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Application of Artificial Neural Network for Building Feature Extraction in Abuja

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ABSTRACT: Extraction of urban features has been conducted over the years using several conventional algorithms usually with the input of satellite imageries of medium spatial resolution. Meanwhile, extraction of distinctive features such as housing units is conducted with the input of imageries of high spatial resolution usually using manual approach, which are cumbersome and slow in the process of map production. An automatic method for the extraction of building features using a machine learning algorithm has been developed in this study. With input of Pleiades data and ENVI software, Artificial Neural network (ANN), a machine learning algorithm, was used to extract building features within the study area. Building footprints were produced by vectorization of the extracted buildings of the ANN process. 80.13% accuracy was obtained, indicating that the building extraction using the ANN is effective with high means of precision like on -screen digitization. The ability to accurately approximate complex non-linear function of the tools as well as its high computational efficiency have been proven by the result of the study. Process of building extraction from satellite imageries has been automated in this study. This will ease the process of map and database update for planning and decision making.

KEYWORDS: Artificial Neural Network, Building, Feature Extraction, Pléiades,

I. INTRODUCTION

Urban building information is vital particularly prior to physical planning growth. Detection and extraction of geospatial data is of great importance for planning, environmental and demographic research as well as input data for disaster modeling and simulation (Khatriker & Kumar, 2018). Urban features such as roads, railways, rivers, and buildings are extracted from images to update maps and Geographic Information System (GIS) database (Wijesingha *et. al,* 2009). The last decades have witnessed the application of remotely sensed image in the extraction of building features using various algorithms, spectral and spatial resolutions (Puttinaovarat & Horkaew, 2017). Extraction of urban features have been conducted over the years using the traditional methods from medium resolutions. The advent of very high-resolution imagery had led to improved urban-related extraction with more details (Puttinaovarat & Horkaew, 2017). Manual feature extraction as well as digitization are cumbersome and slow in the process of map production (Khatriker & Kumar, 2018).

Medium resolution satellite imagery such as Landsat series have been used to extract building information in the urban areas (Cai et. al., 2019) though they do not provide detailed information that gives distinct building features. In urban building extraction, the complexity and heterogeneity of the urban areas, have been complemented by the advent and usage of very high-resolution imagery such as QuickBird, IKONOS, OrbView, etc., which are generally in meter or sub-meter spatial resolution level (Chen, et al., 2012; Jin & Davis, 2005). These provide more accurate and detailed information about building features in urban settings.Conventional methods of urban feature extraction and updating building features, mainly use spectral analysis and mixed pixel decomposition, to analyze differences in spectral reflectance characteristics of surfaces and objects, using traditional statistics classifiers, such as maximum likelihood. The approach assumes that classes are normally distributed whereas the assumptions are often incorrect (Lillesand et al., 2004). To overcome the above and to obtain accurate and near real-time information, Artificial Neural Network (ANN), also referred to as Neural Network (NN), have been utilized (Huang et al. 2018). The ANN algorithm simulates the thinking of the human brain with interconnected neurons processing incoming information. This concept is modelled after the human brain, which is usually designed to perform highly complex, nonlinear parallel computations. They do not make prior assumptions on the data probability distribution, but can adapt from nonlinear and discontinuous data samples for normal distribution of data. This powerful tool for pattern recognition is aimed at identifying distinguishable proof for verifiable objects from the input data (Bhamare, & Suryawanshi, 2019). Integrating neural network with remote sensing has improved the performance of image classification, particularly for heterogeneous urban facets in the environment.

There exist quite a number of research work on urban building feature extraction from GIS and remote sensing. Some of the research works utilized aerial imagery, data from drone (Dai et al., 2017), Light Detection and Ranging (LiDAR) data (Chen, et al., 2012), while some have used very high-resolution (meter and sub-meter) satellite imageries such as IKONOS (Jin & Davis, 2005).In Africa, studies on urban feature extraction have been confined to mainly urban areas in South Africa, Egypt, and a few others. For example, Mudau and Mhangara (2018) used SPOT 6 imagery to take inventory and validate the presence of government houses in Rustenburg city in South Africa, using object-based classification algorithm. Shaker, et al (2011) identified building footprints in high-density residential areas in Greater Cairo, Egypt, using a method that used a digital surface model. In a study by Chew, et al (2018), Deep Learning method was used to extract building structures in Kaduna state. Although a machine learning algorithm was used in their study, the data input was from Bing Maps aerial imagery web mapping services. Yuan, et al (2018) explored convolutional neural network (CNN) and citizen science to automate building features in Kano state, Nigeria. This was validated with building footprint data from open-source data called open street maps (OSM). The study covered the entire state. Since buildings in low and middle-income countries are inadequately mapped and lack adequate available data, a research of this kind is required. To the best of our knowledge, most research on automatic building extractions in Nigeria and Abuja, in particular, have been carried out using medium resolution imagery, which are coarse data. None has utilized Pleiades data and artificial neural network to extract building features in Abuja. This research utilized a method that will automate urban building extraction from a very high-resolution image. This serves as an alternative to manual digitization in building extraction, which will require a large amount of man-hours to delineate the building features.

II. STUDY AREA AND DATA USED

Description of the study area : This study was conducted in Abuja Municipal Area Council (AMAC). Abuja became the capital of Nigeria after the enactment of the Federal Capital Territory (FCT) Act, of 1976. AMAC is one of the six area council in the FCT and it covers a total land area of 250 square kilometers. It is located within latitude 9° 0'41.234" N to 9°6'57.474" N and longitude 7° 26'39.651"E to 7° 31'48.913"E (Figure.1). AMAC is a planned city, and it is the heart of the FCT. The 2012 estimate puts the population of the Abuja Metropolitan Area Council at 979, 876 (NPC, 2012). The phase one of AMAC has five main Districts namely Maitama, Wuse, Central District, Asokoro, and Garki and 14 sub districts namely; Wuse zone 1 to 7, Wuse 2, Garki Area 1, 2, 3, 7, 8, 10, 11 and Garki 2.

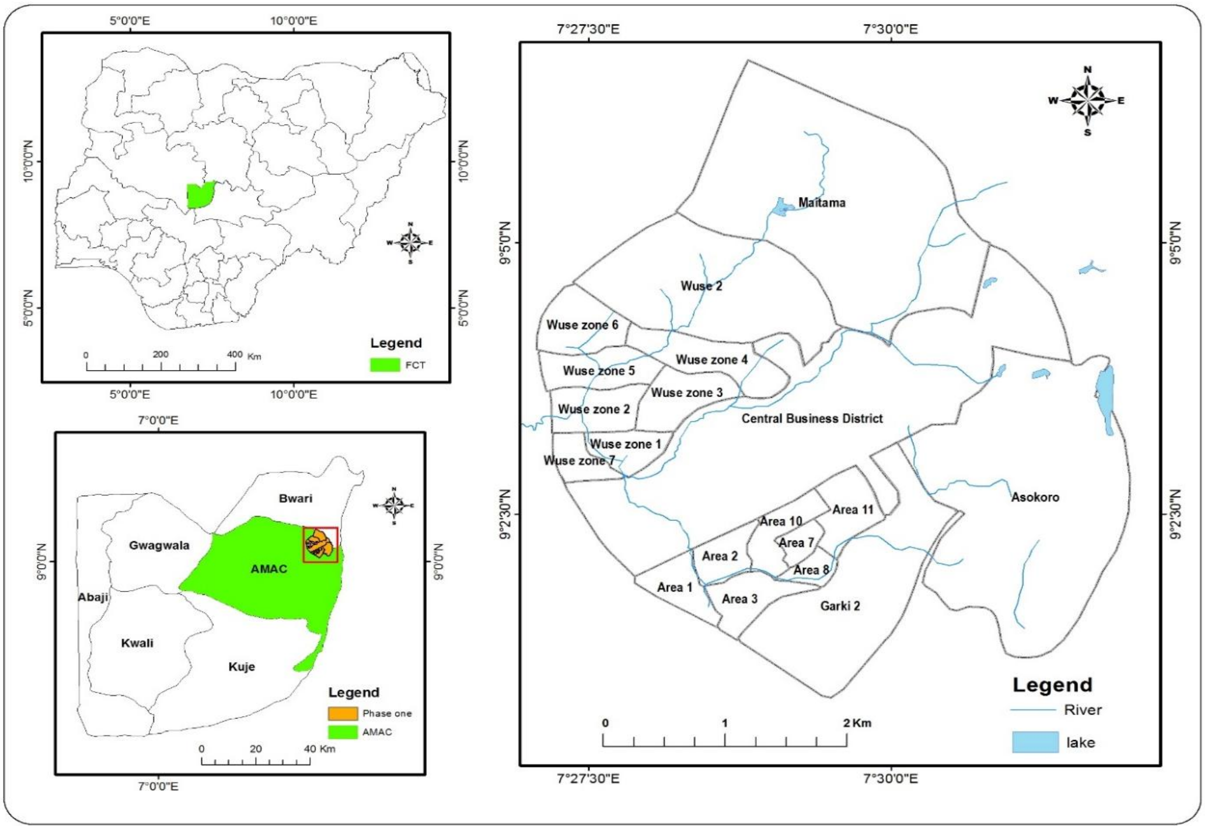


Figure.1: The study area

Scope of the study: The areas majorly covered by this study are the Central Business District (CBD) and section of the Wuse districts located at about 9°2'N to 9°4'N and 7°27'E to 7°31'E.

III. METHODOLOGY

This study was conducted to explore the potential of ANN in automatic building extraction for the urban area from very high-resolution satellite dataset. The data used in the study as well as the processes adopted, where discussed in the following sub-sections. It follows the methodology flowchart (Figure 2).

Data: Building extraction in images is a difficult task due to non-linearity of the building structure and lack of homogeneous arrangement of buildings. Spatial resolution is an important component of the extraction process and is considered as one of the comparative assessment indicators for successful extraction. In this study, very high spatial resolution satellite data were used for building extraction. Plaides image of 2m pan-sharpened to 0.5m spatial resolution, containing 4 spectral bands; Red, Green, Blue and Near-Infrared (Table 1), was used to analyze and evaluate the behavior of algorithm at a medium spatial resolution, with non-linearity and heterogeneity of building structures. The WGS 1984_UTM Zone 32N projection was used. The pixel depth is 8bit in TIFF format.

Table 1: VHR data description of the study area.

Info	**Band**	**Wavelengths**	**Resolutions**
Sensor: Pléiades	BLUE	430-550 nm	0.5
Acquisition: 2013	GREEN	500-620 nm	0.5
Original resolution	RED	590-710 nm	0.5
Panchromatic: 0.5m	NIR	740-940 nm	0.5
Multispectral: 2m			

Data processing and preparation: The Pléiades image was corrected in ENVI 5.3 software, for geometric and radiometric errors that were caused either by sensor or platform distortions, or due to atmospheric distortions. Histogram equalization was performed for radiometric corrections. This maximizes the contrast of the data by applying a nonlinear contrast stretch that redistributes pixels. This was to ensure equal number of pixels under each value within the range. An AOI was delineated from the Pléiades image and training sample was created for extracting the building footprint.

Artificial Neural Networks Classification: ANN consists of a network of connections, in which the neurons work as computational units. In a feed-forward neural network, a bias node was added to each layer. This is a neuron that has a constant output. A weighted average of input was calculated for each neuron from the input layer to the output layer, then activation function is applied which contains the neuron firing rules.

There are various types of activation functions. These activation functions introduce non-linear properties into the network to enable it approximate more non-linear distribution (Lek *et al.*, 1996). The image data was divided into smaller parts. The parts were selected randomly and the algorithm was applied to them.

Accuracy Assessment : An Accuracy assessment was performed to evaluate the correctness or otherwise of the ground reality, represented in the image (Foody 2010). Error matrix is among the most utilized methods of accuracy assessment from which various types of matrices could be extracted for calculating accuracy and errors. This also helps to access and analyze the performance of the model in different conditions using test data. The predictions of the model on the test dataset would be used for generating error matrix, accuracy, kappa, sensitivity, specificity along with two other metrics; Branch Factor (BF) and Detection Percent (DP) (Lin & Nevatia, 1998). DP is how many buildings detected in the image by the algorithms and BF is how many buildings are found improperly. Generating these metrics requires manual digitization and comparison as explained in equations,

Building detection (DP) rate:

$$DP = 100 * \left(\frac{TP}{TP+TN}\right)$$

$$Branch\ Factor(BF) = 100 * \left(\frac{FP}{TP + FP}\right)$$

Where, TP = building detected both manually and by the algorithm (sensitivity),

TN = Building detected manually, but, not by an algorithm (specificity),

FP= Building detected by the algorithm but, not manually. BF is how many buildings are detected erroneously.

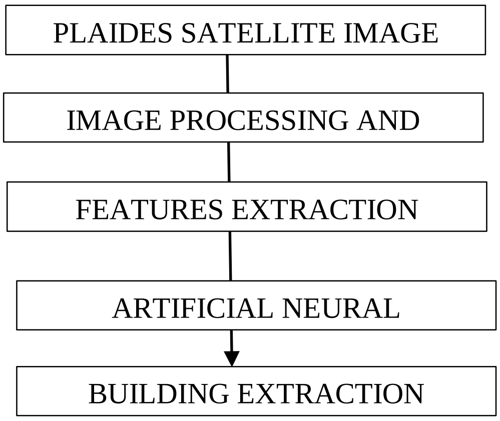


Figure 2: Methodology Flowchart

IV. RESULTS AND DISCUSSION

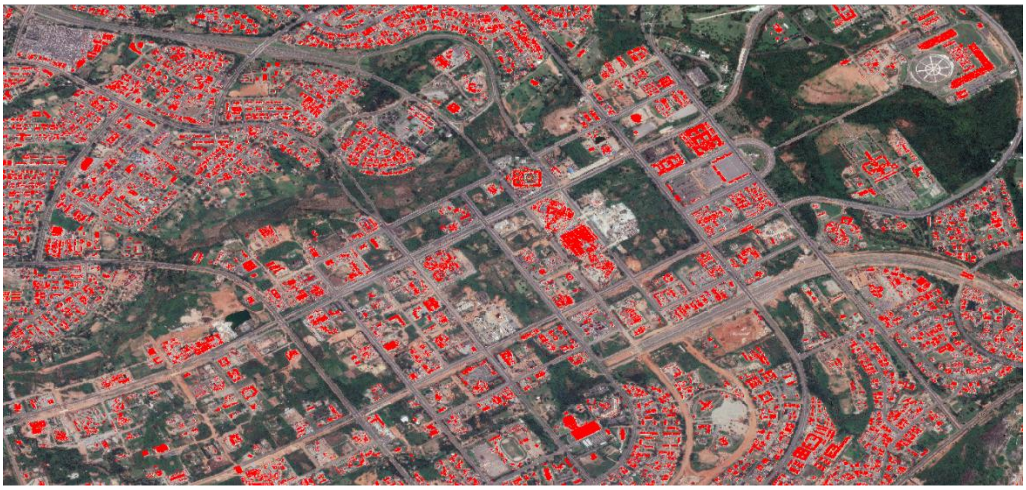
The focus of this study is to explore the potentials of the ANN in building extraction from very high satellite image and to evaluate the performance and accuracy of the algorithm. Findings from the study showed that ANN performed well in uniform building distribution on very high-resolution imagery. The results of the building footprints are shown in Figures 3 a,b,c,d and f., which clearly shows the buildings that are distinguishable from the background. Figures 3a, c, and e represent the raw image tested. The Figures; 3b, d, and f represent the classified images, where the red represent the extracted buildings.

a

b

c. d.

e.



f.

Figure 3. a, c, and e represent the raw image tested while b, d, and f represent the classified images where the red represent the extracted buildings.

The accuracy assessment of the extracted building features was evaluated using reference building footprints. A total of 46,413 buildings were manually extracted using the digitizing method. These features were used as a reference dataset to assess the accuracy of the automatically detected building accuracy. Accuracy of 80.13% was obtained. In another instance, a total of 406 manually extracted buildings were used, which produced a very high accuracy of 99.7% (Table 3.1). This approach is most commonly used to evaluate the accuracy of the building extraction, which also calculates the intersection between a reference building and a sample building counts. The interpretation means that the detected percentage denotes the percentage of building pixels correctly extracted by the automated method. The branching factor is the measure of the commission error, where the system incorrectly labels the background pixels as buildings, while the miss factor measures is the omission error where the system incorrectly labels building pixels as background.

The results of the accuracy assessment derived was found to be 80.13%. This confirmed that the approach has performed reasonably well in building extractions within the study area.

Table 2. Assessment of building extraction detection rate and branching factor for plaides

TN	DP(%)	BF(%)
46413	80.13	19.87
406	99.7	0.3

V. CONCLUSION

The main objective of this research was to develop an automatic method to extract urban building features using a neural network algorithm. The study effectively established a semi-automatic method to extract building features from very high-resolution satellite images by using learning neural network algorithm (ANN). The impact of input parameters on the neural network's ability for building features detection, from high-resolution satellite images, was tested on Pleiades satellite images. The results provided 80.13% accuracy assessment and it can be observed that the algorithm performed well in detecting building features with high accuracy of extraction.

REFERENCES

1. Bhamare, D., & Suryawanshi, P (2019): Review on Reliable Pattern Recognition with Machine Learning Techniques, Fuzzy Information and Engineering, DOI: 10.1080/16168658.2019.161130
2. Cai, G., Ren, H., Yang, L., Zhang, N., Du, M., & Wu, C (2019) Detailed Urban Land Use Land Cover Classification at the Metropolitan Scale Using a Three-Layer Classification Scheme. Sensors. 19, 3120; doi: 10.3390/s1914320
3. Chen, L., Zhao, S., Han, W., & Li, Y. (2012) Building detection in an urban area using lidar data and QuickBird Imagery. International Journal of Remote Sensing, 33(16), 5135-5148
4. Chew, R., Jones, K., Unangst, J., Cajka, J., Allpress, J., Amer, S., & Krotki, K. (2018) Toward Model-Generated Household Listing in Low-and Middle-Income Countries Using Deep Learning. ISPRS Int. J. Geo-inf., 7, 448. doi: 10.3390/ijgi7110448
5. Dai, Y., Gong, J., & Feng, Q. (2017) Building segmentation and outline extraction from UAV image-derived point clouds by a line growing algorithm. International Journal of Digital Earth volume 10, Issue 11.
6. Foody, G. M., (2010). Assessing the accuracy of land cover change with imperfect ground reference data. Remote Sens. Environ., 114, 2271-2285. doi.org/10.1016/j.rse.2010.05.003
7. Huang, F., Yu, Y., & Feng, T. (2018) Automatic Extraction of Urban Impervious Surfaces Based on Deep Learning and Multi-Source. Remote Sensing Data, Journal of Visual Communication & Image Representation. doi: 10.1016/j.jvcir.2018.12.051
8. Ji, X, and Davis, C.H., (2005) Automated Building Extraction from High-Resolution Satellite Imagery in Urban Areas Using Structural, Contextual, and Spectral Information. EURASIP Journal on Applied Signal Processing, 14, 2196-2206.
9. Khatriker, S. & Kumar, M. (2018) Building Footprint Extraction from High Resolution Satellite Imagery using Segmentation. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences (ISPRS TC V Mid-term symposium), Volume XLII-5.
10. Lin, C. and Nevatia, R., (1998) Building detection and description from a single intensity image. Comput. Vis. Image Underst., 72, 101-121. doi.org/10.1006/cviu.1998.0724
11. Mudau, N. & Mhangara, P. (2018) Extraction of low cost houses from a high spatial resolution satellite imagery using Canny edge detection filter. South African Journal of Geomatics, vol. 7. No. 3
12. Puttinaovarat, S. & Horkaew, P. (2017) Urban Areas Extraction from Multi sensor data based. Pattern Recognition and Image Analysis. Vol. 27, No. 2, pp. 326-337
13. Sharma, T.K., Babu, S.S., Mamatha, Y. N., (2013) Satellite Image Feature Extraction Using Neural Network Technique. Proceeding of International Conference on Advances in Computing (AISC, volume 174).

14. Shaker, I.F., Abd-Elrahman, A., Abdel-Gawad, A. K., and Sherief, M. A. (2011) Building Extraction from High Resolution Space Images in High Density Residential Areas in Areas in the Greater Cairo Region. Remote Sens. 2011, 3, 781. doi: 10.3390/rs3040781.
15. Yuan, J., Chowdhury, P., McKee, J., Yang, H. L., Weaver, J., Bhaduri, B. (2018) Exploiting deep learning and volunteered geographic information system for mapping buildings in Kano, Nigeria. Scientific Data, 5:180217 | doi: 10.1038/sdata.2018.217. Available at: www.nature.com/sdata/