover categories is turning into a thriving research issue [24]-[27].

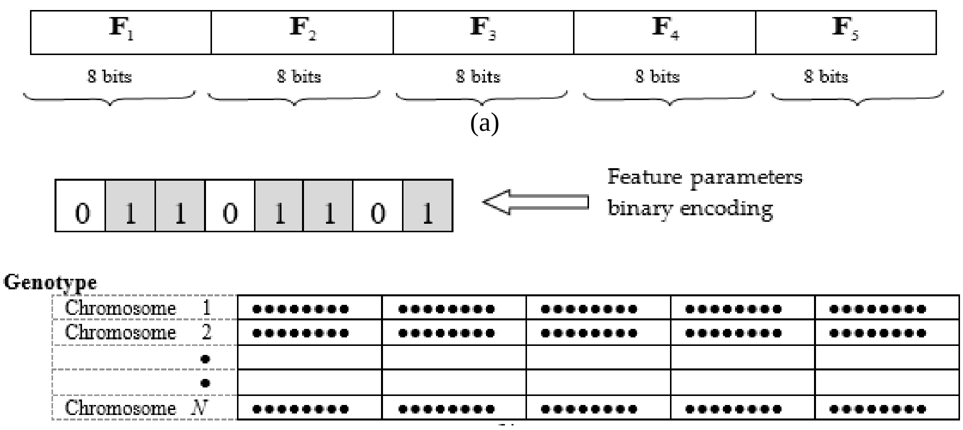
Currently, two principal methods are prevailing for pulling out land cover evidence from high resolution spatial and spectral images. These are pixel oriented image clustering and object-based image investigation [28]-[30]. Pixel-oriented methods investigate the spectral characteristics of every pixel within the range of concern. During investigation, spatial and background information related to these pixels are avoided for consideration [31], [32]. These methods usually employ maximum likelihood classifier and provides less accuracy. Due to the latest remote sensing technology, high-resolution images are providing fine details so that small-scale ground objects are easy to detect. The traditional pixel-based image clustering techniques are unable to fulfil the requirements of these high spatial or spectral resolution remote sensing images, due to their small precision and inadequate application of details information. On the contrary, the object-based methods employ image segmentation into comparatively similar areas generally represented as image objects. Regardless of the outcomes of pixel-oriented and object-oriented image processing methods, the influence of feature selection schemes were justified for urban land cover clustering and agricultural landscapes employing machine learning and soft computing algorithms like decision tree [33], [34], random forest [35], GA [36], [37], support vector machine (SVM) [38], neural network [39] classifiers.

Although the idea behind decision tree and random forest looks similar for data classification, but the basic discrepancy between these two techniques is that a decision tree is constructed over the whole dataset, using all the features of the problem set, whereas a random forest, rather than using just one decision tree, comprising of multiple single trees and randomly selects observations and specific features or variables and then decision is made by determining which evaluation is made maximally by the most number of trees in the forest. GA is organized with the evaluation of natural genetics where superior individuals are selected depending on their fitness values. SVM is a supervised learning technique that takes the data as input and outputs a hyperplane that best differentiates the inputs through two classes by maximizing the margin from a decision boundary. Neural network is inspired by the learning process occurring in human brains and feature selection is established employing the weight decay strategies like features having less discriminating power will get lesser weights. Practical observations reveal that the object-based classifiers out performs the pixel oriented classifiers considering precision and robustness [40]-[43]. Dugan and Uysal [27] investigated the effect of feature selection on metropolitan land use classification. They investigated on components like size/shape, spectral, and texture using correlation-based multivariate and employed random forest, Bayesian network, and SVM as classification algorithms.

This research provides a framework of genetic searching for feature selection. Through this investigation, we predominantly focused on landuse classification optimization with input feature selection. This classification system has been structured on a multilayer perceptron with genetic algorithm (MLPGA). Experimental results demonstrate that this MLPGA based hybrid feature selection procedure performs classification with substantial high sensitivity, specificity and precision.

2. PROPOSED METHOD

The feature selection process is focused on object based classification by detecting the object area in a given image with the knowledge of visual information of the object from remote sensing images. Here some important features are selected automatically which contribute maximum to the prediction variable or output in which we are fascinated. With feature selection, inappropriate and superfluous components from the dataset is discarded, which is an initial phase of object classification. The searching process is commenced on a set of randomly selected population of fixed size *N*. Every single element of the population is considered as chromosome, which signifies a possible solution of the problem. The chromosome structure and encoding mechanism is outlined in Figure 1. The chromosomes are encoded by bit strings consisting of 0s and 1s, known as genes. This research considers the chromosome consisting of five optimization feature parameters, $\{F_i, i = 1,2,\ldots,5\}$, as depicted in Figure 1(a), representing the corresponding features. Figure 1(b) illustrates the structural design of the genotype.



(b)

Figure 1. Structure of (a) chromosome and (b) genotype

Each chromosome is assessed according to an evaluation function which represents the degree of sustainability for survival. Since the most appropriate individuals or 'survival of the fittest' candidates in the population are more expected to be taken for genetic operation, the least apt individuals vanish from future generation. Thus the GA converges to a quality solution of the given problem. Figure 2 illustrates the flowchart of the proposed GA for feature selection. This research employs MLP with back propagation algorithm. The MLP is organized with five possible random features F*i*, (*i*=[1,5]), as shown in Figure 3.

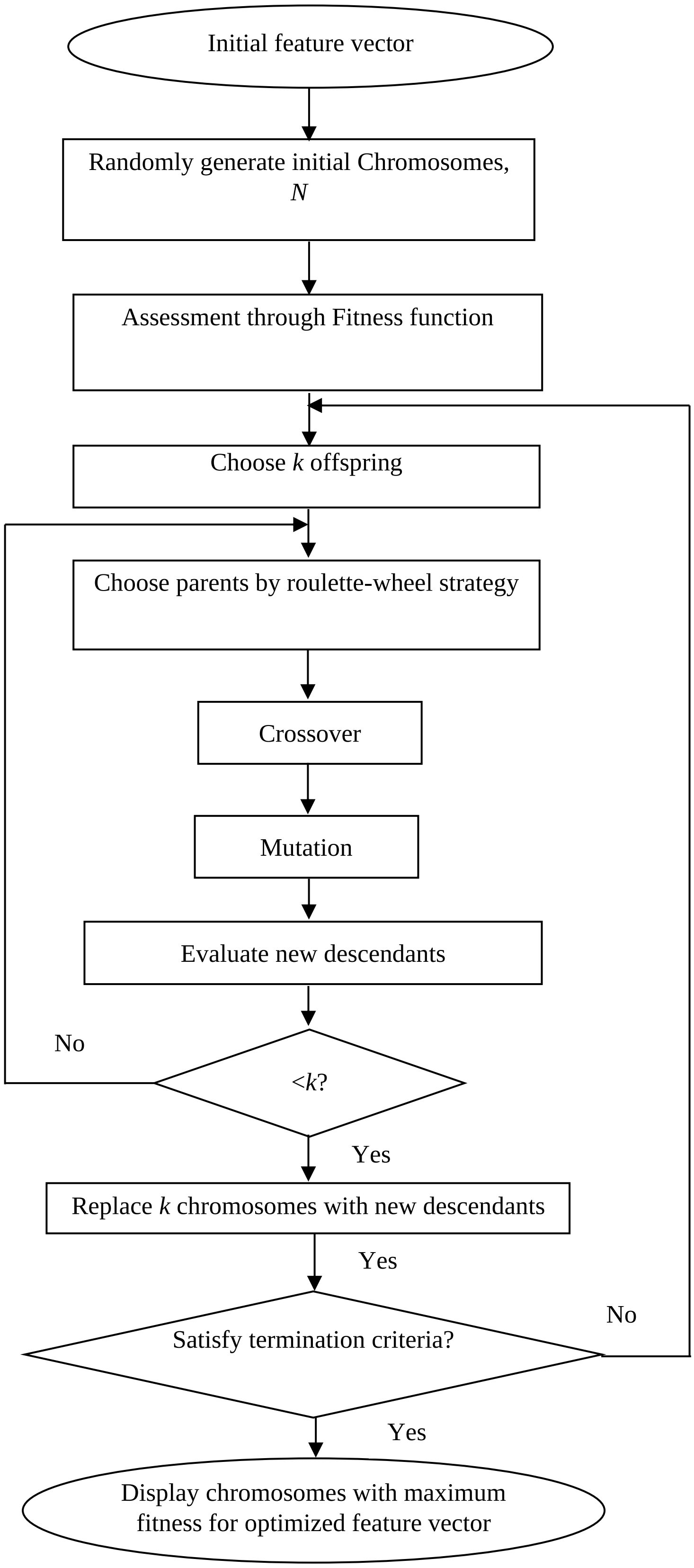


Figure 2. Flowchart of the proposed GA for feature selection

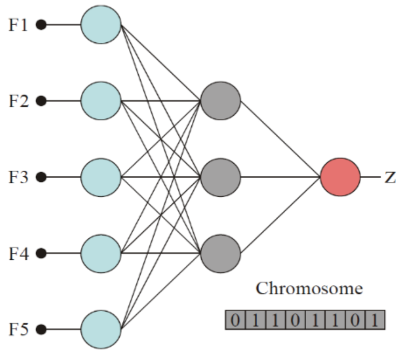


Figure 3. The architecture of the MLP for feature selection

The system initiates with selecting a set of chromosomes of length *L* for reproduction. They are being evaluated through a fitness function. The 'survival of the fittest' chromosomes are selected to sort out for participation in the next generation. This research commences with randomly selected chromosomes and later roulette-wheel strategy has been employed depending on fitness value of individual chromosomes. Then the cross-over process is established on exchanging the genetic information between the parent chromosomes, with a cross-over rate p_c. For this, a crossover point is randomly chosen, where the parent chromosomes 'break', and interchange the genes after that point. The two descendants are produced on merging the fractional structures of two parent chromosomes. In this investigation, we used single point cross-over and uniform cross-over processes with the cross-over rate 0.75. The influence of some restriction of cross-over point has been studied. The cross-over points are selected randomly to exchange the chromosomes' contents but within certain limited chromosome length. In order to make the proposed system more powerful, mutation operation has been applied randomly in between 4 most significant bit (MSB) of the chromosome. In this investigation mutation probability 0.01 was chosen.

The fitness function is used to determine the best possible chromosome in the evolutionary procedure. This assessment function computes the fitness values that can be employed to assess the capability of each chromosomes. This research focuses on distinguishing clusters reasonably accurate by providing the inter-class distance as small as reasonable and intra-class distance as stretched as acceptable. Let us consider the classes C_i and C_j, where ($i,j \in 1 \cdots N$), and C_i and C_j are the members of classes C. The inter-class and intra-class distances are expressed by the (1) [11]:

$$S_w = \sqrt{\frac{\sum_{i=1}^{C}\sum_{j=1}^{N_i}\left[\left(A_{ij}-C_i\right)^T\left(A_{ij}-C_i\right)\right]}{N}}$$
$$S_b = \sqrt{\frac{\sum_{i=1}^{C}\sum_{j=i+1}^{C}\left[\left(C_i-C_j\right)^T\left(C_i-C_j\right)\right]}{n_A}} \qquad (1)$$

where S_w and S_b are the inter-class and intra-class distances respectively, C represents the number of all classes, Ni is belongs to the the number of the samples from class i, A_{ij} denotes the feature vector of sample j from class i, Ci represents the centroid of i, N represents total samples, n_A belongs to the combinations of intra-classes. Thus the fitness value $f(n)$ of for each chromosome n is expressed by the fitness function:

$$f(n) = \frac{S_b}{S_w+S_b} \qquad (2)$$

3. RESULTS AND DISCUSSION

The effectiveness of the proposed approach has been validated over various satellite constellations at numerous environments. The investigations were performed over an Intel® Core ™ i-5 2.2 GHz laptop with 4 GHz RAM using Visual C++. The processing time to locate an object in an image is approximately 2s to 8s. Worldview-1, 2, 3, 4, GeoEye-1, SkySat-1, 2, TerraSAR-X, LANDSAT 8, QuickBird, KOMPSAT-3, IKONOS, satellite image galleries have been used. When a satellite image is exposed to the input, the system provides the resulting output highlighting the image with the given features for the land use information, as shown in Figure 4. A typical (Riyadh city) image collected from the QuickBird Satellite imagery with the resolution of 1461×1452 pixels is as shown in Figure 4(a). The image resolution was made 500×500 pixels during processing. The output image, as shown in Figure 4(b), highlights the prominent features with selected colors. Since most of the buildings are constructed with the same color as that of the soil, the land use information for ground and buildings are distinguished with the shape information. The land coverage was classified with the dominant features like buildings, ground, vegetation, water, roads and others. The distribution of land coverage is illustrate with a pie chart according the number of pixels and percentage of coverage information, as shown in Figure 5.

(a) (b)

Figure 4. Land use information for satellite image (a) image for Riyadh city and (b) land use information

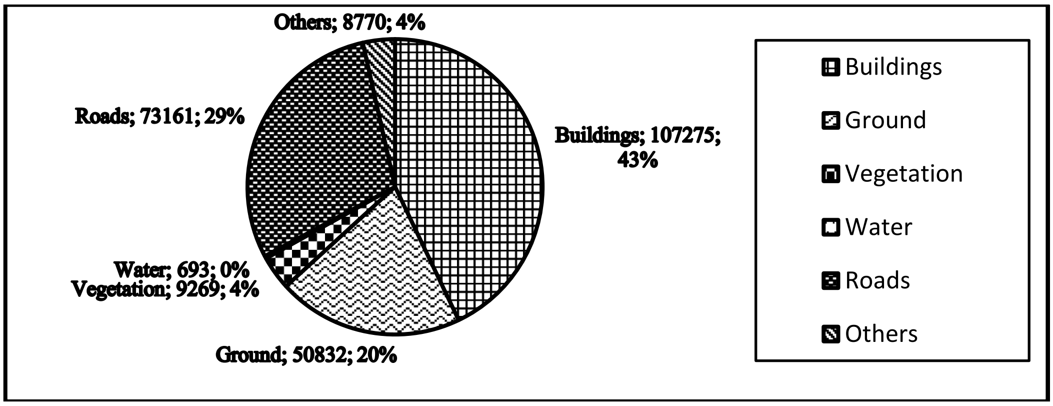


Figure 5. The distribution of land coverage for Riyadh city

The accuracies have been calculated for the five dominant features: buildings, ground, vegetation, water and roads. The proposed neural network based GA hybrid method performed better results for buildings, vegetation and road images. The relative performances in different approaches like ReliefF, simulating annealing (SA), SVM, particle swarm optimization (PSO), GA, GA with Tabu Search (GATS) and Hybrid GA have been justified in terms of their accuracies and furnished in a bar diagram, as shown in Figure 6. Although image enhancement techniques have been applied, but ground and water images do not affect the search mechanism due to bright lighting conditions, which provides some error in the experiment. Another reason behind the failure is the cause of inability of the system to detect overlapped and occluded objects in images. This model provided consistent high classification specificity, sensitivity and precision for five dominant features, which are quite reasonable as shown in Figure 7.

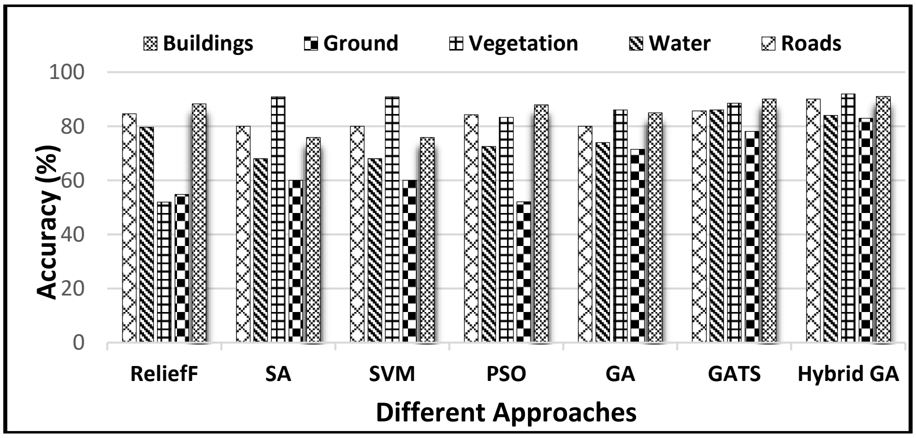


Figure 6. Accuracies of dominant features for different approaches

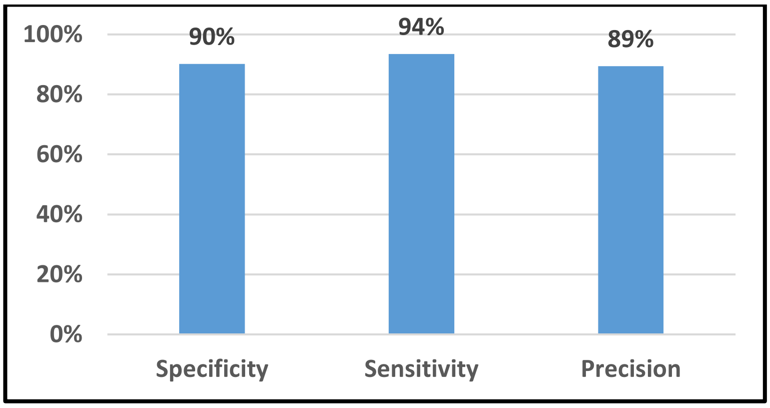


Figure 7. Specificity, sensitivity and precision for five dominant features

Investigation was carried on with the GA employing single point and uniform cross-over at various population sizes. This established the fact that an important decision has to be always made for choosing population size in consideration of the cross-over technique. The present system also examined the impact of some restriction of cross-over point on the process execution time, as shown graphically in Figure 8. Here, when the conventional cross-over takes place the system execution time is high in comparison to modified cross-over. It is noticeable that the same system's execution time gradually decreases when cross-over is restricted in between the bit position 1 to 7, 2 to 7, 2 to 6, 2 to 5.

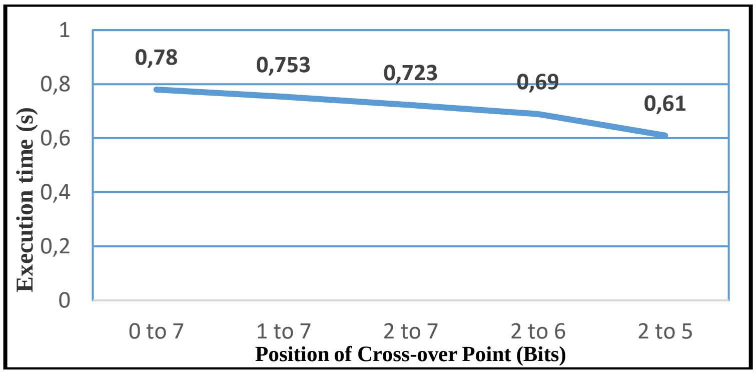


Figure 8. Impact of restricted cross-over point on process execution time

The GA has been investigated with single point cross-over at various pop sizes and the effect is shown in Figure 9, which indicates that the bigger pop size harvests improved results due to the higher pool of various representations accessible with individuals but the inertia of bigger population might provide swellings an erroneous of inferior start as well. Lesser pop size, on the other hand, have the capability of adjusting more quickly and thus unveil improved starting performance. The variation of fitness at different generations for uniform cross-over is furnished in Figure 10, which reveals that lesser pop size performs enhanced output in the case of uniform cross-over, on the contrary, bigger pop size is exaggerated by oscillations. Therefore, a trade-off is always being adopted between pop size and the modes of cross-over.

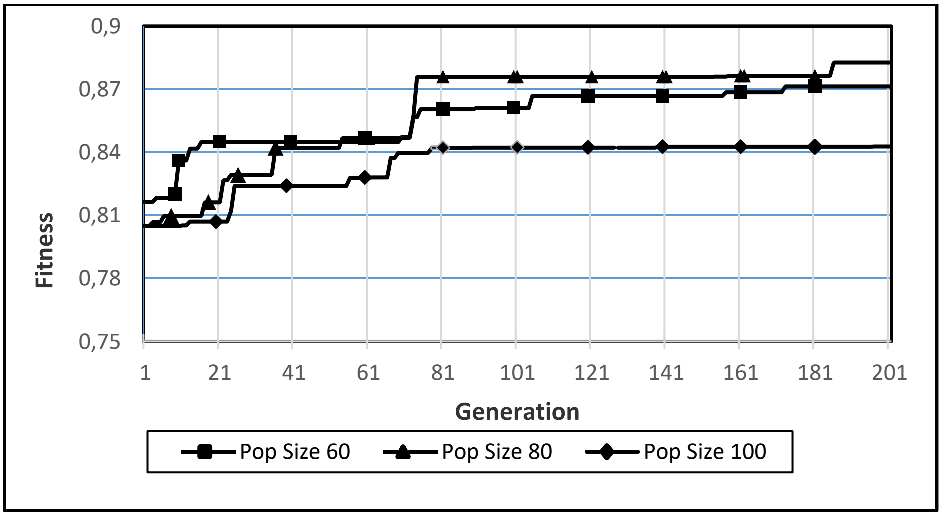


Figure 9. Change in fitness with generations

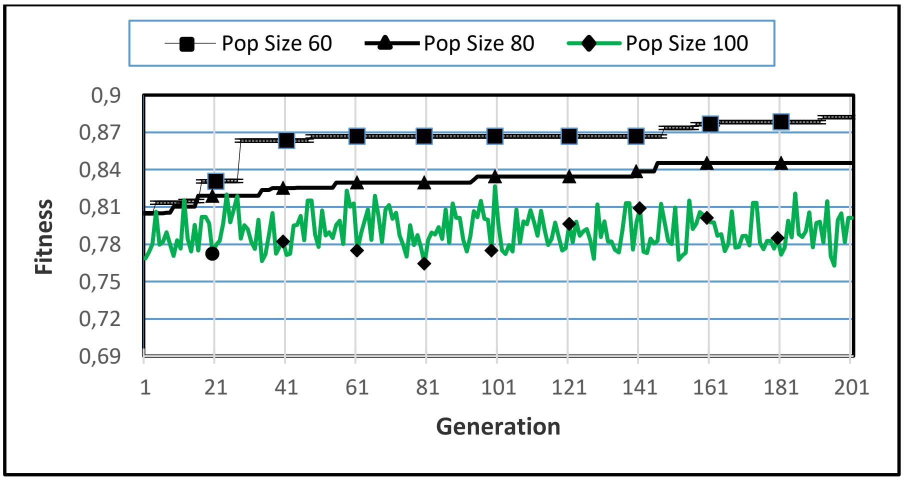


Figure 10. Variation of fitness at different generations

4. CONCLUSION

This research addresses an efficient way of selecting features for urban land cover classification. The proposed feature selection scheme has been outlined and compared with other existing popular feature selection methods like traditional GA, GATS, simulating annealing, SVMs, particle swarm optimization strategies. The analysis was carried out with recently published datasets of Worldview, GeoEye, QuickBird, and SkySat. The evaluations are performed with communal strategies for enhanced precision and high quality assessment constraints. Satellite images are deliberated in five distinct classes: Buildings, Ground, Vegetation, Water and Roads for endorsement of categorized output. Images are assessed in terms of accuracy, sensitivity, specificity and precision for individual and overall classifiers. These analysis and investigations have been carried out with image resolution of 512×512 pixels. This sort of investigation will enhance agricultural development over crop monitoring, irrigation and harvesting and urban development with dissemination of land cover information.

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