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Automatic slums identification around normal and smart cities: using Machine-learning on VHR Satellite Imagery

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ABSTRACT

The slum phenomenon is becoming one of the global issues for the complexity of its economic and social dimensions. UN Habitat has highlighted the dangers, especially in southern countries where the number of people living in these slums is likely to reach 2 billion by 2030. Morocco is one of the most advanced Arab countries in the fight against unsanitary housing and slums. Since the 1950s, and in order to resolve these costly problems, Morocco has tested various approaches and intervention strategies in the elimination of slums, in particular the "Cities without slums" program, which was launched on July 24, 2004. However, this program encountered many constraints, which initially required the intervention of the Royal Center for Space Remote Sensing in Morocco (CRTS), using very high-resolution satellite images (VHRS). This involves drawing up the condition of the slums and monitoring the evolution over time in terms of extension or demolition, and providing technical assistance to the Department of Social Housing and Land Affairs (DHSAF) for the establishment of a Geographic Information System (GIS) for the management and monitoring of the Cities without slums "CWS" program. In this perspective, we will propose in this manuscript an approach based on machine learning, more precisely Support vector machine (SVM) with the introduction of mutual information (IM) during the preprocessing of the satellite image to very high spatial resolution (60 cm) with 4 bands. The goal is to increase the information of the slum data in each band of the image, and to reduce the redundant information and eliminate the unnecessary dataset in all bands and ultimately classify these objects according to several parameters. The results obtained on real instances in a region of Morocco show the reliability of our automatic approach for the identification of slums.

Keywords: Slums, classification, remote sensing, Satellite images (THRS), Mutual information (MI), Photogrammetry, topographic map.

1. INTRODUCTION

The phenomenon of the proliferation of slums due mainly to the combined effects of population growth and massive rural exodus, causing an uncontrollable expansion of cities.

Despite the almost total absence of basic equipment and infrastructure such as access to drinking water and sanitation, endangering environmental security and public health, these slums continue to attract more people. Inhabitants to number nearly a billion globally [1], most of them settled on agricultural land under the form of illegal occupation, without prior organization, and they are often not covered by the documents of town planning. This anarchy was accompanied by profound socio-economic and cultural changes imposing radical changes in the social and spatial organization of urban agglomerations [2].To face this challenge, several countries have initiated various public policies to improve housing conditions. Today, 20 southern countries have recorded considerable efforts, which have earned them recognition from the international community for their efforts in the fight against unsanitary housing. Particularly in Morocco, the efforts undertaken and the performance achieved in this area have enabled it to receive from the United Nations the honorary prize "Habitat 2010" for its national CWS program [3]. This important distinction honors the action of Morocco, which, since the ratification of numerous international conventions relating in particular to the right to housing, has continued to promote the right to access to decent housing in the programs and public policies linked to the development of the territories. Moreover, in accordance with the principles enacted by the new constitution of Morocco.

Despite these major remedial actions implemented since the 1980s, slums have continued to develop within large cities, due to the effects of overwhelming urbanization [4]. In order to maintain the pace of the efforts exerted and to limit this phenomenon, the Moroccan government, represented by the Ministry of Housing and Urbanism and City Policy (HUPV), has embarked on a study aimed at to identify and monitor slum neighborhoods from the analysis of very high spatial resolution satellite images over a period of 7 years (2005-2011), in cooperation with the Royal Space Remote Sensing Center (CRTS). This study focuses on the visual interpretation of VHRS images by following the following steps:

- Programmed acquisition of Quick Bird color satellite images with a geometric resolution of 60 cm covering the study area for year i.
- After preprocessing these images of the first year, they are therefore geometrically corrected with respect to the topographic maps at the scale of 1/50.000. From the second year, the images will be corrected in the same way but taking as a reference for the calibration points the images of the previous year ;
- After the photo-interpretation of the images, the slum situation maps are checked by a third party to detect any photo-interpretation errors;
- A field check is carried out by the territorial services concerned in the event of confusion;
- Once the control and validation has been completed, we move on to the data structuring stage (figure 1).

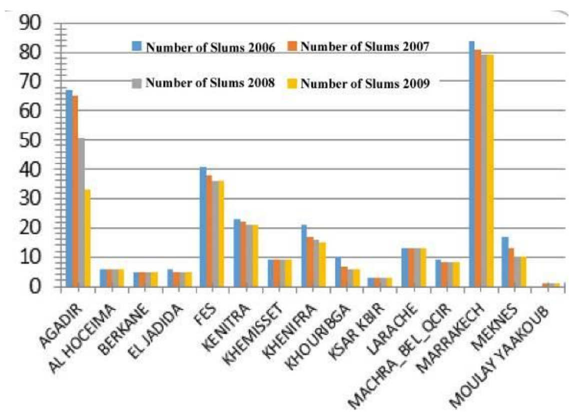

Figure 1: Evolution of slum districts in some cities between 2006 and 2009 (source: MHUPV)

The effectiveness of this approach in monitoring slum neighborhoods and the CWS program is mainly due to the supervision by monitoring committees (the national monitoring committee; the regional coordination committee, the provincial identification committee and of implementation, social support units (CAS)) of production operations of slum absorption units and accompanied by demolition operations of the corresponding barracks.

However, the time taken by all those operations, based essentially on the visual identification of the VHRS images to be acquired in programming (1-3 months), and the verification on office and in the field, is very significant, not allowing to act in a timely manner to stop the proliferation of slums, on the contrary, enough time is left for the establishment of more units in the slums, and we are faced with a fait accompli. It is from this perspective that comes our approach based solely on the use of machine learning, with the SVM algorithm and relying on MI during preprocessing VHRS images.

1.1 Presentation of the study area

The study area is derived from one of the twelve regions resulting from the 2015 territorial division of Morocco. It is the region of Rabat-Sale-Kenitra, which is located in the northwest of Morocco (figure 2).

It is bordered to the north by the Tangier-Tetouan-Al Hoceima region, to the east by the Fez-Meknes region, to the south by the Beni Mellal-Khenifra region and the Casablanca-Settat region, and to the west by the Atlantic Ocean. It covers an area of 18,194 km2 and has 4,581 thousand inhabitants (RGPH 2014) and therefore a density of 251.8 inhabitants per km^2.

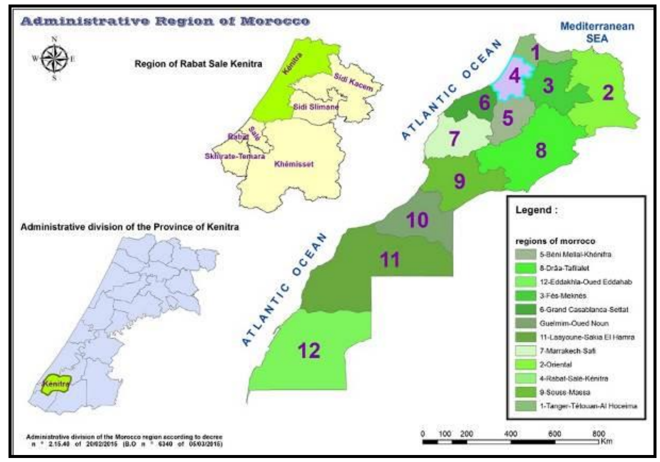

Figure 2: Study Area: Regional Division of Morocco

The district of Ain Sbaa, subject of the present study, is located in the south-west of the commune of Kenitra. The latter falls under the province of Kenitra, part of the new Rabat-Salé-Kenitra region (figure 3).

The study area is located on the communication axis of the A5 highway, near the Maâmora forest.

Figure 3 : Location of the study area

2. METHODOLOGY

2.1 Data-processing and mutual information (MI)

In probability theory and information theory, the MI of two random variables is a quantity measuring the statistical dependence of these variables. It is often measured in bi.

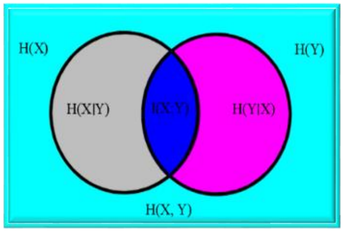

Figure 4: Illustration of MI

The MI of a pair (X, Y) of variables represents their degree of dependence in the probabilistic sense. This concept of logical dependence should not be confused with that of physical causality, although in practice one often implies the other.
Informally, it is said that two variables are independent if the realization of one provides no information about the realization of the other (figure 4). The correlation coefficient is a measure of the special case of dependence in which the relationship between the two variables is strictly linear.

The MI is null if and only if the variables are Independent, and increases as the dependence increases.

Entropy: Mutual information measures the amount of information provided on average by a realisation of X on the probabilities of realisation of Y. Considering that a probability distribution represents our knowledge about a random phenomenon, we measure the absence of information by the entropy of this distribution. Then, MI is expressed by [5]: (1)

$$I(X;Y) = H(X \mid Y) = H(Y) - H(Y \mid X) = H(X) + H(Y) - H(X, Y)$$

Where H(X) and H(Y) are entropies, H (X|Y) and H (Y|X) are conditional entropies and H(Y, X) is the joint entropy between X and Y. So we see that I(X; Y) = 0; I (X; Y) = 0.
The multispectral satellite image (or hyperspectral), contains several bands of the same region, which means a large spectral information with a limited number of training samples. These bands were imaged at juxtaposed frequencies. We are in front of some irrelevant and most of them redundant bands, their high dimensionality complicates the learning system leading to a bad classification model [6].
To overcome this obstacle, it is necessary to introduce dimensionality reduction techniques as a preliminary step in the pre-processing of the supervised classification [7]. There are two types of categories of dimensionality reduction methods:
a) Attribute extraction: these methods transform entities into a small entity space.
b) Attribute Selection: these are methods that identify a subset of the attribute set.

2.2 Support Vector Machines

The Support Vector Machine is a supervised learning algorithm based on the theory of statistical learning initiated by [8].Based on a very solid mathematical foundation; the results obtained by this method are very effective. This is the result of the work of several people over several years [8].

2.2 .1 Principle Linear SVM: Linearly Separable Case [9]

Consider a supervised binary classification problem. let X be the training set which consists of N vectors x_i of the feature space of dimensions k, $(x_i \in \Re^k)$ .the purpose of binary classification is to estimate a response that has only two states, therefore, we define the set of possible response values by yi = {- 1; +1} , is associated with each vector $\vec{x_i}$,each element is represented by a pair $(\vec{x_i}, y_i)$, with ($i = 1.......N$).
Suppose the two classes are linearly separable. This means that it is possible to find at least one hyperplane (linear surface), defined by a vector $\vec{w} \in \Re^k$ (normal to the hyperplane) and a bias $b\,(b \in \Re^k$), which can separate the two classes without error [10].
The membership decision rule can be based on the function $\operatorname{sgn}\left\lfloor f_{\vec{w},b}(x_i) \right\rfloor$, where $f(x,\alpha) \rightarrow y$ (with α parameters of the classifier) is the discriminant (decision) function associated with the hyperplane and defined as: $f(x) = \vec{w}.\mathrm{X} + b$. (2)
In the case of a linear classifier, the function f can be defined using a hyperplane equation $\vec{w}.\mathrm{X} + b = 0$ (with d denote the parameters for the hyperplane respectively a plane normal vector and bias).The classification of a vector $\vec{x_i}$ is given by the sign of the function f , $\operatorname{sgn}\left\lfloor f_{\vec{w},b}(x_i) \right\rfloor$ ie $y_i = \pm 1$.
if $\operatorname{sgn}\left\lfloor f_{\vec{w},b}(x_i) \right\rfloor > 0$ with $\mathrm{y}_i = -1$ if $\operatorname{sgn}\left\lfloor f_{\vec{w},b}(x_i) \right\rfloor < 0$
The SVM approach consists in finding the optimal hyperplane that maximizes the distance between the closest training sample and the separating hyperplane (see figure 5), and which allows the data to be correctly classified as well as its distance vectors (learning example).The closest vectors are then called the "support vector" and the distance is the optimal range.

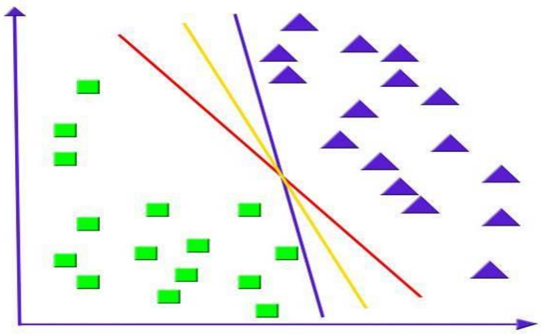

Figure 5 : Principle of SVM: (a) Research the optimal hyperplane

The geometric margin between the two classes (the distance between the two hyperplanes H1 and H2) (figure 6) is given by the quantity $\frac{2}{\|\vec{w}\|}$ where $\|\vec{w}\|$ refers to the norm of the vector $\vec{w}$. The concept of margin is at the heart of SVM approach, because it measures its capacity for generalization. The larger the margin, the higher the expected generalization [11]. As a result, it turns out that the optimal hyperplane can be
determined as the solution of the following convex quadratic programming problem: minimize:

- $1/2\|\vec{w}\|^2$; (3)
- $y_i(\vec{w}.\vec{x_i}+b)-1\geq 0$, $\forall i=1,....,N$

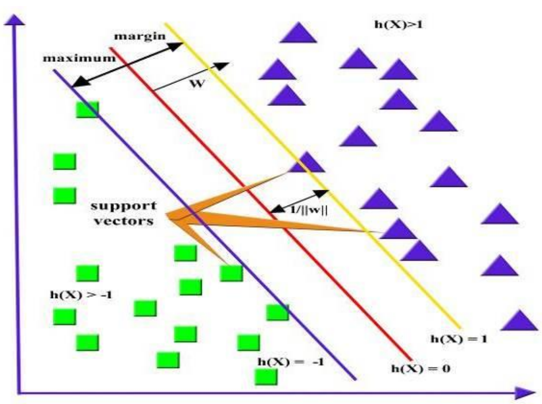

Figure 6: Optimal hyperplane, margin and support Vector.

This classical linearly constrained optimization problem can be translates (using a Lagrangian formulation) into the following double problem :

$\vec{w}^* = \sum_{i=1}^{N}\alpha_i^* y_i \vec{x}_i$ with the α^* are the Lagrange multipliers are determined only for non-zero points $\vec{x_i}$.

It can be estimated using quadratic programming (QP) methods [11]. The discriminant function associated with the optimal hyperplane becomes an equation depending both on the Lagrange multipliers and on the training samples, i.e., located exactly "on line", that is to say The calculation b^* is performed either by taking an individual i (a learning sample) by averaging all of the b^* vector obtained for each carrier.

Is then $\nu s=\{j\in\{1,2......l\}\mid \alpha_j^*\neq 0\}$ all indices of support vectors. Once the parameters calculated α^* and b^*, the rule for classifying a new observation $\vec{x}$ based on maximum margin hyperplane is given
by :

$$\text{sgn}(\textstyle\sum_{j\in \nu s} y_i\alpha_j^*\vec{x}.\vec{x}_j+b^*) \quad (4)$$

2.2.2 Nonlinearly separable case:

However, to handle input vectors that are not directly linearly separable, we will introduce the kernel function Φ in order to provide the scalar product of the vectors in feature space. The said k(xi, xj) can be considered as a means to obtain a value of angular similarity between vectors in many cases, the drive samples are not linearly separable. The procedure then is to introduce a function Φ for projecting the data into a higher dimensional space (D) where they become linearly separable (see Figure 7):

$$\Re^k \rightarrow \Re^D \text{ With D>>d} \qquad \vec{x}\rightarrow\Phi(\vec{x}) \quad (5)$$

Just like the previous approach, we are looking for the optimal

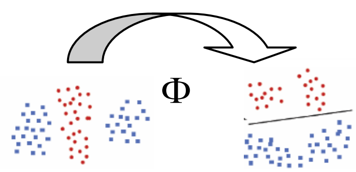

Figure 7: Representation of the kernel trick

hyperplane in this new space by applying the following:

$$f^*(\vec{x})=\vec{w}^*.\Phi(\vec{x})+b^* \quad (6)$$

Such as

$$\vec{w}^* = \sum_{i=1}^{n}\alpha_i y_i\Phi(\vec{x}_i) \quad (7)$$

$$f^*(\vec{x})=\sum_{i=1}^{n}\alpha_i y_i\Phi(\vec{x}_i).\Phi(\vec{x})+b^* \quad (8)$$

Then: It should be noted that the data of the scalar products between points is largely sufficient for the calculation of the function f^*. so instead of looking for the representation of the function $\Phi(\vec{x})$,it suffices to calculate the term:

$$\Phi(\vec{x}_i).\Phi(\vec{x}_j)=\text{k}(\vec{x}_i,\vec{x}_j). \quad (9)$$

The term (dot product) $\text{k}(\vec{x}_i,\vec{x}_j)$ is called the kernel. And among the kernels frequently used in the field of classification of satellite images, mention may be made of the Gaussian kernel or the RBF kernel (for Radial Basic function).

In this way, as long as there is some higher dimensional space in which φ(.) is just the dot product of that higher dimensional space, the kernel can be written as a dot product and used directly into the optimization problem in form:

$$k(x,y) = \exp\left(\frac{\|x-y\|^2}{2\sigma^2}\right) \qquad (10)$$

Or the polynomial kernel: see: [12] [13] and [14].

$$k(x,y) = (x.y+1)^p \qquad (11)$$

2.4 Methodology :

The main objective of this study is the extraction of slums from VHRS images and we will need the data shown in Table 1:

Table 1: Data used

Images/map/Data	Resolution/Scale	Description/Source
Quick BIRD	0.6 m	4 Bands / CRTS
ORTHO PHOTO	1/2000	Source : AUKSS
Topographic survey	1/1000	
Censuses	2004/2014/2017	HCP/AUKSS

AUKSS: urban agency; HCP: High Commission for Planning

As already noted and as shown in figure 8, we have a QuickBird satellite image with four bands (R, G, B and IR):

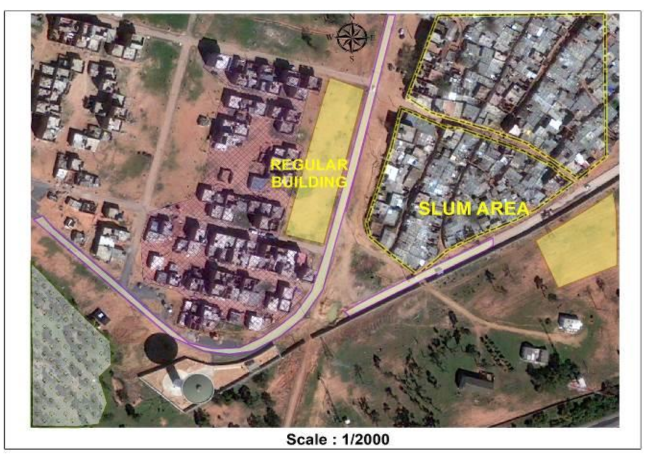

Figure 8 : Extract from the satellite image under study

The land use plan in this image shows the different existing classes namely: slums, ordinary construction, roads, vegetation and soils.

The first step of this work begins with a preprocessing via an algorithm (as shown on figure 9)[6], based on MI to filter the relevant bands on the one hand and improve the concentration of the information of the slum within each band apart, and on the one hand. End we will apply it to the resulting image (figure 10):

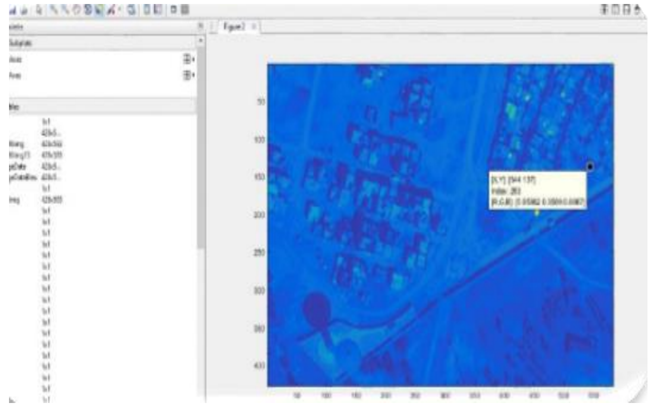

Figure 9 : Extract from Mutual Information Algorithm band

To the image reprocessed with the mutual information algorithm, we will apply a multi-resolution segmentation. This is an image processing operation, which consists in grouping pixels having predefined criteria to obtain homogeneous subsetsor regions. Indeed, segmentation attempts to associate a label with each pixel of the image by relying on information on gray levels, color or spatial distribution. For a given image, there are always several types of segmentation possible. A good segmentation method will therefore be the one that will allow us to arrive at a good interpretation. It is therefore necessary to simplify the image without having reduced its content too much. An analysis of some of these methods can be found in [15], [16] and [17].

After the segmentation comes the classification step with the SVM-RBF (radial basis function) classifier [18], and we proceed to a comparison of this chosen method [19] with four other supervised classifiers namely:

- **SVM1 : (SVM-RBF)**, [20] it is the same classifier as for the proposed method without applying the preprocessing algorithm based on mutual information [21]**.**
- **SVM2 : (SVM- LINEAR)** .
- **SVM3 : (SVM- SIGMOID)**.
- The simple **likelihood method** explained in [22].

```
MATLAB
Command Window
x=128    ;
y=455       ;
Y=[imageData(x,y,1),imageData(x,y,2),imageData(x,y,3)];
for i=1:428
for j=1:583
M16img(i,j)=M16([imageData(i,j,1),imageData(i,j,2),imageData(i,j,3)],Y,256);
end
end
imagesc(M16img);
imshow(M16img,[])
>> %amplification du bleu par IM
imageDataBleu=imageData;
for i=1:428
for j=1:583
imageDataBleu(i,j,3)=imageDataBleu(i,j,3)*1000*M16img(i,j);
end
end
>>
imagesc(imageDataBleu(:,:,3));
>> %amplification du bleu par IM
imageDataBleu=imageData;
for i=1:428
for j=1:583
imageDataBleu(i,j,3)=imageDataBleu(i,j,3)*1000*M16img(i,j);
end
end
```

Figure 10: Application of our IM algorithm on the blue

The training areas are topographic surveys at a scale of 1/1000 at different dates and ortho-photo plan images at a scale of 1/2000 from aerial photogrammetry. The results extracted from the classifications in vector formats will attribute to the update of the map identifying the slum cores at the level of the study area. By comparing the results obtained with the existing data from the database made up of topographic surveys and available land and plot surveys, we will set up a geographic information system that will serve as an observatory for monitoring the proliferation of slums. The functional diagram of the overall methodology is illustrated as follows:

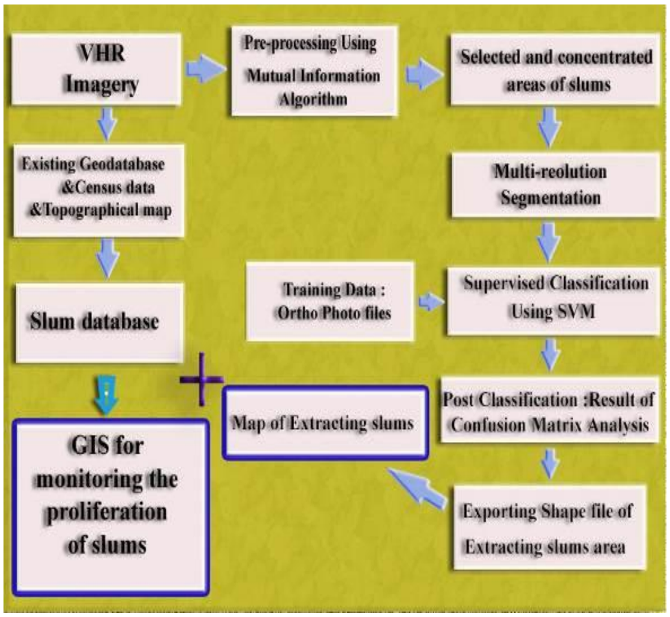

Figure 11: Flowchart of the overall methodology

3. RESULTS AND DISCUSSION

3.1 Pre-processing results

The first step of this study was to select the relevant bands from the datasets, this was done using a filtering method based on MI, and we obtained an image, which indicates that the data of the "slum" is present in terms of concentration than the other classes. In addition, the results presented graphically in figure12 and which illustrates the performance of our approach.

Figure12: Result of the preprocessing using the MI algorithm.

3.2 Segmentation results.

The result of the multi-resolution segmentation of VHRS image above is illustrated in the following map:

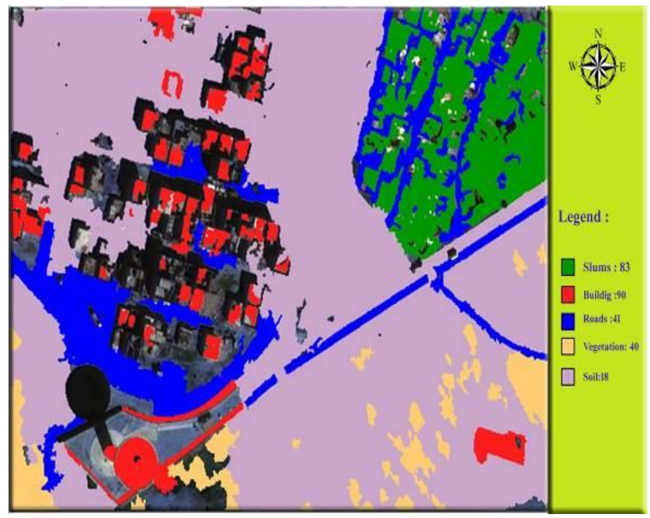

Figure 13: Multi-resolution segmentation result

The segmentation of the pre-processed satellite image (figure 13) faithfully respects the types of buildings [22]. It differentiated well between slums and regular housing (figure11).
Almost all roads are segmented by a single segment.
The total segmentation error is about 5.1%, in other words, we can say that 94.9% of the segments faithfully represent the corresponding objects.
As a result, the present segmentation is very satisfactory, and can be widely used in the classification process (figure14).

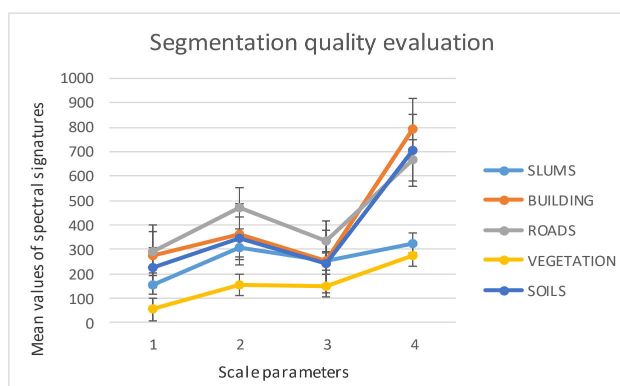

Figure14: Assessment of the quality of segmentation (class separability)

3.2 Classification result

The quantitative assessment of the classification is based on statistical tools developed within the framework of a nominal measurement scale, the main element of which is the confusion matrix [23] pages (338-343). From this matrix, several indices are deduced, each characterizing a particular property of the results: the most used are the overall precision (Overall Acuuracy) and the Kappa coefficient.

Table 2: results of the performance of the classification methods used:

Classificati-on input		Overall Accuracy (%)	Prod Accuracy SLUM (%)	User Accuracy SLUM (%)	Producer Accuracy Building (%)	User Accuracy Building (%)	kappa
SVM	MI-RBF Proposed Method)	97.2774	99.30	9.48	81.68	98.73	0.9655
	RBF (SVM1)	95.7523	96	96.84	87.52	86.61	0.9312
	Linear (SVM2)	92.5480	89.85	78.94	52.46	97.93	0.8806
	Sigmaoid (SVM3)	89.9751	94.21	73.05	54.83	80.55	0.8634
Maximum likelihood		90.2720	78.85	94.67	45.02	45.59	0.8374

Based on these results, most of the classification methods used in this study achieved an overall accuracy rate (Oveall Accuracy) of over 89.9% as shown on table 2, so we can say that these methods work well. We also note that the proposed method based on the preprocessing of the satellite image at (THRS) by an algorithm based on the IM and using the SVM-RBF classifier, gave a better result in terms of the overall precision, which reached 97.28%. While the application of the same classification algorithm: (SVM-RBF) that we called SVM1, and without preprocessing of the satellite image by IM gave a remarkable result with an overall accuracy rate of the around 95.75%, but significantly lower than the result obtained by the proposed method.
The comparison of some methods with the proposed method allowed obtaining the results illustrated in figures 15 and 16.

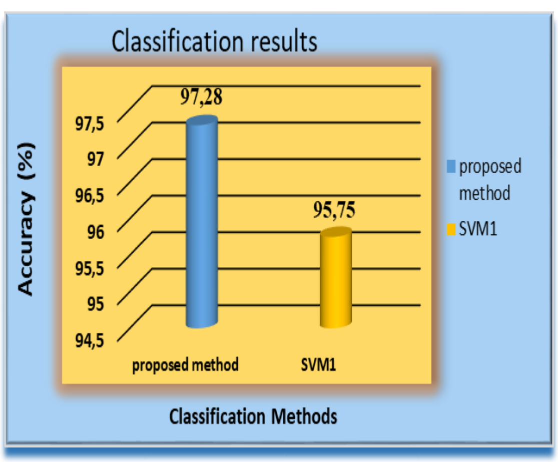

Figure15 : Comparison of classification methods : Method proposed with SVM1 (SVM-RBF).

Likewise, we can notice that the SVM-LINAR (SVM2) gives better classification results than those of the SVM-Sigmoid (SVM3).

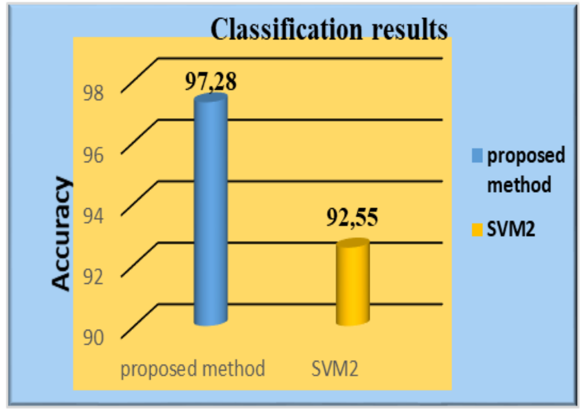

Figure16: The evaluation of the classification quality of the SVM2 method (SVM-linear).
And in summary here is in figure 17, the result of comparisons of the classification methods used in this study:

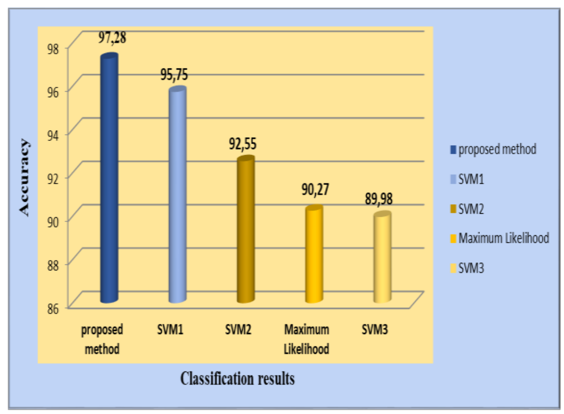

Figure17: global comparison of the methods used

We finally obtain and as shown in table 3:

Table n ° 3: results of classifications of the methods used in the study.

Classifiers	Overall Accuracy (%)	KAPPA
Proposed method	97.28	0.9655
SVM1	95,75	0,9312
SVM2	92,54	0,8806
Maximum Likelihood	90.27	0.8374
SVM3	89,98	0,8806

Also we have the confusion matrix of the proposed method illustrated in table4.

Table 4 : the confusion matrix corresponding to the proposed method : (IM-SVM-RBF).

	Slums	Vegeta--tion	Soil	Roads	Build--ing	Total
Unclass - ified	0	0	0	0	0	0
Slums	**285**	0	0	0	30	**315**
Vegeta - tion	0	**226**	0	0	0	226
Soil	0	0	**348**	0	0	348
Roads	0	0	0	**307**	5	312
Build--ing	2	0	0	0	**156**	158
Total	**287**	226	348	307	191	1359

From the analysis of these figures and tables, we can see that the technique of preprocessing of the VHR satellite imagery, object of the study with the algorithm based on MI effectively allow to identify information on slums compared to the results obtained by SVM and RBF-SVM. Thus, this difference can be justified by the confusion matrix which gives small classification errors, especially between slums and regular housing, especially for small structures, this is mainly due to the similarity of morphological characteristics and materials roofing of the two housing categories.
Thus, in the slums and following field experiments, we notice that some plots are made up of zinc paved rooms and other small non-regulatory units with hard paving.
Likewise, in the neighborhood bordering the slum areas, there are houses of regular housing, which have outbuildings, either on the ground floor or upstairs, zinc paving serving as storage room, or unit of rabbit or hen farms.

4. CONCLUSION

The rapid climate changes over the last decade have undeniably affected the agricultural sector, with industrial and economic development, the city has become a pole of attraction par excellence and the employment opportunities it offers, hence a rural exodus very strong in cities and consequently a growth of the population of the slums.
Despite this rapid environmental change, the results reveal that slums, often viewed as illegitimate, makeshift and temporary settlements, are places experienced by many residents as permanent communities. Adaptation processes have become institutionalized over time, as a new generation of people imagine staying and (re) organizing themselves to achieve a higher level of functioning through various risk reduction strategies.
With this staggering increase in slum cores and the population they occupy, cities today face several challenges, social, economic and urban infrastructure and service provision, in addition to the Covid19 pandemic, to the during the year 2020, whose high population densities of slums contribute to a rapid and wider spread of the infection, which accelerates transmission and household overcrowding makes it difficult for behaviors like social distancing [24].
This rapid urbanization requires strong strategies and innovative planning, based on perfect knowledge reliable information about these slum cores in order to use them for monitoring and managing their growth.
This article showed how slums can be automatically detected and subsequently mapped, and fed into a geographic information system.
This approach will make it possible to overcome the almost critical insufficiency of this information, and to respond to the data of the location of these nuclei, and to the data of analyzes through the existing and updated land and plot surveys, in addition data from different censuses.
This information collected was previously used to choose one of the methods of classic interventions in the fight against unsanitary housing, namely: (resettlement, rehousing or restructuring), but we are leaning towards modern methods which have the same objectives of the need to provide an adequate housing supply to accommodate slum residents.
These are the methods proposed in the context of smart cities ensuring housing that meets the needs of the population in terms of accessibility, size and type [4].
In this regard, special attention will be paid to the provision of adequate housing to the low-income category as well as to the economically weaker vulnerable categories in order to avoid the formation of slums.
In these settlements, a social, intelligent and sustainable infrastructure must be put in place in order to create a dynamic society and ensure an atmosphere that facilitates business, and the aim of all this is to ensure that the daily needs of all categories are satisfied.
Remember that this work is mainly based on the processing of satellite images at THRS. While with the advent of low-cost drones (also called UAVS: unmanned aerial vehicles or remote piloted aircraft systems (RPAS)) [25], and in addition to the use of automated photogrammetry software and especially open source (ex: OpenDroneMap), The data of ortho photo plan images are now available and in a minimum of time.
And the method used in this article can be exploited all over the world.
In the next work, we are interested in introducing a new method based on intelligent hybridization between the machine-learning [26] SVM algorithm and genetic algorithms [27][28] in order to improve the performance of image identification related to our problem.

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