Automatic Extraction of Buildings Boundaries Using Satellite Imagery with High Spatial Resolution and Deep Learning Methods

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SUMMARY

In recent years, rural and urban spatial information are becoming one of the most crucial tools in applications like developing new databases and maintaining the ones that already exist, among other things. One of the most significant elements in both rural and urban regions are buildings. Building detection, which involves identifying each building's location within the data set being used, and building reconstruction, which entails reconstructing each building's two- or three-dimensional geometric model, are the two main sections that create the procedure of extracting buildings from the images. To extract significant features, such as a building, innovative and effective techniques for image processing (active contour models) must be adopted and developed. In the current study, the border of the building was extracted from an image of Shahru in the province of Hormozgan utilizing data from the Worldview-2 satellite. The Margon model was implemented in the MATLAB programming environment to identify the main components of the structure after preprocessing the image and utilizing the maximum likelihood classification method. The output of the proposed methodology was compared with the manually generated map in the ArcGIS environment to assess the results. The results indicate a 90% overall accuracy rate.

1. INTRODUCTION

Today, due to the particular importance of buildings as one of the most crucial development infrastructures in each country in different applications, their information extraction has become an important challenge in related sciences.

One of the technologies that have been widely used in this field is remote sensing, along with the science of digital image processing. Currently, identifying and mapping features from aerial and satellite images provided by expert operators will account for the most significant part of the cost and time taken to produce a map of these images. Therefore, the automatic extraction of features from these images is one of the fundamental research questions of photogrammetry and remote sensing, followed in the direction of automatic mapping.

The automatic extraction of features can be known as identifying and determining the location of features in images without the direct involvement of the human factor. This leads to reducing the required time and subsequently increasing the efficiency and cost-effectiveness of the methods for producing spatial information by reducing or eliminating the role of the human factor in producing the map.

The automatic extraction of aerial and spatial images is part of a high-level image processing analysis, and a comprehensive system that can automatically extract features without any intervention from the human operator is not marketed yet. Thus, this branch of science is in the research phase.

Today, rapid population growth, urban development, and natural resource constraints have created such problems for humans that planning is considered necessary for all countries. The evacuation of villages, the expansion of cities, and the urbanization tendency, especially in developing countries, have such complications that ignoring them will increase social and economic problems.

The majority of the significant and strategic decisions taken by managers and planners are related to the situation and location of human handicaps in urban and rural areas. One of the cases that can be cited in the planning and analysis of the experts is the analysis of maps resulting from aerial and satellite images. The building is one of the most important terrains on large-scale urban and rural maps.

Photogrammetric and remote sensing methods, in terms of the extension of the covered area on the one hand and the acceptable accuracy of these methods on the other hand, are known as suitable methods for producing and updating spatial information and covert maps. Therefore, its detection from aerial and satellite images is one of the major concerns of photogrammetric and remote sensing specialists.

Increasing speed, reducing the role of the human operator, increasing accuracy, and reducing cost are the reasons that increase the need for automatic and semi-automatic extraction through the processing and analysis of images.

1.2. Literature Survey

In this field, Shouji Du et al. in 2017 presented a method for extracting buildings from LiDAR point cloud data by combining point-based and network-based features. To accurately distinguish buildings from vegetation, they proposed a point property based on the variance of natural vectors. For robust building extraction, a diagram cutting algorithm was used to combine the features and consider neighboring texture information. As the network feature calculations and diagram-cutting algorithm are performed on a network structure, a DSM interpolation method with the feature retained in this paper is presented (Shouji Du et al., 2017).

Wen Hao et al., in 2013 they present a complete strategy for extracting buildings from ground-based laser scanning data. First, a new partitioning method was proposed to facilitate the building extraction work. First, points were grouped based on standard and adjacent relationships. Second, flat surfaces were identified based on the results of segmentation based on Gaussian image properties. Finally, buildings are extracted from urban point clouds based on point sections such as shape, natural direction, and topological relationship (Wen Hao et al., 2013). Masakazu Iwai et al., in 2020, by accelerating the computational speed, used the automatic building extraction method, which used a diverse inferential Gaussian mixture model to perform color clustering (Masakazu Iwai et al., 2020).

Arvind Pandey et al., in 2020, aimed to automatically extract the building of an urban area using high-resolution data and fuzzy membership logic to classify the image object using electronic recognition software. As a result, the object-oriented method was implemented, and high-resolution Quick-Bird images were used for the automatic extraction of buildings (Arvind Pandey et al., 2020). Yuting Zhu et al., in 2021, To solve the convolutional neural network (CNN) problem in their research, a new semantic segmentation neural network called Edge-Detail-Network (E-D-Net) was proposed to divide the building from visible aerial images. The results showed that the proposed ED-Net offers significantly stronger and higher building extraction performance (Yuting Zhu et al., 2021). Yuwei Jin et al., In 2021, built a new network with a conscious loss of a specific boundary is embedded, called the Boundary-Aware Refined Network (BARNet). They extracted BARNet performance on two popular datasets that include different urban scenes and various building patterns (Yuwei Jin et al., 2021). Nitin L. Gavankar & Sanjay Kumar Ghosh in 2018 proposed a top-hat morphological filter method and the K-means algorithm for extracting buildings with light and dark roofs.(Nitin L. Gavankar., Sanjay Kumar Ghosh., 2018) Also, other researches have been conducted in this field (Shrivastava, N., Rai, P.K., 2015; Pushparaj, J., Hedge, A.V., 2017; Raikar, A., Hanji, G., 2016; Aguilar et al., 2014; Gharibi et al.; Amarsaikhan D et al.; 2009; Zhang J., 2009; Floyer, E.A., 1882; N. Haghipour, J.P. Burg. 2014; Rottensteiner et al., 2005; Baillar d and Maitre, 1999; Vestri, 2006).

Geometrical active contours consist of two significant types of edge-based and region-based active contours. Edge-based methods primarily use gradient information to locate object boundaries in the images; one of the famous models in this topic is snake mode. In 2005, S.D. Mayunga et al. Showed that modified snake models and the developed radial casting algorithm improved this extraction rate by 23% and made a significant contribution to improving building extraction from high-resolution satellite imagery. (S.D Mayunga and Y. Zhang et., 2005). Thanh Huy Nguyen et al., in 2019, motivated by the limitations of existing snake models in building extraction, present an unattended and automated snake model for extracting buildings using optical images and unregistered LiDAR data set in the air, without manual starting points or training data (Thanh Huy Nguyen et al., 2019). By Selassie Mayunga in 2016, a semi-automatic method for extracting buildings in planned and informal settlements in urban areas from high-resolution images has been introduced. The proposed method uses a modified snake model and a radial casting algorithm for the initial start of snake lines and the correction of building lines (Selassie Mayunga in 2016). Zhenfeng Shao et al., 2020 proposed a new deep learning network, called the Remaining Rehabilitation Network (BRRNet), for accurate and complete building extraction. The BRRNet consisted of two parts: the prediction module and the remaining purification module (Zhenfeng Shao et al., 2020). In 2010, Mustafa Kabolizade et al. improved the border extraction method based on the GVF snake model. Using a genetic algorithm, the snake model requires fewer operators and increased speed. Experimental results showed that this model could work intensely with images taken from urban areas with buildings with complex structures. (Mustafa Kabolizade et al., 2010). In 2010, Salman Ahmadi et al. built an improved active contour model and used aerial imagery to extract buildings automatically. Other researchers have contributed to improving this model (Siddiqi et al., 1998; Pi et al., 2007; Ying et al., 2009a,b; Lu D., Weng Q., 2007; D. Koc-San et al., 2014; S. Ghaffarian, 2014).

One aspect of the innovation in this research is the use of the output of the maximum probability classification method to determine the location of the initial curves of the model. Another aspect of the innovation in this study is to limit the production of the Margon model to the boundary of buildings. In order to determine the initial curves of the Margon model, the maximum probability classification method was used, which is described below.

2. MATERIALS AND METHODS

According to the flowchart (Flowchart1), the steps involved in this research are as follows:

1. Collecting the required research data including, satellite imagery, large-scale maps of the area,

2. Preprocessing and preparing input data

Preparing input data to conduct this research requires preprocessing, which makes the desired results achievable. Preprocesses include geometric correction, radiometric correction, integration, or panchromatic image.

3. Determining the initial curves of the Margon model

As previously mentioned in the description of the Margon model, an initial curve is guided to the edge and boundaries in a repeat process. Therefore, several initial curves on the surface of the image are needed. The researchers have adopted various methods to determine the initial curve, each of which has its advantages and disadvantages. In this research, the production of the margon model is limited to the border of buildings. In order to determine the initial curves of the Margon model, the maximum probability classification method was used.

Thus, in the first step, the user needs to introduce the points of the building area in the input image of the algorithm. These points will be considered as educational data in the maximum likelihood classification method.

Then, a plot like an area and size apply to the results of the previous step. Also, to improve the performance of the Margon model, changes were made to the results of the previous step to determine the initial curves of the Margon model.

4. Preparing the input of the Margon model

The input of the initial Margon model is a single-band image. The image used in this research is a four-dimensional multivariate image. In general, the goal of remote sensing projects is to use the complete spectral and geometric information in the image with minimal computational cost. Therefore, selecting the optimal input in accordance with the Margon model is another aspect of the innovation of this research.

5. Implementing the Margon Curve Model

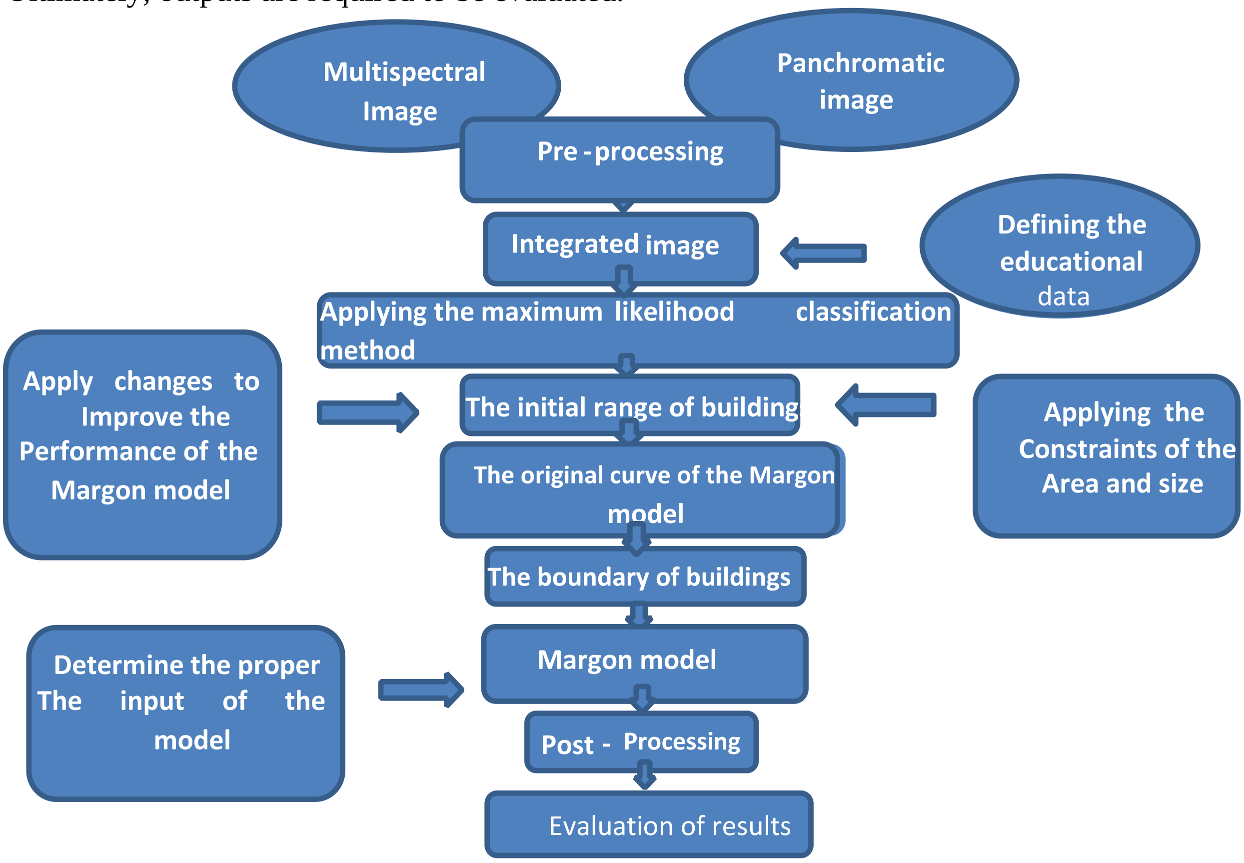
After determining the initial location of the curves and preparing inputs of the Margon model, it is necessary to implement the model. The steps in this section are implemented in the MATLAB programming environment.

6. Post-processing

At this stage, processes need to be applied to the outputs of the Margon model. The result of these processes will improve the outputs for loading in the spatial information systems.

7. Evaluation of results

Ultimately, outputs are required to be evaluated.



Flowchart 1: Steps of the approach.

2.2 The study area and data

Hormozgan is one of the southern provinces of Iran, and it is situated in the north of the Strait of Hormuz. Hormozgan province is located between northern latitude 25º 24' to 28º 57' and eastern longitude 53º 41' to 59º 15' from the Greenwich meridian (Fiq1). Due to its urban planning and geomorphological importance, the area has undergone numerous investigations since the 18th century; (i.e., Floyer, 1882, Lees, 1928, and Haghipour and Burg (2014)). Despite the attention it has received, this area has yet to receive the coastal classification. In this study, the world view-2 image was used (Table 1). The area in this study is Shahru in Hormozgan province, and the image was taken on March 21, 2017, from this region.

Launch time into space	2009
The height of the satellite orbit	770 km
The angle of the satellite orbit	97.2 °
Swath width	16.4 km
Radiometric resolution	11 bits
Band number	8 spectral band
Panchromatic spatial resolution	46 cm
Multi-spectral spatial resolution	1.84 m

Figure 1: Hormozgan Province location

Table 1: The technical specifications of the satellite world view-2

3. RESULT AND DISCUSSION

3.1 Pre-process

For this purpose, the image obtained from the integration process was corrected geometrically, with the help of 10 control points in the image and PCI geomatica software environment with a precision of 0.7 pixels. In addition, required control points were extracted from the large-scale map of the existing area for geometric correction. In the below figure (Figure 2), the process is shown in the software environment mentioned above.

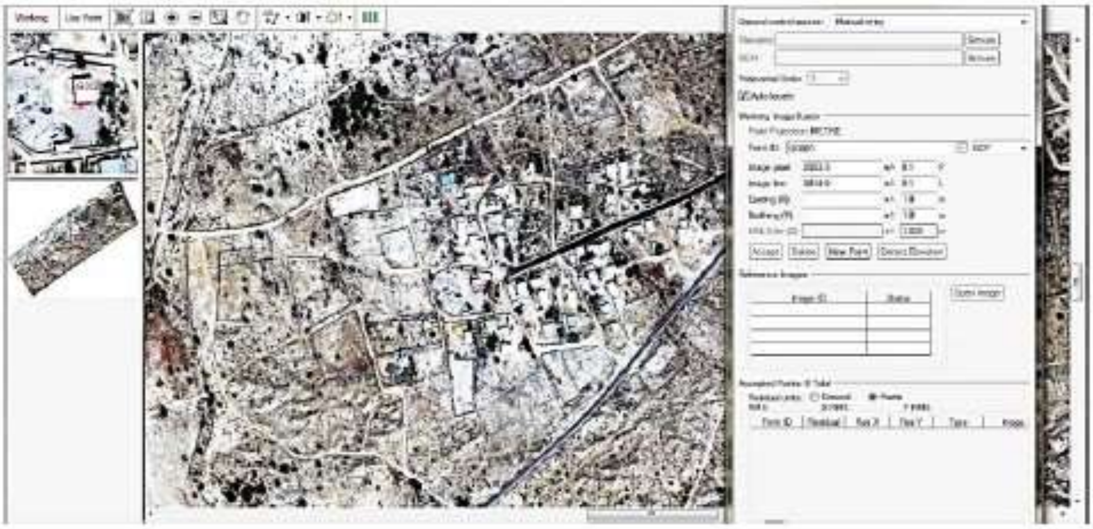


Figure 2: Geometric Correction of integrated Image in PCI Geomatica Software

3.2 Applying morphological filter on classification results

After applying the classification method, constraints like size and area of building pixels are applied to classification results according to the research objectives that extract the boundary of the building in rural areas. For this purpose, morphological filters were used: (Figure 3) Dilation operation, Erosion operation, Opening operation and Closing operation.

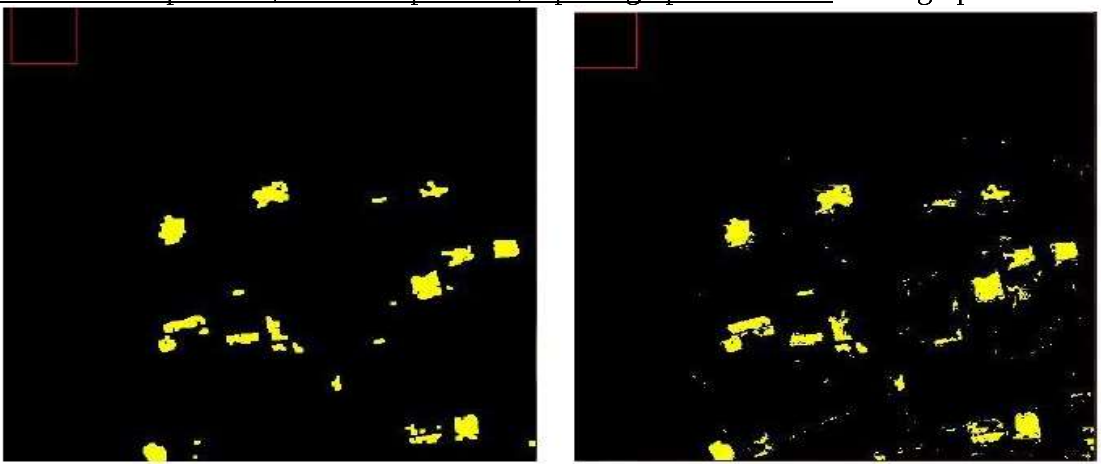


Figure 3: The impact of the threshold on eliminating terrain. Right (before applying), Left (after applying)

This step is significant from two perspectives: first, unwanted effects; in other words, output noise will be minimized. Secondly, you can control the size of the extracted effects by changing the size of the threshold. In other words, the extraction precision of the boundary of the building will increase.

Relationship (3-1):

$$\boldsymbol{P(w_i|x)^n = \frac{p(x|w_i)P(w_i)^{n-1}}{p(x)}}$$

$\boldsymbol{p(x)}$: Probability Density Function x

$\boldsymbol{P(w_i)}$: Posterior probability of class i

$\boldsymbol{P(w_i|x)^n}$: Probability of belonging x to the class i

$\boldsymbol{p(x|w_i)}$: The conditional probability density function of class i

3.3 Preparing the input of the Margon model

Margon model works with a single band. In other words, the input of this model is just a visual band. The image used in this study is multi-spectral with four bands of blue, green, red, and near-infrared. Principal Component Analysis is a conversion that is often used to reduce the dimensions of the data. Principal Component Analysis was performed on the quad-band image of the preprocessing stage in the ENVI software environment. (Figure4)

Figure 4: The first component of the principal component analysis

3.4 Implementing the input of the Margon model

After determining the initial position of the curves and preparing inputs of the Margon model, it is necessary to implement it. The steps in this section are implemented in the MATLAB programming environment so that the inputs of the Margon model can be stored in .tiff format. Then, they are called in the MATLAB environment. In the present study, the input image was considered as the first component of the PCA conversion. The stop condition was also considered as algorithmic repetitions. In a way, those different repetitions were tested 5, 10, and 15 times. The output of the proposed method for repetitions 10 and 15 is shown in the following figure. (Figure6 & Figure5)

Relationship (3-2):

$$\boldsymbol{E(c) = \mu.length(c) + \nu.Area\big(inside(c)\big) + y_{10}\int_{outside(c)} |u - c_{in}|^2 dxdy}$$
$$\boldsymbol{+ y_{20}\int_{outside(c)} |u - c_{out}|^2 dxdy}$$

Relationship (3-3):

$$\boldsymbol{Quality\,percentage = 100 * (\frac{TP}{TP + FP + FN})}$$

Relationship (3-4):

$$\boldsymbol{Completeness = 100 * (\frac{TP}{TP + FN})}$$

Relationship (3-5):

$$\boldsymbol{Correctness = 100 * (\frac{TP}{TP + FP})}$$

Relationship (3-6):

$$\boldsymbol{Omission = (\frac{FN}{TP + FN})}$$

Relationship (3-7):

$$\boldsymbol{Commission = (\frac{FP}{TP + FP})}$$

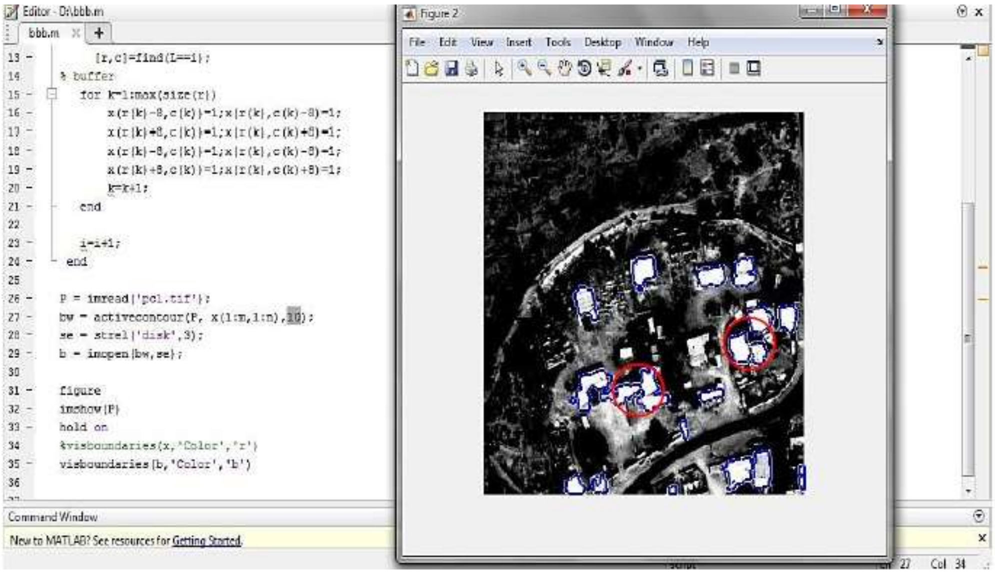


Figure 5: The output of the proposed method in 10 repeats

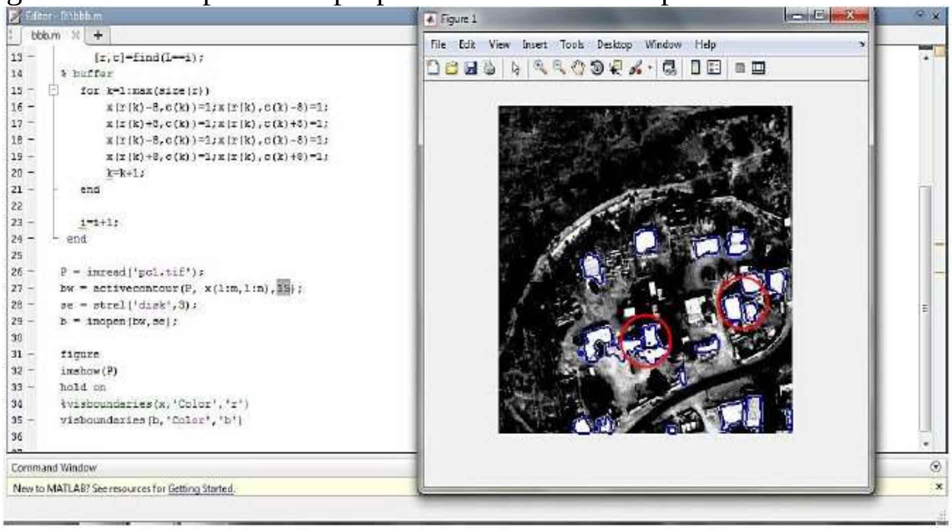


Figure 6: The output of the proposed method in 15 repeats

By comparing the above shapes in the areas of red circles, one can find the effect of repetition on the output of the proposed method. Repetition has completely removed the boundary of the building in the neighboring buildings. By evaluating the results of repetition 15, the output associated with this is optimal. For this purpose, the range of buildings within the image was manually digitized inside the ArcGIS software environment. Then, the base image was used as a comparison of the results. The figure below (Figure 7) shows how to create the base image and digitize the construction boundaries in the software environment.

Figure 7: production of the base map

4. Conclusion

The most common way to express the accuracy of the maps generated from remote sensing images is to provide a superficial percentage of the image that has been correctly classified. The overall accuracy percentage represents the percentage of units that the result is correct. By comparing the base map and the output of the proposed method, the percentage of accuracy was calculated and equated to 90%. In other words, in the area studied in this research, 90 percent of buildings have been extracted correctly. No building has been extracted in the yellow square by examining the abovementioned figure and comparing the results of the proposed method and the input image. In the proposed method of this research, the classification method has been used as an innovation to determine the initial curves of the Margon. This is one aspect of the difference between the proposed method and the other methods developed by researchers in invalid papers. Using the classification method for determining the location of the initial curves has advantages such as increasing the speed of convergence of the algorithm, reducing the implementation time, and increasing the accuracy of the outputs. Furthermore, the proposed method in this research can be used to detect the boundary of other features such as path, vegetation, etc., in the image. In other words, the proposed method of this study is highly capable of generalizability compared with other methods developed invalid papers. In the early stage of education, it is sufficient to introduce the desired terrain as educational data to the algorithm.

Classification is one of the methods used to process images for the automatic extraction of features. Our proposed method is usable in post-classification analysis to increase the accuracy of outputs. This is another advantage of the proposed method in comparison with the methods of other researchers in the world. Using the maximum likelihood classifier is one aspect of innovation to determine the initial curve in this research. The benefits are as follows:

- This research aims to extract only the boundaries of buildings, not all in the picture. The boundaries of the buildings have to be only extracted. Thus, by adopting the proposed solution, the algorithm's output will be limited to the boundaries of the building.

- Despite the many advantages and widespread use, classification methods are primarily defective. For example, the classification and extraction of buildings influence outputs by any change in the ceiling of the houses like a shadow, color, or other effects in rooftops. However, in the proposed method, the detail of the interior does not affect the quality of the results due to the movement of the curve from the outside to the edges of the building. This is an important issue in increasing the level of detection of buildings.
- The proposed method can be applied as a post-processing of classification methods. In this way, the disadvantages of the methods are covered.

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