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# DETECTION AND EXTRACTION OF BUILDING FOOTPRINT FROM HIGH-RESOLUTION SATELLITE IMAGERY

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**Abstract**: Remote sensing satellite images are developed rapidly regarding quantity, quality, and applications to detect and extract various natural and artificial features on earth's surface like(vehicles, buildings, trees, roads, water, aircraft, ships). These satellite images provide important information in various applications like urban planning, disaster management, and environmental management. Different algorithms and methods are introduced by researchers to extract the specified features from satellite images. In an urban scenario, buildings are one among the foremost elementary structures and play an important role in the field of urban development, urban planning, climate studies, disaster management, map making, land use analysis, and change detection. The study aims are to extract building footprints employing a machine learning algorithm. various methods for extraction of building footprints are discussed in various studies However, extraction of rooftop of buildings from an metropolitan place has been a difficult task, since building rooftops have different shape, size, and spectral properties. In addition to that, other urban features, such as, road, barren land, etc. exhibit spectral properties similar to that of building rooftops. so that building extraction technique has become a vital and tough research problem receiving better recognition. The proposed technique uses a Machine Learning algorithm for classifying the building and non-building pixels. To eliminate false-detected building pixel use median filtering, morphological operator, and connected component labelling are used .the technique has been evaluating by pixel and object-based criteria with the consideration of precision, recall, quality of building(urban object).

***Index Term*: a satellite image, machine learning, connected component, filtering**

## I. INTRODUCTION

Automatic building detection and extraction from high-resolution multispectral satellite images found many applications in various areas of land use and land cover mapping, planning, disaster management, and far more socioeconomic activity. However, the application of Remote sensing increases day by day, due to the availability of high-resolution satellite data from high-resolution satellite-like IKONOS, QUICKBIRD,Word View. High-resolution satellite image provides important information about object present on the world surface the thing like building, road, trees, vehicles, water body, and lots of more natural and man-made objects. Since the manual Extraction of an urban object from multispectral high-resolution images requires to be qualified domain experts and an oversized amount of effort, hence there's a requirement to develop an automatic building extraction method that may reduce time and price. The taking out of building from satellite images has been an always complicated task thanks to many reasons like building structure, shape, the similarity between pixel values, and also the presence of obstacles like trees, high rise buildings. In many studies, building extraction uses features like edge/line, segment. Building in a geographical region doesn't have an analogous shape, texture, size so extraction of building from the urban scenario may be a very difficult and challenging part[15]. And therefore, the traditional method not performing well in these situations. Recently machine learning has extended its application in remote sensing shown important involvement in labeling and classification. Machine learning algorithm map the initial input to a chosen binary, or multiple labels (classification problem).the powerful representation of the training ability of machine learning algorithms replaces the normal thanks to classification applications[14].

The target of this study is to pull out the building from very high- resolution multi-spectral satellite imagery using machine learning techniques with less involvement of humans. Further morphological approaches like opening, closing, dilation, and erosion and different filters like Laplacian, median, edge-preserving filters accustomed to reduce misclassification error from a classified image by the machine learning algorithm. The proposed methodology follows the pixel-based classification and performance of the proposed methodology evaluated employing a confusion matrix. The proposed methodology uses the Erdas imagine 2014 for Digitization purpose to arrange dataset of given image and reference building mask.

## II. LITERATURE SURVEY

Extraction of building footprint from remotely sensed data have always been a difficult task due to many reasons, such as, varying building size and shape, presence of obstacles posed by surrounding objects, such as, trees and adjoining high rise buildings. Low contrast of building and its surrounding region and different spectral characteristic of varying roof material further adds to difficulty in detection and extraction of building footprint. Lin and Nevatia (1998) explained component detection based definitely techniques for constructing rooftop extraction the utilization of geometric and projective constraints from a single depth image. however, this approach solely detects rectilinear structures, which limits its utility to the areas masking solely rectangular constructions [5]. Wei,Zhao, and Song(2004) proposed an unsupervised clustering and edge detection based totally approach for building extraction from QUICK BIRD panchromatic imagery having shadow as a piece of evidence, however this technique failed to discover a small object [6]. Jin amp; Davis (2005) used spectral facts along with structural and contextual vital points the use of IKONOS satellite imagery of Columbia city, Missouri to extract small buildings. In the proposed technique, structural and contextual details have been used to distinguish buildings from parking and extraordinary factors having related spectral information. The technique has been located efficient, which extracts 72.7% of the building vicinity with a pleasant share of 58.8%. However, it is located that integrating facts from structural, contextual, and spectral consequences has been an exceedingly difficult technique [10]. Advanced morphological operators, such as Hit or Miss transformation with a number of dimension and shape of structuring elements have been used by using means of Lef`evre, Weber, and Sheeren (2007), to extract buildings from HRS QUICK BIRD panchromatic imagery. The accuracy of the methodology has been computed in phrases of precision rate, which has been 88% with a kappa value of 63% [11]. Koc San and Turker (2010) has studied the Hough transformation and Support Vector Machine (SVM) classification technique to extract rectangular and circular buildings from HRS panchromatic and pan-sharpened IKONOS imagery. The consequences have been examined on identified industrial and residential areas in the imagery the usage of parameters, such as Building Detection Percentage (BDP) and Quality Percentage (QP). For industrial buildings, the values for BDP and QP have been 93.45 and 79.51%, respectively, a in a similar way residential vicinity having rectangular and round buildings, BDP and QP values for rectangular buildings are 95.34 and 79.05% and 78.74% and 66.81% for circular constructions [12].Belgiu and Dragut (2014) proposed and compared supervised and unsupervised multi-resolution segmentation techniques mixed with the random forest (RF) classifier for building extraction the use of high-resolution satellite photos with average accuracy between 82.3% and 86.4% [1]. Alshehhi et al (2017) defined a single deeper patch-based CNN structure for the extraction of roads and buildings simultaneously. A global average pooling (GAP) layer is used rather of a completely linked (FC) layer to reduces the localization ability. A new postprocessing approach that is based on low-level spatial points (adjacent simple linear iterative clustering (SLIC) regions) is used to beautify the CNN output. The effects of all of the above-mentioned research confirmed tremendous consequences in extracting constructions the usage of aerial or high-resolution satellite imagery. The above approach does not perform nicely on a large and complicated building.[4] Renxi Chen, Xinhui Li (2018) defined edge regularity indices and shadow line indices as new points of constructing candidates acquired from segmentation techniques and employed three machine learning classifiers (AdaBoost, RF, and support vector machine (SVM)) to pick out buildings. all the classifiers can gain an basic accuracy from 82.9% to 89.8% [2]. Shrestha and Leonardo (2018) proposed a entirely linked network-based building extraction strategy blended with the exponential linear unit (ELU) and conditional random fields (CRFs) the usage of the Massachusetts constructing dataset [3].Gavankar and Ghosh(2018) defined the morphological based automated approach for the extraction of constructions using a High-resolution satellite tv for pc image. The proposed method integrates morphological Top-hat filter, and K-means algorithm to extract having bright and dark rooftops.they additionally in a position to put off false buildings. But if they use semantic segmentation using deep gaining knowledge of strategy results could be better because CNN takes time for education but it additionally extracts the plenty of aspects from pictures [7].Khalel et al. (2018) defined U-Nets which routinely label the structures from high- decision satellite images. However, the present technique effects suffered from terrible boundaries, and the accuracy can be in addition multiplied [8].Bittner et al. (2018) proposed an end-to-end FUSED- FCN4S, which consists of three parallel networks merged at a late stage to research spatial and spectral constructing aspects from three-band(RGB), panchromatic(PAN), and normalized digital floor model(nDSM)images [9].For Evaluation of automatic building detection and extraction, different techniques are reachable due to the fact there is no right approach that identifies correct detection [Shufelt (1999)]] and assessment result carried out in unique approaches such as Visual inspection [[Vogtle and Steinle (2003)]]. to consider build ing severely a variety of current pixel-based primarily based and object-based methods used for evaluation of the proposed algorithm.

## III. STUDY AREA

Study Area The performance of the proposed method has been tested on IKONOS Pan sharpen Multispectral image having 0.82 m resolution, The extents of the image covers an area between latitude 33.69° to 33.71° N and longitude 117.91° to 117.90° E, which is equivalent to an area of about 1.60 sq. km (1.10 km × 1.45 km). Santa Ana is situated in Southern California, adjacent to the Santa Ana River, the second-largest metropolitan area in the United States. It is located at Latitude 33.75° N and Longitude 117.87° W.


Figure 3.1. Study area.

## IV. METHODOLOGY

The block diagram of the proposed methodology for automatic building detection and extraction based on machine learning and Image processing techniques shown in below Figure.

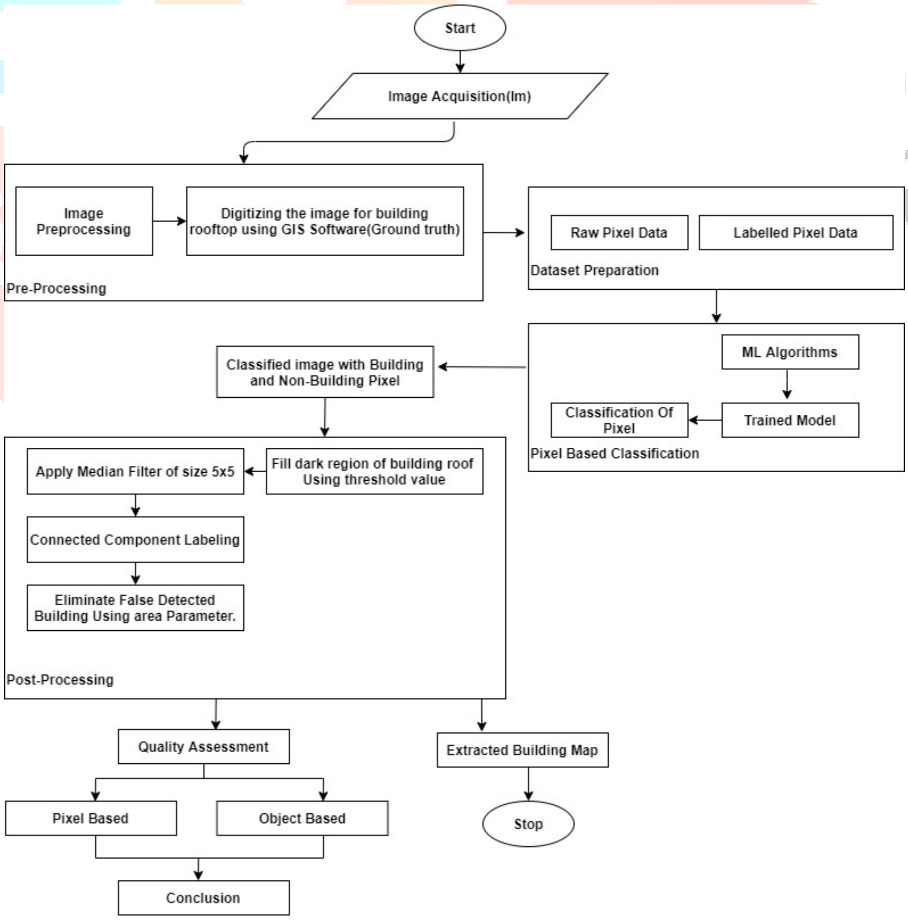


Figure 4.1. The methodology of Building Footprint Extraction.

### 4.1. Image Acquisition

A scene which include quite a number size, shape, and texture of building tops has been chosen as enter captured in the location Santa Ana, California in the USA by HRS IKONOS multispectral sensor. The scene selected includes a number city feature, such as road, water bodies, trees, vehicle, and parking area.

### 4.2. Image Preprocessing

Image pre-processing used for removing noise, image correction, and image enhancement. For improving multispectral image quality from 3.2 m to 0.82 m here we use a pan sharping process [17] which merge low-resolution multispectral image and high resolution panchromatic to create the high-resolution multispectral image. The pre-processed pan-sharpened image set as the input to the proposed approach.

### 4.3. Image Digitization

In image digitization, we collect the ground truth of the data from the geo-registered multispectral image shown in Figure 3.2. In which we select a building and non-building pixel for further dataset preparation

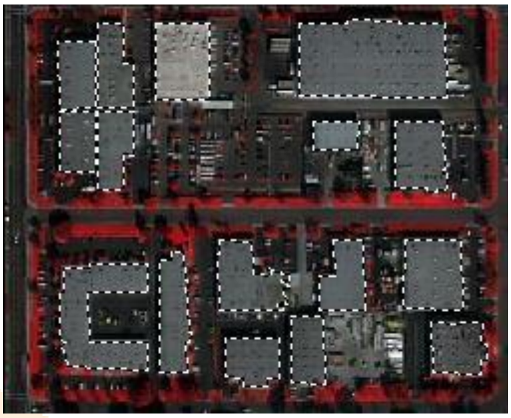

Figure 4.2. Digitized Image

### 4.4 Dataset Preparation

After extracting raw building and non-building pixel from a digitized satellite image, the building pixel labeled as 1 and non-building pixel labeled as 0. this labeled data further given to the machine learning algorithm for training.

### 4.5 Classification

In this section, we give the labeled data to different machine learning algorithms that come under the ensemble learning approach [18]. Which give better classification result in less time as compare to SVM, Na¨ıve Bayes, KNN, decision tree, etc[19]. because these algorithms are good for the small dataset which gives results in less time where algorithms like Random Forest [21], Ada boost [22], XG boost [20] Classifier gives encouraging result in the minimum amount of time for large dataset.

### 4.6 Quality assessment

Assessment of accuracy for extraction of building in several studies has been carried out on the basis of extracted building counts. However, metrics used during assessment of accuracy have not been sufficient to justify the accuracy of extracted results. In order to further critically evaluate the accuracy of building extraction results (Singh et al., 2012) provided ten quantitative indexes, such as, correctness, correctness, and quality. Before applying these measures, the extracted candidate building segments have been categorized into three classes as explained below.

**1. True Positive (TP):** are the buildings (objects) among the extracted buildings (objects) that are actually buildings.

**2. False Positive (FP:** are the buildings (objects) among the extracted buildings (objects) that are not buildings and falsely extracted as buildings

**3. False Negative (FN):** are the buildings (objects ) that are the true buildings; however, they are not extracted and left as a non-building area. After categorization, the quality measures have been applied, which are defined as below.

**Completeness** This determines percentage of buildings in the reference map which have been correctly extracted using proposed methodology. It has been calculated as.

$$= \frac{\text{Extracted buildings are true buildings}}{\text{Total number of buildings in scene}}$$

$$\approx \frac{TP}{TP + FN}$$

**Correctness** determines the threat of being a building of every extracted candidate building segment and it has been calculated as.

$$= \frac{\text{Extracted buildings that are true buildings}}{\text{Total number of extracted buildings}}$$

$$\approx \frac{TP}{TP + FP}$$

**Quality** tells us how good the approach is. It has been the measure of both completeness and correctness. It can be calculated as.

$$= \frac{\text{Extracted buildings that are true buildings}}{\text{Number of buildings extracted in output}}$$

$$\approx \frac{TP}{TP + FP + FN}$$

### 4.7 Data set Split

The dataset consists of total building and non-building pixel present in an image. further that dataset split in 60:40 ( 60 (%) training set and 40(%) test set) standard ratio use for training machine learning algorithm. Here we validate 40(%) building pixels to check how well algorithms get trained on a given training sample. Below is the table which shows the comparison results of the above two mention ratio.

**Table 1. Comparison results of algorithms**

| Algorithm | Building Pixel | TP | FN | FP | Accuracy |
|---|---|---|---|---|---|
| Random Forest | 567843 | 538692 | 29151 | 72391 | 84.13% |
| Ada Boost | 567843 | 543622 | 24221 | 83605 | 83.44% |
| XG Boost | 567843 | 549827 | 18016 | 74316 | 85.62% |

By considering the above results XG Boost always performs better than other algorithms so we conceive to use the XG boost algorithm For classification. the parameter of the classifier was selected by parameter tuning where the random search method was used to select the foremost effective parameter for a classifier[24]. XGBoost has been generally engaged in many fields to recognise latest consequences on some information challenges (e.g., Kaggle competitions), which may be a tremendously high quality scalable computer gaining knowledge of system for tree boosting [23 ]. XGBoost is optimized beneath the Gradient Boosting framework and developed through Chen and Guestrin [20], which is intended to be quite efficient, flexible, and portable. the primary thought of boosting is to mix a series of vulnerable classifiers with low accuracy to shape a strong classifier with higher classification performance. If the susceptible learner for each step depends on the gradient route of the loss function, it's called the Gradient Boosting Machines. The performance of the XG-Boost algorithm had been compared with other machine learning algorithms like Random forest and AdaBoost which are utilized in previous studies for classification of information. XG Boost Machine Learning Parameter Identifying optimal parameter for XGboost is time-consuming and this may be a tougher task because Xgboost features a giant selection of tunable parameters, for optimal performance several which using python implementation of XGboost, we've restricted our scope during this work .thus by using random search[24] method we obtain the only parameter for Xgboost for this work, which able to improve its performance. the parameter like learning rate =0.1, n estimators=130, max depth=9, min child weight=5, gamma=0.0, subsample=0.8, colsample bytree=0.7,reg alpha=3, objective= 'binary:logistic', have been taken for consideration .

**Table 2. Parameter tuning result**

| Algorithm | Building Pixel | TP | FN | FP | Accuracy |
|---|---|---|---|---|---|
| XGboost (Before Tuning) | 567843 | 549827 | 18016 | 74316 | 85.62% |
| XG boost (After Tuning) | 567843 | 551393 | 16450 | 68307 | 86.67% |

**4.8 Removal of false-detected building segments**

In the classified image, some building rooftop pixels detected as non-building pixels so first using the otsu thresholding method find threshold value then using that threshold value we fill the hole present in building rooftop.

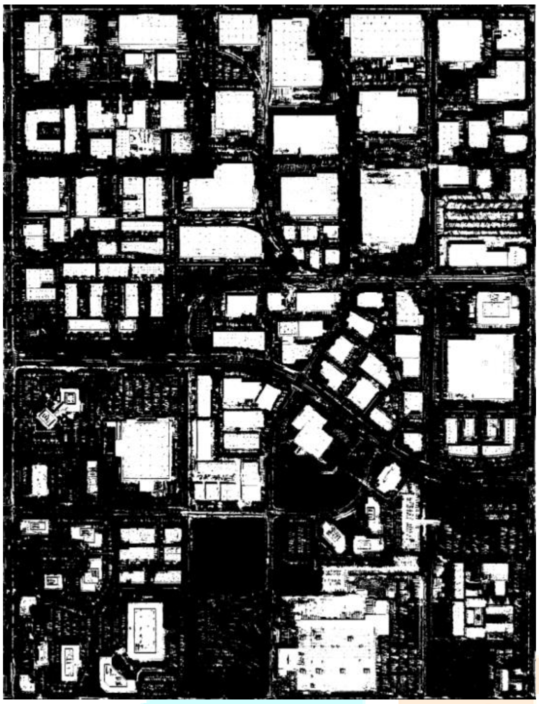

Figure 4.3. Classification Result of XGboost Algorithm.

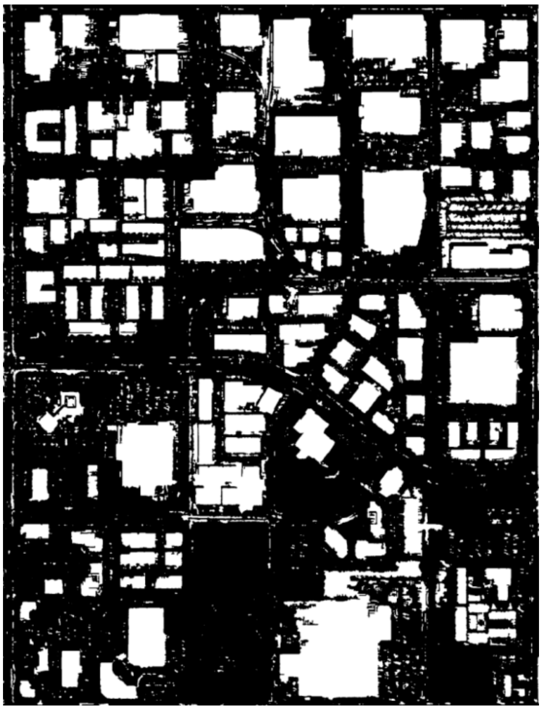

Figure 4.4. Dark building Roof Top Fill

**4.9 Median filter**

Image filtering is the technique that is used to get rid of an undesirable pixel (noise) from the image. on the other hand getting rid of undesirable pixel from picture and discover an unique image is that the one amongst the predominant essential difficulty in image processing even if in literature there are distinctive filtering techniques are accustomed remove noise from a photo .the fashionable median filter [7] has been utilized in many picture processing utility thanks to simplicity, edge-preserving property and its robustness to impulsive noise. Moreover, a median filter of size 5 × 5 is tremendous to take away the "salt and pepper" noise, which has been generally determined in a image transmission.

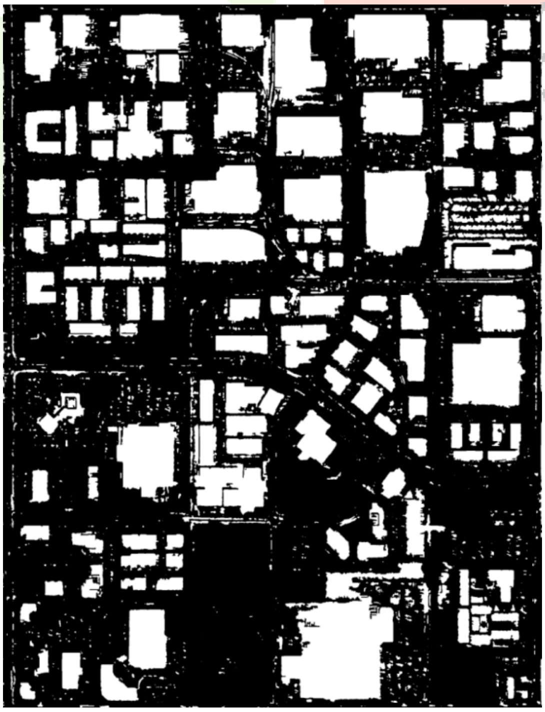

Figure 4.5. Result After Median Filter

**4.10 Connected component labeling**

Connected component labeling has been used to identify the connected pixels (segment) and assign a unique label (Ck, k = 1, 2, ..., n) for each extracted segment[16]. Moreover, a Median filter has been used before connected component labeling to reduce noise and misclassification problems. Usually, segmentation has been done after removing non-interested pixels; however, in this study; different parameters have been used to eliminate non-building segments. After connected component labeling, it has been observed that the candidate building segments include non-building objects, such as road, parking lots, and other urban features. During segmentation, due to similar reflectance properties, these objects have been misclassified in building class. However, to filter out these false candidate building segments, initially, all the extracted segments have been numbered (Bn), where n = 1,2,3,......n.

### 4.11 Segment area

The area of every candidate building segment has been the number of pixels within the corresponding connected region [25]. In general, false detected non-building urban features, such as road and barren land are usually either elongated or cover large areas on the bottom and really small features, such as vehicles cover very small areas on the bottom. However, structures in populated areas generally cover widespread areas on the floor at an equal time their region on the ground isn't very large. Considering the everyday building region inside the study area, the proper threshold range (900–40,000 pixels) has been set[7], specified very tiny features, such as car and in reality massive features, such as road, infertile land, etc. are eliminated. Building candidates that have well worth within the facet range ( Minimum and Maximum) are established as actual buildings. However, the threshold may additionally vary if image resolution get changes.

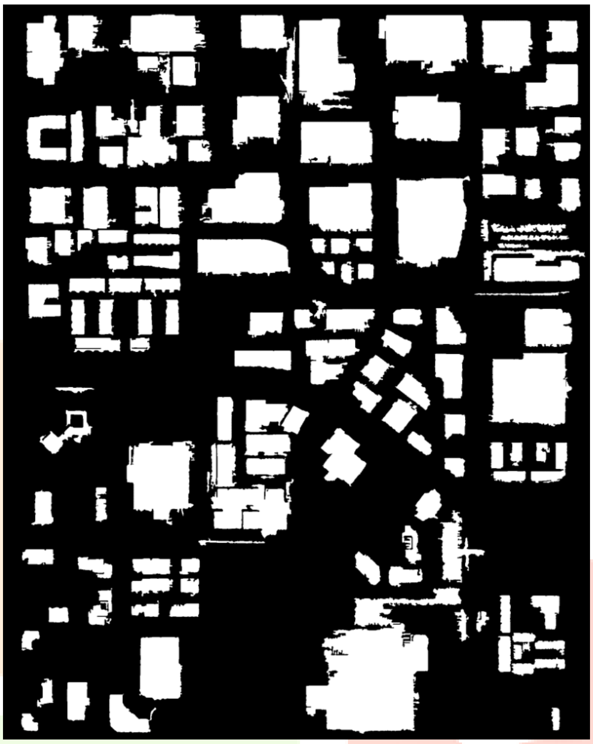

Figure 4.6. Building area with pixel range from (900-40000).

## V. Result and Analysis

The proposed methodology for automatic building detection and extraction technique based on machine learning and image processing algorithm which divide building and non-building regions. however, misclassification of building pixel observed in feature extraction has been removed using median Filter, connected component labelling , and area parameter. Further, the post-processing image compares with an original mask. And find TP, FP, and FN Part. Intersection image contains only those pixel which is present in the processed image and original mask (TP part).

### 5.1 Pixel Based Evaluation

During an object-based assessment strategy, there has been no such special criterion to decide whether an object has been TP or not. Further, [28] regarded a pixel-based metrics which has been greater goal than object-based metrics. During pixel-based analysis, the extracted resulting image has been compared with the original mask [29]. The evaluation of results has been introduced as a picture, which represents the spatial distribution of the TP, FP, and FN. Further, the assessment parameters completeness, correctness, and quality got via pixel-based analysis are denoted via Completeness , Correctness , and Quality , respectively.To severely analyze the overall performance of the proposed methodology pixel-based assessment [29] has been meted out. During the pixel-based evaluation, the 40% building and non-building pixel records of region envisage checking what proportion percent mannequin learns from the give 60% data for training. Below is that the table which shows the outcomes of the XG-Boost algorithm on 40% trying out data which is not used for coaching by making use of Quality Parameter.

**Table 3. Result After Applying Quality Parameter**

| Region | TP | FN | FP | Completeness | Correctness | Quality |
|---|---|---|---|---|---|---|
| Santa Ana | 551393 | 16450 | 68307 | 0.97 | 0.88 | 0.86 |

### 5.2 Object Based Evaluation

The objective of the object-based comparison is to find real building segments(TP), misclassified non-building (FP), and non-extracted correct building (FN) through evaluating extracted building segments and original building mask. The origanl building mask has been acquired through digitizing the input satellite image and further used for comparison. In general, for the duration of the object-based evaluation, the extracted building segments which encompass a sure minimum overlap, usually 50–70%, with buildings inside the reference building map are widely wide-spread as TP [26] [27]. However, throughout this study, the extracted constructing segments which have overlap greater than 70% are identified TP, while ultimate extracted segments are considered as FP. Further, the evaluation parameters completeness, correctness, and quality bought by using object-based evaluation are denoted by using Completeness, Correctness, and Quality, respectively. During an object-based evaluation, the digitized reference building mask has been compared visually [30] with extracted last output image.

**Table 4. Results of visual comparison with Quality parameter.**

| Region | TP | FN | FP | Completeness | Correctness | Quality |
|---|---|---|---|---|---|---|
| Santa Ana | 143 | 0 | 15 | 1 | 0.90 | 0.90 |


Figure 5.1. Non–building region remain as building.

## Conclusion

Building detection and extraction from multispectral satellite images has been considered an essential area of research in remote sensing and computer vision . In this study, we proposed an efficient building extraction method that can successfully extract buildings from multispectral satellite images having different size and shape with minimal human intervention. Further, the problem of misclassification has been removed by using median filter ,connected component labelling and segment area method. analysis of obtained result shows that buildings with very bright and dark roof tops have been however some non-building pixel are extracted as building pixel .by applying quality parameter it has been observed that all building rooftop extracted correctly. The accuracies of pixel based evaluation are 97% for completeness, 88%for correctness,86% for quality and The accuracies of object based evaluation are 1.0 for completeness, 90% for correctness,90% for quality The proposed methodology is easy and quick, which does not require any extra information, such as digital elevation model which improves accuracy. Proposed methodology can be further used to extract other natural and man-made object from multispectral satellite images.

## References

**[1]** Belgiu, M. and Drˇagu¸t, L., 2014. Comparing supervised and unsupervised multiresolution segmentation approaches for extracting buildings from very high-resolution imagery. ISPRS Journal of Photogrammetry and Remote Sensing, 96, pp.67-75.

**[2]** Chen, R., Li, X. and Li, J., 2018. Object-based features for house detection from RGB highresolution images. Remote Sensing, 10(3), p.451.

**[3]** Shrestha, S. and Vanneschi, L., 2018. Improved fully convolutional network with conditional random fields for building extraction. Remote Sensing, 10(7), p.1135.

**[4]** Alshehhi, R., Marpu, P.R., Woon, W.L. and Dalla Mura, M., 2017. Simultaneous extraction of roads and buildings in remote sensing imagery with convolutional neural networks. ISPRS Journal of Photogrammetry and Remote Sensing, 130, pp.139-149.

**[5]** Lin, C. and Nevatia, R., 1998. Building detection and description from a single intensity image. Computer vision and image understanding, 72(2), pp.101-121.

**[6]** Wei, Y., Zhao, Z. and Song, J., 2004, September. Urban building extraction from high-resolution satellite panchromatic image using clustering and edge detection. In IGARSS 2004. 2004 IEEE International Geoscience and Remote Sensing Symposium (Vol. 3, pp. 2008-2010). Ieee.

**[7]** Gavankar, N.L. and Ghosh, S.K., 2018. Automatic building footprint extraction from highresolution satellite images using

mathematical morphology. European Journal of Remote Sensing, 51(1), pp.182-193.
**[8]** khalel, A. and El-Saban, M., 2018. Automatic pixel-wise object labeling for aerial imagery using stacked U-nets. arXiv preprint arXiv:1803.04953.
**[9]** Bittner, K., Adam, F., Cui, S., K¨orner, M. and Reinartz, P., 2018. Building footprint extraction from VHR remote sensing images combined with normalized DSMs using fused fully convolutional networks. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 11(8), pp.2615-2629.
**[10]** Shan, J., and Lee, S.D., 2005. Quality of building extraction from IKONOS imagery. Journal of surveying engineering, 131(1), pp.27-32.
**[11]** Lef`evre, S., Weber, J. and Sheeren, D., 2007, April. Automatic building extraction in VHR images using advanced morphological operators. In 2007 Urban Remote Sensing Joint Event (pp. 1-5). IEEE.
**[12]** San, D.K. and Turker, M., 2010. Building extraction from high-resolution satellite images using the Hough transform. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Science, 38(Part 8).
**[13]** Wikipedia contributors. (2019, September 14). Satellite imagery. In Wikipedia, The Free Encyclopedia. Retrieved 12:37, September 24, 2019, from https://en.wikipedia.org/w/index.php?title=Satellite imageryoldid=915724486
**[14]** building Extraction in Very High Resolution Remote Sensing Imagery Using Deep Learning and Guided Filters
**[15]** Fully Convolutional Networks for Multisource Building Extraction From an Open Aerial and Satellite Imagery Data Set
**[16]** Morgan, M., Tempfli, K. (2000). Automatic building extraction from airborne laser scanning data. International Archives of Photogrammetry and Remote Sensing, 33(B3/2; PART 3), 616–623
**[17]** Turlapaty, A., Gokaraju, B., Du, Q., Younan, N.H. and Aanstoos, J.V., 2012. A hybrid approach for building extraction from spaceborne multi-angular optical imagery. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 5(1), pp.89-100.
**[18]** Zhang, C. and Ma, Y. eds., 2012. Ensemble machine learning: methods and applications. Springer Science Business Media
**[19]** https://towardsdatascience.com/overview-ensemble-learning-made-simpled4ac0d13cb96
**[20]** Chen, T. and Guestrin, C., 2016, August. Xgboost: A scalable tree boosting system. In Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining (pp. 785-794).
**[21]** Bosch, A., Zisserman, A. and Munoz, X., 2007, October. Image classification using random forests and ferns. In 2007 IEEE 11th international conference on computer vision (pp. 1-8). Ieee.
**[22]** Jozdani, S.E., Johnson, B.A. and Chen, D., 2019. Comparing deep neural networks, ensemble classifiers, and support vector machine algorithms for object-based urban land use/land cover classification. Remote Sensing, 11(14), p.1713.
**[23]** Babajide Mustapha, I. and Saeed, F., 2016. Bioactive molecule prediction using extreme gradient boosting. Molecules, 21(8), p.983.
**[24]** Bergstra, J. and Bengio, Y., 2012. Random search for hyper-parameter optimization. Journal of machine learning research,13(Feb), pp.281-305.
**[25]** Singh, K.K. and Mehrotra, A., 2014, March. Building extraction from VHR imagery using Morphological Shadow and Building Operator. In 2014 International Conference on Computing for Sustainable Global Development (INDIACom) (pp. 463-467). IEEE.
**[26]** Matikainen, L., Hyyppa, J. and Hyypp ¨ a, H., 2003. Automatic detection of buildings ¨ from laser scanner data for map updating. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 34(3/W13), pp.218- 224.
**[27]** Zhan, Q., Molenaar, M., Tempfli, K., Shi, W. (2005). Quality assessment for geospatial objects derived from remotely sensed data. International Journal of Remote Sensing, 26(14), 2953–2974. doi:10.1080/ 01431160500057764
**[28]** Shufelt, J.A., 1999. Performance evaluation and analysis of monocular building extraction from aerial imagery. IEEE Transactions on Pattern Analysis and Machine Intelligence, 21(4), pp.311-326.
**[29]** Rutzinger, M., Rottensteiner, F. and Pfeifer, N., 2009. A comparison of evaluation techniques for building extraction from airborne laser scanning. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2(1), pp.11 20.
**[30]** singh, D., Maurya, R., Shukla, A.S., Sharma, M.K., Gupta, P.R., 2012, March. Building extraction from very high resolution multispectral images using NDVI based segmentation and morphological operators. In Engineering and Systems (SCES), 2012 Students Conference on (pp. 1–5). IEEE.
**[31]** anon, 2020. Ensemble learning. Wikipedia. Available at: https://en.wikipedia.org/wiki/Ensemble learning [Accessed March 15, 2020] .
**[32]** vadim Smolyakov (2017). Ensemble Learning to Improve Machine Learning Results. [online] Medium. Available at: https://blog.statsbot.co/ensemble-learningd1dcd548e936.
**[33]** varghese, D. (2019). Comparative study on Classic Machine learning Algorithms. [online] Medium. Available at: https://towardsdatascience.com/comparative-studyon-classic-machine-learning-algorithms-24f9ff6ab222 [Accessed 15 Mar. 2020].
**[34]** shah, T. (2017). About Train, Validation and Test Sets in Machine Learning. [online] Towards Data Science. Available at: https://towardsdatascience.com/trainvalidation-and-test-sets-72cb40cba9e7.
**[35]** Wikipedia Contributors (2019). Pareto principle. [online] Wikipedia. Available at: https://en.wikipedia.org/wiki/Pareto principle.
**[36]** analytics Vidhya (2016). Complete Guide to Parameter Tuning in XGBoost (with codes in Python). [online] Analytics Vidhya. Available at: https://www.analyticsvidhya.com/blog/2016/03/complete-guide-parametertuningxgboost-with-codes- python/.
**[37]** docs.scipy.org. (n.d.). scipy.ndimage.morphology.binary fill holes — SciPy v0.16.1 Reference Guide. [online] Available at: https://docs.scipy.org/doc/scipy0.16.0/reference/generated/scipy.ndimage. morphology.binary fill holes.html [Accessed 15 Mar. 2020].