IDENTIFICATION OF ILLEGAL BUILDINGS USING LIDAR DATA

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ABSTRACT:
In developing countries, urbanization is rapidly growing. To manage such urbanization, identifying and tracking building construction to keep it up to date in all dimensions is the essential and challenging job of the government. The objective of this research work is to find the individual building height and identify the illegal buildings in the selected area located in the Godavari municipality of Kailali district, Nepal. For this research work, the latest airborne LiDAR and cadastral datasets were acquired from the Survey Department. It reduces the manual field survey effort, gives accurate results, and minimizes interference from the external environment. One of the most important dimensions of LiDAR data is the z-axis value, which gives the accurate height of the object. A normalized digital surface model is calculated with the help of DTM and DSM. By utilizing the normalized Digital Surface Model (nDSM), precise building heights were extracted, which facilitated the estimation of the total number of floors per structure. This derived floor count data was then cross-referenced with municipal records to identify discrepancies. By adopting this process, the municipality can systematically verify building heights and automate floor-area and floor height calculations to ensure alignment with local building codes, and perform more accurate property tax assessments.

Introduction

Urbanization is a global phenomenon where a large portion of the population is migrating from rural areas to developed towns and cities [1][2] in search of higher living standards [3]. It is also extensively growing in Nepal [1]. A certain level of development in cities and towns is necessary for the overall development of the nation [4]. The exponential pace of building construction is presenting unforeseen urban management challenges, including the disruption of public services, unregulated urban density, and environmental degradation. Addressing these problems requires the implementation of robust, sustainable urban planning and management strategies [5]. These urban centers are disproportionately vulnerable to catastrophic natural disasters, including floods, landslides, and other systemic risks[6].

The government has to track, manage, and control such types of construction activities [7] and has to develop sustainable infrastructure. The government has to develop infrastructure and make plans for these cities. Moreover, the expansion of informal settlements into agricultural areas will strain critical services, especially water, sanitation, and transport networks [8]. Urban citizens may be significantly influenced by the structural density of buildings and the extent of surrounding vegetation. So, it is important to identify buildings, vegetation[9], and to have control over the building construction process. For this, building identification and tracking are imperative and a preliminary responsibility [10] of the government. Untracked and unmanaged building construction may lead to unhealthy urban living conditions, increase vulnerability to natural disasters, and pose a significant threat to public safety [11]. Illegal or informal buildings may hinder the people's access to essential public services [12]. To control this, the government of Nepal has formulated and implemented rules and regulations. The National Urban Policy [13], the Building Acts [14], the National Building Code, the National Urban Development Strategy [15], and associated directives provide the legal basis for the building construction process.

Informal settlements are residential areas where housing is developed without a land ownership certificate [16]; residents have no legal claim to the building or the land [12][17], often termed sukumbashibasti. Additionally, structures that have violated local building code, bylaws, or National Building Code (NBC) 2015 are called illegal buildings, even if the land itself is legally owned [18]. The property owner can construct or modify the structure of buildings only after having permission and approval from the relevant government authorities [19]. The Government invests significant time and financial resources to track such works and update databases for building footprints, heights, and floor counts[20].

Light Detection and Ranging (LiDAR) is the latest technology that is becoming popular and attractive for area and height extraction with less interference from fog, rain, storms, and other external environmental factors[21][22].

Compared to conventional technologies, it is faster, cost-effective [23], and requires less effort and resources [22], while maintaining high accuracy [21]. With the help of LiDAR data, developing countries are solving land zoning issues, designing and developing urban plans [23] and infrastructure- such as roads, canals, sewerage, water supply, transportation networks[24] - creating a digital world and a digital twin [22]. LiDAR data can generate a large-scale 3D model of modern cities and towns and provides an actual picture of the ground using less time, less effort, and low cost –[25]. So, it has gained the highest position among the other geospatial technologies[26]. LiDAR is a modern optical remote sensing technology that is a powerful tool and the fastest method to capture and store accurate geographical data [27] and detailed attributes of the points[28].

1. **Objective:**

The main objective of this research is to identify illegal buildings using LiDAR Data. To achieve this, the following specific objectives have been established:

- To extract the building footprints of selected study areas.
- To estimate the building height and determine the corresponding number of stories
- To identify discrepancies between the LiDAR-derived building height and official municipal records to detect illegal buildings.
- To quantify the resulting revenue loss and annual tax deficiency caused by these unregistered or non-compliant structures.

2. Related Work

Currently, LiDAR data is becoming a reliable, accurate, easy-to-use, and primary source of information[29]. For processing LiDAR data, numerous automated procedures - such as open-source libraries, applications, and scanning tools - make the workflow fast, easy, and user-friendly[30].

M. Liu et al.[31] used a deep learning approach, specifically the Mask R-CNN, to extractthe building footprints; the DELaMa model was used to process the Digital Surface Model (DSM) to derive building heights in the rural area of Pingquan, Hebei Province, China. Faten Hamed Nahhas et al. [32] discuss a deep learning approach for building height detection usingLiDAR data and orthophotos. R. Wang et al.[33]derived a normalized height model by subtracting the DTM from LiDAR data to extract building height. Buildings were separated from vegetation. Shapes were reconstructed as rectangles using the Hough transformation or as regular polygons using SLT and EHT.

Arzu Erener et al.[34] studied Istanbul, Turkey, and estimated the heights of buildings using the nDSM from point clouds; the accuracy was about 79%. Y.He et al.[35] classifiedLiDAR data into ground, vegetation, and buildings using an energy-based method, with VDP optimizing vertex selection. A hybrid approach combined explicit modeling for regular edges and implicit modeling to fill gaps. The method is robust to noise, achieves a low RMSE, and produces accurate building polygons independently.

Mohammad Awrangjeb et al.[36] have identified an automatic building detection technique using LiDAR and multispectral imagery. This work uses primary and secondary building masks from LiDAR data, extracts line segments, and applies NDVI to remove vegetation. In another study,Mohammad Awrangjeb et al.[37]useda LiDAR dataset and a region-growing technique to find the roof type for data classification. Data were classified according to the clustering of points. Building detection correctness was 89%. Ala'a Al-Habashna[38] developed an open-source system designed for the automatic extraction of building height from street-view images. This system usesdeep learning (DL), advanced image processing techniques, and geospatial data to enhance the accuracy of building height estimations. Xiangyun Hu et al. [39] differentiate flat roofs from rough vegetation rapidly and extract buildings from dense LiDAR data. It uses scan line analysis and the Douglas-Peucker algorithm for segmentation. It was processed by applying simple geometric rules and a region-growing algorithm.Z. Zhou et al. [40]introduce a deep learning-based method to automatically detect residential buildings from airborne LiDAR data.This methoddoes not require any pre-defined geometric or texture features. Building height is calculated using a normalized Digital Surface Model (nDSM).

Different researchershave used normalized digital surface models to estimate the heights of buildings. They have used the Digital Terrain Model and the Digital Surface Model to calculate the Normalized Digital Surface Model. In the case of a sloped roof, the height difference is calculated. Buildings are artificial objects consisting of piecewise and continuous surface segmentsthat can be described as polyhedral forms. Alternatively, building boundaries are defined by planar surfaces and lines[33].

Materials and Methods:

This research work focuses on a selected area within Attariya, located in Godawari Municipality-2 of the Kailali district, Nepal. The building stock in this region primarily consists of commercial complexes, residential structures, institutional facilities, and industrial or warehousing units. The area maintains a population density of approximately 320 per km^2. Attariya is a major transportation artery and economic gateway of the Far-Western region of Nepal[41]. Situated approximately 483 kilometers west of Kathmandu by air[19], but about 650 kilometers by road. Reinforced Concrete (RCC) frame structures are the most common modern buildings. Load-bearing brick masonry is common in the residential wards surrounding the main market. The area is characterized by the flat topography of the Terai plains, which facilitates accurate DTM extraction. The altitude lies between 170 and 200 meters above sea level. The settlement pattern features buildings clustered linearly along the highway and transitions into scattered rural clusters. Traditional Terai dwellings (Kucha/Semi-Pukka) can be found as you move away from the highway toward the more rural parts of Municipality. Public and institutional buildings differ from standard residential blocks. This region's cultural mosaic is composed of a blend of the indigenous population and migrants from the neighbouring hilly

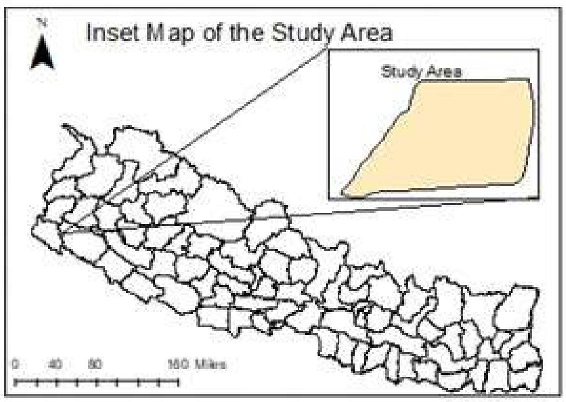


Figure 1: Inset Map of the Study Area

For this study, an airborne LiDAR dataset was acquired from the Survey Departmentof Nepal. The dataset consists of 2,117,418pointscovering an area of 273,984m^2. The average point density is 18.04 samples/m^2, with a point spacing of 0.24 m. The elevation within the study area ranges from a minimum of 194.11 m to a maximum of 220.79 m. The aerial view of this extent is presented in Figure2.

Figure 2: Aerial view of the selected area

Data acquisition: Building construction permit records were obtained from Municipality Office, which serves as the regulatory authority, and is responsible for issuing permits and maintaining building records within its municipal area.

Computational Framework: In this study, the Global Mapper and the Python Programming Language were used to extract building height and calculate the number of stories. The research employs a Python-based pipeline for the processing and analysis of LiDAR datasets. The Laspy library serves as the core interface for reading, writing, and modifying LiDAR data in the LAS and LAZ file formats, ensuring the integrity of point format versions and header metadata. Vector operations, including height thresholding, distance computations, and spatial transformations, are performed using NumPy and SciPy. For the extraction of structural features, scikit-learn is employed to implement the DBSCAN clustering algorithm and to group discrete points into distinct building clusters. The geometric boundaries or "footprints" of these classified clusters are then generated using Alphashape and Shapely. Additionally, Whitebox Tools is integrated via its Python wrapper to leverage advanced pre-built functions, such as the Simple Morphological Filter, for efficient ground classification.

Methodology and Data Processing: To ensure the spatial integrity of the airborne LiDAR and cadastral datasets, the WGS 84 / UTM Zone 45N coordinate reference system was adopted. The LiDAR dataset is classified into categories including ground, buildings, vegetation, power lines, poles, and noise points. This classification process involves assigning classes to LiDAR data points based on their height and other characteristics.

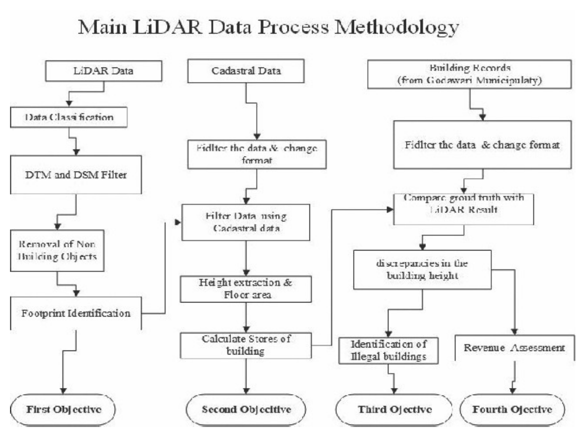


Figure 3: Main LiDAR Data Process Methodology

There are several methods to classify data. In the point cloud classification process, the following methodology was used. The classification workflow distinguishes between ground and non-ground points [43]. Without classifying the ground points, other classes cannot be identified because they are related to ground height [44]. For this process, the Global Mapper software was utilized. It uses two types of algorithms for ground data classification. The Maximum Likelihood algorithm is a geospatial algorithm designed to classify LiDAR data into ground and non-ground points [45]. It filters non-ground points by calculating local surface curvature, typically in smaller grid cells, making it ideal for a lower-density dataset. Vegetation, buildings, electric lines, towers, etc., belong to the non-ground class.

Following the ground extraction, non-ground points were further classified into Medium Vegetation, Building, Wire Conductor (Phase), and Transmission Tower classes based on their height above the ground surface[46]. After classification of LiDAR data, buildings are illustrated in Figure 3. The result from the classification process is checked manually using visualization tools. Noise points were removed, and misclassified data were corrected. Any LiDAR data cluster that was incorrectly categorized as a separate class was merged back into the suitable class [47]. After classifying ground and non-ground points, the final classification output is ready. The building category (Class 6) is clearly defined. In geospatial analysis, accurate Digital Terrain Model (DTM) and Digital Surface Model (DSM) generation are the fundamental steps to determine building heights, as they provide the "zero-elevation" baseline for the ground [60]. A normalized digital surface model (nDSM) was generated to isolate above-ground features. This nDSM was calculated by subtracting the DTM from the DSM[48].

By removing the DTM surface from the DSM, the remaining data belongs to objects on the surface of the earth. From that, we identified the building points. Building points are distinguishable from other objects like vegetation, shrubs, roads, and vehicles. Consequently, features can be differentiated by shape, size, height, and texture by visual interpretation in point cloud data [49]. LiDAR data has high-precision building elevation information. We can exactly differentiate between building and tree using LiDAR data[50].

During the building extraction process, the classified building features were filtered and output as polygonal geometries.

Building footprint extraction involves the identification and delineation of building 2D ground-level perimeters.

To refine the dataset and remove non-building objects-- such as vegetation, vehicles, and temporary structures— a combination of geometric and shape-based filtering techniques was applied. These methods identify buildings based on structural characteristics, such as planar surfaces and well-defined edges, while excluding smaller objects (e.g., cars or small sheds) that fall below a minimum area threshold of 10 m².

Planarity checks and eigenvalue analysis were used to distinguish smooth, consistent building surfaces from the irregular, high-variance structure of tree canopies. Additionally, a Normalized Digital Surface Model (nDSM) enables height-based filtering. Algorithms like the Cloth Simulation Filter (CSF) were employed to separate the ground from non-ground points, allowing objects below a specific threshold of 3 m to be reclassified as low vegetation or vehicles.

Further refinement was achieved through morphological operations—including regularization, erosion, and dilation—to sharpen building boundaries and separate overlapping features like overhanging tree limbs.

To distinguish true structures from dense canopies, RANSAC (Random Sample Consensus) is used to detect planar roof surfaces, while eigenvalue/covariance Analysis identifies the shaggy or scattered spatial signature of trees versus the smooth, planar surface of buildings.

Clustering techniques, such as DBSCAN implemented in Python libraries like laspy, help identify and remove outliers based on point density.

The height of each building was determined by subtracting the Digital Terrain Model (DTM) from the Digital Surface Model(DSM)[51][52].

nDSM = DSM – DTM

Floor and story calculation: in the Terai region of Nepal,average floor height and basement elevations are 1 m and 3.3 m respectively determined by the building construction regulation of Nepal [53].

$$n = \frac{h - z_y}{k_y}$$

Where n is the number of stories; h is the calculated height of the building from the LiDAR-derived nDSM; z_y is the plinth height (standardized at 1m for the Terai region); and k_y is the average floor height (standardized at 3.3 m per the Building Construction Regulation of Nepal[53]).

Illegal buildings are identified by intersecting the building vector layer derived from LiDAR data with the cadastral parcels [54]. A structure is classified as illegal if it exceeds the maximum height or floor count permitted for its specific land-use zone.

Finally, manual quality control—using 3D profile visualization and targeted class corrections—ensures high-precision results by allowing analysts to verify and resolve any remaining misclassifications.

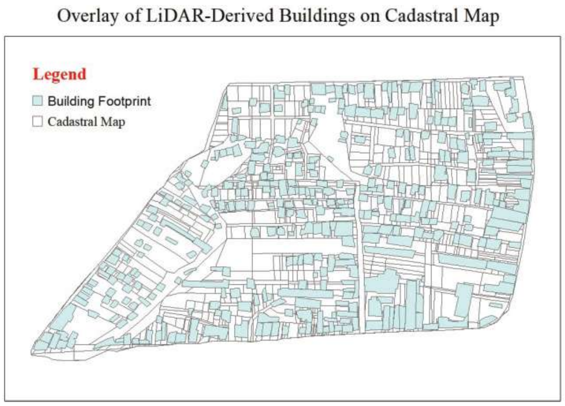


Figure 4: Overlay of LiDAR-Derived Building on Cadastral Map

1. Result and Discussion

Processing the airborne LiDAR cloud point dataset following outputs are generated, which accurately represent the physical condition of the study area.

Point cloud classification Result:

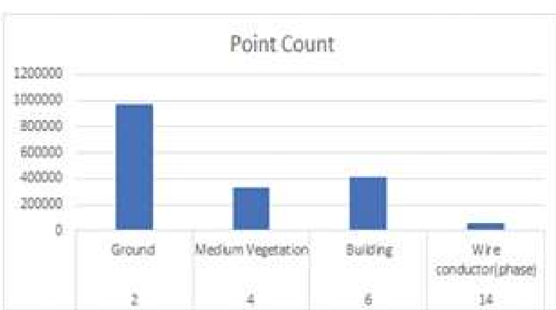
LiDAR point cloud is classified into the following classes.

Table 1: Point classification

S. No.	Class-code	Class	Point Count
1	2	Ground	967698
2	4	Medium Vegetation	330063
3	6	Building	410819
4	14	Wire conductor(phase)	60580

Classification of Buildings: The resulting building classification from the LiDAR dataset is shown in the figure 4.

Table 2:Point Cloud Count Graph



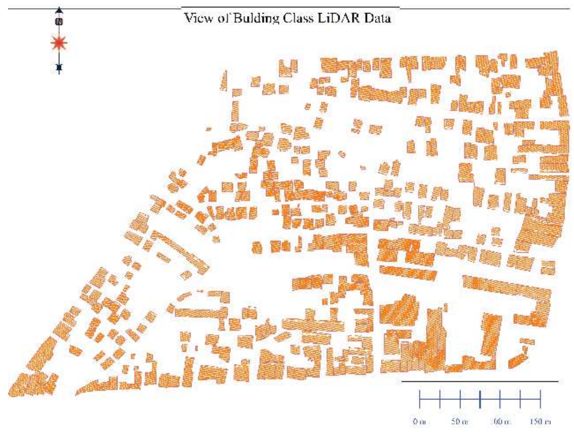


Figure 5 : LiDAR data After classification of buildings

Calculation of building height:

For calculating nDSM, there is need to calculate the DTM and DSM is as the following.

Digital Terrain Model: To generate the Digital Terrain Model (DTM), the entire point cloud dataset is selected, and the DTM is produced as shown below.

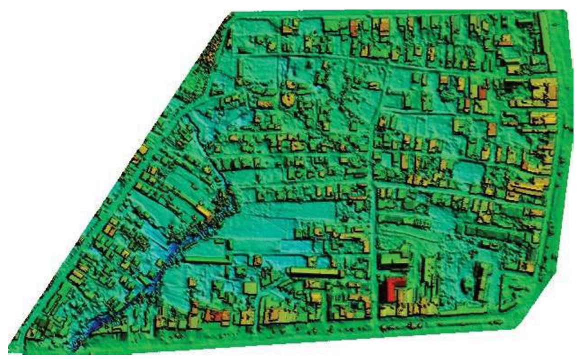


Figure 6: Digital Terrain Model of the study area

Digital Surface Model: After generation of the Digital Terrian Model, point cloud data were used to compute the Digital Surface Model (DSM). The output of DSM is illustrated in the Fig 6.

Figure 7: Digital Surface Model of Attariya

Building Footprint:

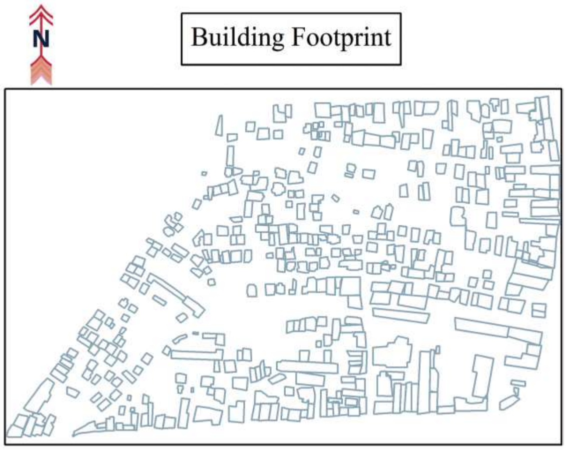


Figure 8: LiDAR-extracted Building footprints of the study area

Building Height Extraction: Following the generation of the Digital Terrain Model (DTM) and the Digital Surface Model (DSM), the normalized Digital Surface Model (nDSM) was derived to isolate building heights. The resulting values are detailed in Table 2, with a representative sample of these calculations provided below.

Table 3: Comparative Analysis of Building Stories and Area (LiDAR vs. Municipal Records)

A1	B1	LiDAR Data				Municipal Record		Difference	Difference	Remark
		C1	D1	E1	F1	G1	H1	J1	K1	L1
1	523	13	4	904	3608	3	2731	101	877	
2	447	10.2	3	872	2616	2	1943	949	623	

Note

1. A1: S.No, B1: Parcel No, C1: Height of Building(in meters), D1: Calculated Storey of Building, E1: Unit Area of Floor, F1: Total Area of all Floor, G1: Stories of Buildings, H1: Total Area of Buildings, I1: Stories of Building, J1: Area of Building, K1: Total Difference of Area.
2. In the same way, all the data is compared, and the difference is calculated.

Table 3: Summary of Comparative analysis of LiDAR-Derived data vs.Municipality data (Number and Area)

Number of stories	Municipality data		LiDAR Derived Data	
	Storey of buildings	Area of Building (feet)	Storey of buildings	Area of Building(feet
1	58	54575.54	73	85093.23
2	66	132261.8	79	183419.4
3	45	143327.2	59	209462.3
4	12	83247	17	101261.4
5	0	0	9	66020.3
Total	180	413411.5	237	645256.6

Total Area Difference=LiDAR Derived Area – Municipal Recorded Area

= 645256.6 - 413411.5

= 231845.1

Table 4: Accuracy Assessment and Error Metrics for LiDAR-Derived Heights

S.No.	Performance Metric	Calculated Value	Units
1	Correlation (r)	0.936	
2	Mean Absolute Error (MAE)	1286.34	Foot
3	Root Mean Square Error (RMSE)	1297.11	Foot

Table 5: Accuracy Assessment and Error Analysis of LiDAR Data

S. No.	Statistical Parameters	LiDAR Derived Data	Municipal Records
1	Count	237	181
2	Average	2722.60	2284.041547
3	Median	2204	1920
4	Mode	2440	1850
5	Standard Deviation	2049.13247	1760.656931
6	Variance	4198943.89	3099912.83
7	Minimum	645	0
8	Maximum	16125	13765
9	Sum	645256.6	413411.52

Revenue Loss Estimation: Two distinct categories of revenue loss were identified and evaluated: the estimated Direct Permit Revenue Gap (DPRG) from building permits and the Estimated Annual Property Tax Deficiency (EAPTD).

Direct Permit Revenue Gap: From the above table, the discrepancy between LiDAR-derived measurements and municipal records is 231,845.1 square feet. And the rate for construction permission is Rs. 5 per square foot. The total DirectPermit Revenue Gap(DPRG) for this selected area is as follows.

DPRG = Difference in Area × Rate per Square Foot

= Rs. 231,845.1*5

= Rs. 1,159,225

Note: In the Municipality, the building permit certificate rates vary between 5 and 8 (Financial Act, 2082); however, the minimum rate of Rs. 5 per square foot has been applied for these calculations.

Estimated Annual Property Tax Deficiency: In the same way, there is an Estimated Annual Property Tax Deficiency (EAPTD). Annual tax rate is Re. 1 per square foot. The total

EAPTD = Difference of area X rate per square foot

= Rs. 231,845.1*1

= Rs. 231,845.1

In accordance with the law, the precise calculation of the tax rate is multifaceted. The municipality applies different rates based on floor level and building location. For simplicity, an estimated lowest flat rate of Rs. 1 per square foothas been utilized for this purpose

Penalties and interest charges have not been included in this calculation.In the actual field, there are many temporary tin shades or shade-like structures found above the buildings. LiDAR data cannot differentiate the temporary tin shade other building like structuresfromthe actual storey.

Challenges in Extracting Building Heights

Roof Objects: In the building there may be non-structural things like transparent roof for heat and light, Building water storage vessel, water Tank shed, climate control machinery, heat exchange equipment, Active air exhaust systems, Emergency power supply, Solar Panels, Electricity generator, thermal panels for water, glass panels for natural light, insulation layers, outdoor lounging area, High-end aquatic facilities, haystack, corn-stack stock, big umbrella, chairs, tables and other enumerable obstacles are found in top of the room complicates the calculating height of building.

Object that effects on classification of data: Overhead drying rack/wire looks like wire, and data is classified into the wire category. Haystacks look like extra room. Rooftop room for views, Stair or elevator access enclosure, Area for basking is also considered in calculating the height of the building. Garden in the roof also classifies data into the vegetation area.

Shades and temporary structures: There are older houses, which were built before the rule and regulation started, or the municipality's establishment; are also without permissions. Temporary shelters look like buildings so it needs to identify manually these shelters whether they are permanent or temporary.

Problem of cadastral Number: Data is collected from the municipality office is based on the parcel number. Whereas LiDAR data have no parcel number, so without any proper key it is impossible to compare building data with data derived from LiDAR data. To solve this type of problem and identify every LiDAR data by parcel number, the LiDAR data must contain the parcel number. To solve this problem cadastral map of selected area is collected from survey Department.

the process of overlaying building footprints with cadastral data begins with Coordinate Alignment, where datasets are re-projected to meet specific projection standards for high precision. Once aligned, the LiDAR-derived footprints are overlaid onto the official cadastral map. By linking this information together through a spatial join, a cadastral number can be automatically assigned to each identified building. Finally, both visual inspections and statistical analyses are conducted to verify the accuracy of the overlay.

After the overlay of cadastral data and point clouds, we can analyse and find the parcel number for each point cloud and make it easy to compare individually every building data with the LiDAR data.

For this purpose, it is necessary to add a new attribute, parcel number, in LiDAR data according to the overlay of the cadastral parcel.

Land ownership certificate: There are many land owners who do not have a legal land ownership certificate. Without a land ownership certificate, the municipality does not give permission to construct a building.

Implementing any model within the government sector is a formidable task. One must navigate numerous obstacles, including rigid regulations and multi-layered decision-making processes

5. Conclusion and Recommendations

The main aim of this study is to identify the informal buildings of selected area by calculating building height and the number of stories of building. For this, it has used LiDAR data and cadastral data are obtaimned from Survey Department. The calculated result is compared to municipalBPRs. Based on this comparision, buildings without the permissions or different from the legal permissions are identified.Based on this result loss of revenue and annual tax loss is calculated. This study is helpful for local bodies to find out about informal buildings.

These results empower governments to refine urban planning and resolve zoning disputes while addressing critical housing needs. Furthermore, they facilitate the design and development of resilient infrastructure, ranging from utilities like water and electricity to transportation networks, while enhancing disaster management and environmental risk assessments.

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