Detection of Unauthorize Construction using Machine Learning: A Review

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***Abstract* - Detection of unauthorized construction or illegal buildings poses a significant problem to municipal parties across the countries. Every country faces some form of problem related to unauthorized construction. In this review we presented concise summary of recent research papers. Summary includes method, technique and problem faced by authors, Table [1] include comparison of research paper on 6 different parameters that are Primary Technique used, Dataset, Algorithm Enhancement, Processing Speed, Target Object, Difference in Technique. Fig 1 shows a general process used by authors to detect unauthorized construction, Fig 2 shows percentage of how many authors used Machine learning, Deep learning and other methods in their research paper.**

Keywords: Unauthorized Construction, Illegal Buildings (IB), Unmanned Aerial Vehicles (UAVs), Geographic Information System(GIS)

I. Introduction

Illegal construction, also known as unauthorized construction or illegal buildings, can be defined as the process of constructing buildings on land without obtaining approval from respective municipal authorities. Unauthorized construction may have tiny objects inside the tops of buildings. Many countries around the world are experiencing an increasing number of unauthorized buildings due to rapid development. Many developing countries like India, China, Brazil, etc. are facing significant issues of unauthorized construction. This poses a significant challenge to economic and social stability.

With the rapid urbanization of cities, spatial databases and aerial sensing technology were used to minimize unauthorized buildings. These processes need the workforce to tally data as well as invest substantial amounts of resources and labour, alongside an extended recognition cycle.

Author proposed a technique for observing unauthorized building construction assisted by photo shots with unmanned aerial vehicle drones. [6]

Geometric analysis, recognition of construction, and further 3D representation perform a significant role in the scope of civic/urban applications. Finding the height of a building is among the vital geometric parameters utilized to change the 2D ground area to a 3D model. Finding the height of buildings from numerous buildings for investigation is resource-consuming. So, finding an effective and cheap method to evaluate the height of a building is significant. So, for automatic approximation of the height of a building using a single lens ultra-high resolution multi-spectral pan-sharpened satellite photos to identify unauthorized building parts. [5]

The present technique of IB recognition is utilized, which is quick and cheap. This process uses multi-temporal satellite images and spatial up-to-date. It significantly deducts the computation cost, manpower plus expensive cost. [4]

Further, Image classification is used to identify the illegal buildings. It is defined as an image comprehension method based on prior

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understanding. A deep convolutional network can link the graphical features of images with advanced, meaningful ideas using the deep learning method. There are objects of different dimensions; some of them cover full-image, plus the remaining occupy a handful of pixels. The condition in the method of learning properties plus segmentation charting is modified, and the conventional multi-level overlapping of convolutional kernel alongside fixed size is altered to a process that joins the multi-level sensory domain concurrent handling. A compact association CRF is utilized for separation outcome. It reveals high recognition precision for illegal buildings in a particular area. [3]

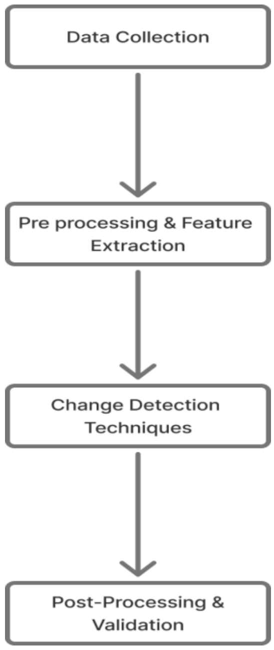

Fig 1: Unauthorized Construction Detection Process

II. Related Work

In this study, the author discusses the limitations of traditional techniques that have caused problems in identifying subtle changes in structures methods such as the IR_MAD, Change Vector Analysis (CVA), and Principal Components Analysis-K-means. Slight changes to antennas, water tanks, solar panels, and other small structures are not able to be captured or noticed by these techniques. The author talks about a new method that combines the object-based detection method (OBCD) and deep learning to fix such issues. Deep learning components are best for detecting larger changes but fail to detect smaller and more complex changes. However, these changes are best detected by OBCD. This limitation can be overcome by merging the outcomes of both approaches. The OBCD component uses the IR-MAD technique, and the deep learning component uses morphological analysis. [1]

Detection of unauthorized construction has conventionally been work-intensive, depending on satellite images, GIS, and GPS. As image evaluation and machine learning enhanced automation, issues with accuracy and proficiency persisted. Current deep learning techniques like CNNs improved detection yet face difficulties with expensive computational burdens and can only recognize current structures. We introduced YDHNet, an improved YOLOv4 model, to overcome the problem. YDHNet improves accuracy while lowering parameters by using the H-Swish activation function and replacing CSPDarkNet53 with DenseNet121 for better characteristic collection. These enhancements make YDHNet a faster and more effective solution by improving mAP, recall, F1-score, and precision. [2]

Detection of an Unauthorised construction building using remote sensing images encounters obstacles with conventional fully convolutional networks (FCNs) that utilizes predefined filters and pooling layers, which minimize spatial resolution and result in loss of accuracy in segmentation. Although these techniques work well to categorise the basic images, they struggle with complicated structures that involve accurate boundary recognition. To tackle this issue, the author introduces a new image segmentation technique merging multi-scale convolution, Conditional Random Fields (CNF) and asymmetric decoding. Multi-level convolution implements convolution of different sizes concurrently, gathering spatial aspects at varying scales, which enhances the recognition of complicated structure. Adaptive decoding ensures retention of spatial details during decoding technique, enhancing the recovery of fine features. CRFs improve object contours, confirming with higher accuracy, particularly in complicated or intersecting areas. Collectively, these advancements allow the prototype to segment complicated structures accurately and precisely recognise unauthorised construction in remote sensing images. [3]

The author introduces a technique to identify whether an underdevelopment building is authorized using a municipal property database, multi-temporal satellite images and a city map. This technique initiates with the accumulation of multi-temporal satellite images, followed by the application of K-means clustering to categorize the images into modified and unmodified images. This process enables the detection of the adjustments in standalone buildings by evaluating the satellite images with latest city map and estimating the percentage of modified pixels to spot under development buildings.

When a building is recognised which is under construction, its license status is authenticated by

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comparing with municipal databases. This technique was implemented in Tehran, Iran where combined 343 buildings were examined. Among these, 19 buildings were identified as under development, calculating 6% of all constructions that modified within four months. Based on municipal data, at that time, 24 buildings were in the process of construction, leading to an accuracy of 79% for the proposed technique. Moreover, the process exactly recognised 3 in 4 unauthorised structures, reaching an accuracy of 75%.[4]

This paper introduces a unique technique for the recognition of unauthorized constructions leveraging 3D point cloud segmentation, eliminating the limitations of conventional 2D image-based and remote sensing techniques, which often struggle with separating unauthorised structures, particularly once they are hidden with protective sheet or vegetation. The proposed technique harnesses LiDAR technology and includes three primary steps: first, efficient point cloud encoding to minimize the data volume while maintaining geometric accuracy, which improves computational functionality. Next, ground point removal is used to remove unnecessary ground data, separating ground and above-ground structures. At last, building cluster recognition is conducted with a region-growing procedure that determine collection of points depicting building. This technique substantially enhances the recognition of unauthorized constructions, especially in situations where building are planned to be merged with environment, providing a more effective and accurate answer for inspecting urban areas. [5]

Paper highlights the limitations of satellite-based unauthorized construction recognition because of low image quality. To enhance the accuracy, the author presents a drone-based technique that capture high resolution images under favourable conditions. These images are collected with property information and time records, changed into greyscale, and examined using the Structural Similarity Index (SSI) to identify changes. Notable discrepancies mark possible illegal constructions for additional examination. This technique improves accuracy allows live data tracking and is more affordable than satellite imagery. [6]

Unauthorized buildings that surpass assigned heights parameter present a major problem for regulatory bodies in controlling urban expansion and ensuring conformity with law. To streamline the process of recognising such breach, Abdelatif Rajji et al. outlined a technique where they planned building heights using high quality satellite images. Their method includes spotting buildings and their overcasts in the images, evaluating the shaded extents, and using trigonometric calculation to evaluate the building evaluation. By evaluating the sun's elevation angle and the shadow extent, the framework compute automatically elevation of every building, conveying a precise and flexible solution for detecting buildings that surpass height restrictions. This technique not merely helps in inspecting city areas but also supports officials in effectively detecting and tackling unauthorized construction. [7]

Detecting buildings in cities and rural areas used to be a difficult task that required a lot of time and manual effort to go through satellite images. Now, with deep learning, we can detect them automatically and much more easily. In this research paper, the author tested two approaches first approach focused on a special U-Net model and second approach uses models that use pre-trained encoders like VGGNet to improve feature representation. The results of the author's observation showed that the U-Net model with a VGGNet encoder performed better than the standard U-Net, achieving an impressive 89.28% accuracy and a 74.70% IoU on a small dataset. This shows that using a pre-trained encoder can really boost performance when compared to traditional U-Net models and Mask R-CNN, which is a popular model for segmentation. [8]

Evaluating floors of a building is critical for identifying unauthorized construction, but conventional stereo photometry is inefficient, costly and ineffective for wide scale surveillance. To find a solution, the author introduces a monocular optical image-based technique that adopts computer vision and deep learning to find floors from an individual image. This technique refines the process, computational burden and enhances flexibility, developing live urban tracking more effectively and accurately. [9]

Most change detection algorithms use nadir images (top-down view), which can sometimes be inaccurate due to occlusions (visual obstructions), shadows, and limited perspective. To address these limitations. This offers several advantages, such as - an enhanced ability to judge depth, better ability to notice slow changes, fewer problems with objects blocking the view, and more precise image alignment. S2Looking images provide a 3D view that makes it much easier to spot changes in structures that might be missed in nadir images (top-down views). This dataset not only sets a new standard for testing change detection algorithms but also inspires the creation of more advanced deep-learning models that can work with oblique satellite images. [10]

Prior technique for evaluating building elevation from shadows posed challenges with intersecting shadows, incorrect vegetation classification and defective shadow retrieval. They periodically

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misrecognized shadows because of poor segmentation and usage on multiple images. The Shadow-Overlapping Algorithm (ASO) addresses these challenges using the Ratio-Band Algorithm for accurate shadows identification and Graph Theory for precise building blueprints. It replicates computed shadows determined by solar metadata and align them with real shadow utilizing the Jaccard Similarity Coefficient. Analysed in Cardiff, UK, ASO minimizes the mean deviation by 21% and obtains 80% accuracy, enhancing it is reliability and more effective than earlier models. [11]

In this study, the author talked about how previous models were unable to detect illegal buildings due to manual surveys, low-resolution satellite images and inaccurate change detection methods such as basic image comparison and manual inspections. Previous methods, such as manual surveys, were slow, costly and unreliable, and due to low-resolution images, models were unable to capture small structures those methods used simple pixel subtraction and thresholding, which often misclassified natural changes, which led to inaccurate results. To overcome those issues, the author presented a novel method that uses Pixelwise Fuzzy XOR Operator and GIS (Geospatial Information System), which ensures faster, automated, and highly accurate detection of illegal buildings compared to previous methods. The author used these methods in Tehran using three satellite systems GeoEye-1, IRS-P5, and QuickBird. As a result, this method was able to detect unauthorised buildings with an accuracy of 100%, 66%, and 83% respectively.[12]

This study shows how previous models were unable to detect illegal buildings due to inefficient manual monitoring of sites, poor quality of satellite images, and inefficient deep learning techniques, which led to slow and error-prone detection, these models were lacking in specialised evaluation metrics, which generated highly inaccurate and unreliable results. To overcome the problems which he found in pervious models, the researcher used semantic segmentation with U-Net, transfer learning, and IoT and integrated them. The researcher conducted a study using his integrated technologies collectively calling it Unet_mini model on a Japan building dataset containing 1,506 images; in this study, the Unet_mini model achieved 85.88% accuracy, outperforming other models. With 91.90% accuracy for Class 0(legal buildings) and 35.51% for Class 1(illegal buildings), it significantly improves the efficiency of detection, real-time monitoring, and automated enforcement for urban planning.[13]

In this study, the researcher aims to solve the inefficiency, high costs, and delays in previous illegal building monitoring methods. Traditional models were using UAV-based models, which had flight restrictions, inefficient manual operation, and were only able to provide an accuracy of 60-70%, while satellite images suffered from long revisit periods, high costs, and cloud cover issues. The researcher proposed a solution spatiotemporal sensor network with titled stereo cameras on high-lying zones that enables real-time, automated monitoring with over 90% accuracy. The researcher conducted a study on his technique in Beijing, Shanghai, and Guangzhou, it removes all manual data processing, reduces costs by using solar power in his technique, and transmits instant alerts over wireless networks, ensuring faster enforcement and improved urban planning.[14]

Table 1: Comparison of Different techniques used in detection of unauthorize construction

Papers	**Primary Technique used**	**Dataset**	**Algorithm Enhancement**	**Processing Speed**	**Target Objects**	**Difference in Techniques**
[1] Discovering Potential Illegal Construction	Semantic segmentation with depth-channel improved UNet-DB	UAV imagery of Yangzhou, China (2017-2019)	Two-step change detection, Atrous Spatial Pyramid Pooling	Moderate	Potential illegal construction (PIC) on building roofs	Semantic segmentation focuses on pixel-level detection of building-level and small PICs, leveraging depth data for enhanced accuracy.
[2] A New High-Precision and Lightweight Detection Model for Illegal Construction Objects Based on Deep Learning	YOLOv4-based detector with DenseNet121 backbone	Custom dataset (31 categories, 14,046 images)	H-Swish activation, lightweight neck and head, DenseNet for better feature reuse	High	General illegal construction-related objects	Lightweight object detection focusing on real-time performance, leveraging DenseNet and Depthwise Separable Convolution for efficiency

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[3] Illegal Constructions Detection in Remote Sensing Images Based on Multi-Scale Semantic Segmentation	Multi-scale semantic segmentation with context-sensitive convolution	Urban building dataset (Massachusetts); manually labeled subregions	Multi-scale convolution and Conditional Random Fields (CRFs) for boundary detection	Moderate to low	Illegal constructions in urban and rural settings	Uses multi-scale convolution for segmentation, emphasizing context-aware detection with strong boundary precision using dense CRFs.
[4] (Automatic Illegal Building Detection)	K-means clustering on multi-temporal satellite image	IRS-P5 satellite images, Tehran municipal database	Automated change detection, minimizing manual intervention	High speed (advantage of K-means)	Buildings under construction and illegal structures	Focused on clustering and satellite data integration
[5] Outdoor Illegal Construction Identification Algorithm Based on 3D Point Cloud Segmentation	3D Point Cloud Segmentation	ISPRS Public Dataset	Lossless point cloud compression (minimum spanning tree), multi-scale filtering, region growing	High due to optimized compression and filtering	Buildings in outdoor environments	Uses 3D LiDAR data for segmentation instead of traditional 2D imagery
[6] Identification of Illegal Construction using Image Processing	Image Processing (Computer Vision, SSIM, OpenCV)	Drone-captured aerial images	Uses OpenCV for preprocessing, SSIM for image comparison, contour detection for anomaly marking	Moderate (depends on drone image processing speed)	Buildings, additional floors, encroachments	Uses 2D aerial images and compares historical images to detect changes
[7] Building Height Estimation from High Resolution Satellite Images	Shadow-based height estimation from satellite images	High-resolution Google Earth images	PCA-based segmentation, vectorization of building shadows, trigonometric height Calculation	Moderate (dependent on image resolution and processing algorithms)	Buildings (focus on height estimation)	Uses shadow-based height estimation instead of direct object detection
[8] Detecting Buildings and Non buildings from Satellite Images Using U-Net	U-Net (Deep Learning)	Open dataset from Xinxing County, Guangdong, China	ResNet and VGGNet encoders for improved feature extraction	Moderate (depends on deep learning model training)	Buildings vs. non-buildings	Uses semantic segmentation instead of traditional object detection
[9] Number of Building Stories Estimation from Monocular Satellite Images Using a Modified Mask R-CNN	Mask R-CNN (Deep Learning)	GF-2 satellite images from nine cities in China	Added a new head to predict the number of stories in buildings	Moderate (deep learning-based, depends on dataset size)	Building story estimation (low-rise, mid-rise, high-rise)	Predicts building stories directly rather than using height estimation first
[10] S2Looking: A Satellite Side-Looking Dataset for Building Change Detection	Deep Learning (Various models tested)	S2Looking dataset (5000 bitemporal satellite image pairs	Introduces off-nadir imaging for improved detection of changes	High (depends on dataset processing and deep learning model)	Building change detection (newly built, demolished)	Uses side-looking satellite imagery instead of traditional nadir-view images
[11] A Shadow-Overlapping Algorithm for Estimating Building Heights From VHR Satellite Images	Shadow Detection & Overlapping Algorithm	VHR satellite images (WorldView-3) from Cardiff, UK	Morphological fuzzy processing, graph theory for building footprints	Moderate	Building height estimation	Uses shadow region overlap rather than direct height computation
[12] Performance Evaluation of Three Different High-Resolution Satellite Images in Semi-Automatic Urban Illegal Building Detection	Change Detection using Pixelwise Fuzzy XOR Operator	GeoEye-1, IRS-P5, QuickBird images (Tehran, Iran)	Comparison of satellite images to find the best for illegal building detection	High	Illegal buildings (under construction)	Uses fuzzy XOR instead of machine learning for change detection

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[13] Dynamic Monitoring Method of Illegal Buildings Using Spatiotemporal Big Data Based on Urban High-Lying Zones	Spatiotemporal Big Data & Stereo Camera Monitoring	Urban sensor networks and stereo cameras (China)	High-lying zones for optimal monitoring, automated stereo photogrammetry	High (real-time monitoring)	Illegal buildings	Uses real-time monitoring via urban sensor networks instead of periodic satellite imagery
[14] Semantic Segmentation of Optical Satellite Images for Illegal Construction Detection Using Transfer Learning	Transfer Learning (U-Net, ResNet, VGG)	IEEE Dataport (satellite images from Japan)	Uses pre-trained deep learning models (U-Net, VGG, ResNet) for improved accuracy	Moderate (depends on model complexity)	Moderate (depends on model complexity)	Uses transfer learning for segmentation instead of traditional image processing

The table [1] presents a comprehensive comparison of 14 research papers that utilize different techniques for the detection of unauthorized construction, analysed across six key parameters: primary technique used, dataset, algorithm enhancement, processing speed, target objects, and differences in techniques. The research papers reviewed employ a variety of methods, ranging from deep learning-based approaches such as YOLOv4, U-Net, and Mask R-CNN, to more traditional techniques like K-means clustering and shadow-based estimation.

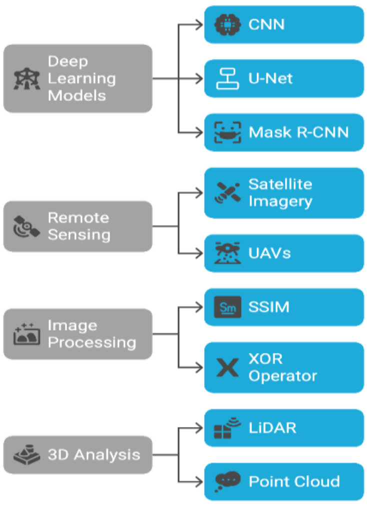

Fig 2: Common Techniques Used in Detection of Unauthorized Construction

III. METHODOLOGY

In this systematic research paper, we have used a search strategy to identify relevant literature. This search strategy has been applied to different databases, and the following search terms have been used: "Detection of illegal construction," "Detection of changes in buildings," and "Estimation of height using remote sensing." All research papers extracted from the database inception until 2024 include review papers and journal articles, and all of them are published in English only.

We have used the PRISMA statement for selection criteria. Our research primarily focuses on mapping existing literature on the detection of unauthorized construction using machine learning. The search span was from 2015 to 2024. Articles from all countries were considered, but only those published in English were included. A total of 160 results were excluded, and 24 records were extracted at this stage.

All selected articles are primarily conference papers, review papers, and research articles. To ensure the quality of the review, all records were thoroughly checked, and duplicate results were removed. The abstract of each paper was carefully examined for analysis and refinement to maintain the quality of the study. At a later stage, each research paper underwent evaluation.

In the next exclusion phase, we limited the selection to English-language papers only. Ten papers in non-English languages were excluded. Additionally, papers that focused solely on differential privacy without applications in recommender systems were also removed. Ultimately, 14 papers were selected, with each article assessed according to inclusion and exclusion criteria.

Data Extraction Phase

During the data extraction phase, 14 articles were selected based on the following characteristics:

1. The article must be a conference paper, review paper, or original research paper.
2. The article must be published in English and belong to the field of Computer Science and Engineering.
3. All selected articles must have been published between 2015 and 2024.

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IV. Result

Our main motive to write this review paper was to provide a comprehensive analysis on what different kind of technique and method were used to detect unauthorized construction or illegal buildings. In this review paper we have found that the researcher mostly used deep learning for detection of unauthorized construction [1][2][3][8][9][10][14]. Mostly all author used muti temporal image to detect unauthorized construction in a city. In this paper [1] author used a novel method that combines object-based change detection (OBCD) and deep learning which showed great results. We have also find out that CNN based method shown higher accuracy in comparison with other methods, and for change detection similarity indexes like SSIM and Cosine Similarity were used. Some authors also used different method like Point cloud segmentation, shadow-based height estimation. Only one author [6] used drone based image for detection.

Overall, we can say every method have their advantages and disadvantages but those paper who have used deep learning for detection have shown greater results that other method and different methods that are used are shown below in Fig 3

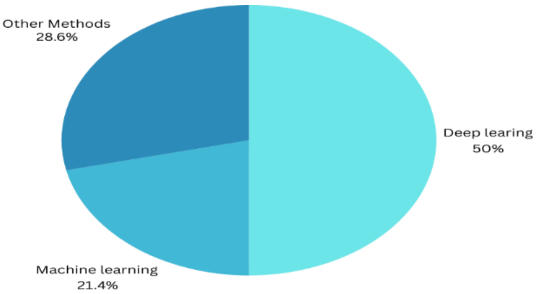

Fig 3: Comparison of Different techniques applied

V. Conclusion

Many municipal and authorities of cites faces a common problem of unauthorized construction mostly in developing countries like India China and Brazil. Historically people used method like manual survey, visiting sites and other method which were inefficient and costly but as the introduction of technologies such as remote sensing and image processing many municipal and researchers started to used these technologies to analyse and detect unauthorized construction and illegal buildings but they faced significant problems as these method were highly inaccurate and inefficient but improvement in the field of machine and deep learning researcher across the world started to uses these method technologies to enhance the accuracy in detection of unauthorized construction and it proven highly efficient and accurate which eliminated the need of manual survey and labour intensive work which the make the process efficient and fast. But despite this advancement their problems that need to resolve such as high cost of satellite data, cloud cover issue, real time processing, inaccurate data. In future researcher should focus on the improving the machine and deep learning algorithm in order detect more complex structures. Overall Machine and deep learning shown a significant improvement in detection unauthorized construction.

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