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ILLEGAL BUILDING DETECTION USING MACHINE LEARNING

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ABSTRACT

The paper addresses the significant issue of detecting illegal buildings using satellite imagery, a critical concern for urban planning and regulation. This involves the complex challenge of interpreting remote sensing data and verifying it against cadastral maps. To tackle this, you propose a methodology that combines image processing techniques with deep learning tools to automate the detection process. The methodology consists of three main components: region proposal generation, building classification, and legality verification. Region proposals are generated by integrating four computer vision-based techniques, including edge-detection methods like Canny-edge-detection to identify building boundaries, and segmentation methods such as thresholding and clustering (e.g., K-means) to distinguish buildings from their surroundings. Then these praposals are classified using a retrained GoogLeNet convolutional-neural-network (CNN), and finally, the detected building areas are validated for legality against state cadastral maps. Your tests with satellite imagery the datasets demonstrates that this approach achieves acceptable results in both building detection and legality assessment.

Keywords: Illegal Buildings Detection, Satellite Imagery, Googlenet CNN, Cadastral Map, Region Proposal Generation, Transfer Learning

I. INTRODUCTION

Illegal Building Detection using Image-Processing and GIS presents a novel method for identifying unauthorized constructions in urban areas. This research makes use of satellite imagery and geospatial information systems (GIS), and image processing techniques to detect illegal buildings efficiently and accurately. With the urban population growing, the need for new buildings increases annually. However, some constructions lack proper permits, resulting in unstable structures and violations of building regulations. This threatens urban infrastructure, and current monitoring methods in Iran rely on human inspectors, which are outdated, time-consuming, costly, and prone to inspector-constructor collusion. An efficient, automated, and rapid detection method is needed to cut costs, save time, and reduce manpower. Accurate, up-to-date spatial information is vital for effective management and planning. Automatic monitoring can significantly lower costs and manpower requirements, and prevent collusion. Various studies on building researchers have used different methods to conduct change detection.

The proposed method uses multi-temporal satellite images to analyze the change in the urban landscape over time, such as new constructions, modifications, and demolitions. GIS is essential for processing and analyzing these images, allowing for the automatic identification of potential illegal buildings based on criteria like size, location, and zoning regulations.

Satellite imagery is now widely used for map production, replacing traditional surveying and aerial photogrammetry. The IKONOS satellite has revolutionized remote sensing by providing high-resolution images that make Earth's features such as buildings, streets, cars, and walls visible in detail. This rapid, high-quality data source allows for the creation of more detailed maps. Change detection, which involves identifying changes in the condition or state of an object or phenomenon over a period of time., relies on multi-source imagery captured at different epochs. In the past, people used to compare datasets visually or manually to detect changes over time. The study [1] aims to detect changes in rural and urban areas using ortho-images from the IKONOS satellite captured at different times. The case study focuses on the Marmaris region as a rural area and Birlik Mah.-ANKARA as an urban area in Turkey. The last part of the study includes evaluating how accurately changes were detected in both areas by visually comparing temporal datasets (superimposing one over another), measuring the coordinates of known points (such as building corners and road intersections) in each layer, and calculating the root-mean square-error (RMSE) for each case, which is around 1m in both areas. The study concludes that for accurate mapping using satellite imagery, it must be rectified to fit a map projection, and the accuracy of image registration process (geometric differences) is crucial for the validity and reliability of change detection outcomes.

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The paper [2] highlights that population growth in the Greater Istanbul Municipal area is causing numerous changes in built environment, many of which are illegal. This issue is particularly critical in protected water catchment areas, where illegal housing is not accepted by the municipality. Consequently, near real-time detection of new buildings is necessary, along with information for urban planning. To address this, the municipality area of 5378 km^2 is regularly monitored using satellite imagery, with the surrounding Marmara region also inspected due to its impact on the Greater Municipality area. The change analysis based on a time series of Landsat images, providing an overview of land classes, supplemented by complete coverage of the Marmara region with SPOT 5 super mode pan-sharpened images and IKONOS scenes covering the municipality area, captured every three months. Using pansharpened IKONOS images, shapefiles including all buildings in the Greater Istanbul Municipality area have been generated. For controlling illegal housing and supporting urban planning, a time series of IKONOS scenes with a three-month repetition rates has used since June 2005. Approximately 10 scenes cover the entire Greater Istanbul Municipality area, with additional images ordered in cases of partial cloud coverage. However, the 1m ground-resolution does not allow for automatic identification of new buildings, as they are often too small, under construction, or in preparation. Additionally, changes in vegetation and atmospheric conditions, along with varying shadow lengths, make automatic change detection unreliable with very high-resolution space images.

The paper[3] introduces a likelihood-based method for extracting the buildings from remote-sensing images to manage diverse data characteristics a flexible hierarchical framework is developed to generate different building appearance models using elementary feature based modules an overarching optimization process was employed to determine a best building configurations by integrating observed data prior knowledge and interactions among neighboring building components the effectiveness of this approaches are assessed on several sets of aerial images which contains more than 500 buildings and its performance is benchmarked against two advanced techniques.

II. METHODOLOGY

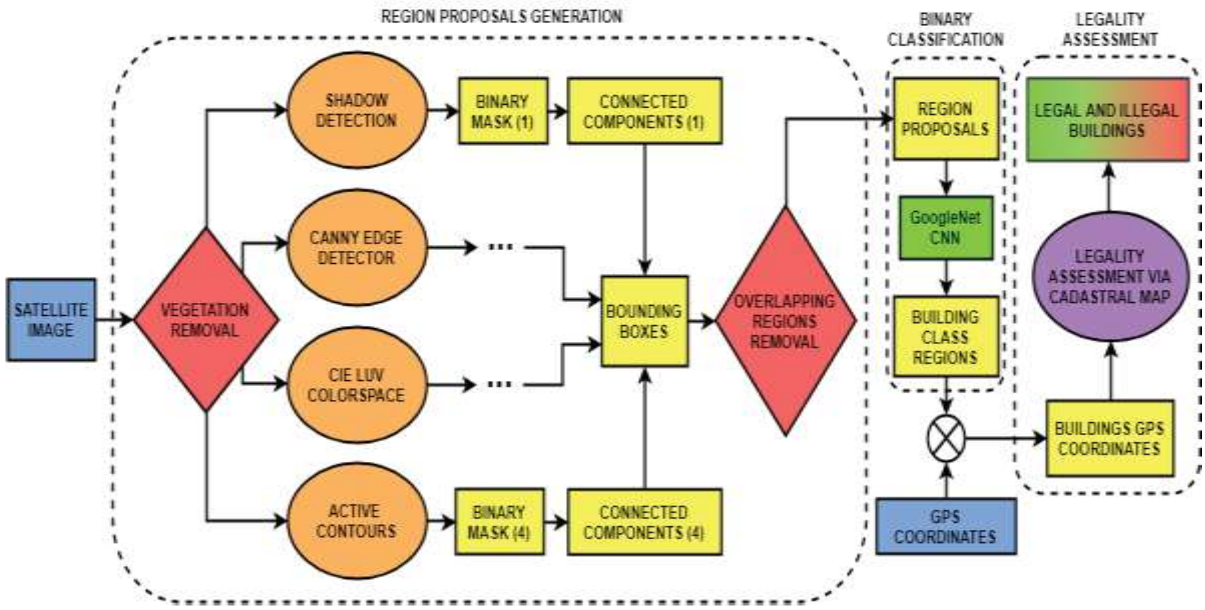

Fig 1: System Architecture

Satellite Image Input: The methodology begins with obtaining satellite images of urban area to be analyzed. These images serve as the primary source of data for detecting changes in buildings and other structures.

Vegetation Removal: The starting step in pre-processing involves removing vegetation from the satellite images to focus solely on the built environment. This step includes shadow detection to eliminate shadows that could obscure details, application of the Canny edge detector to highlight edges within the image, conversion to CIE LUV color space for improved differentiation of various image elements, and a use of active contours to accurately outline structures.

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Creation of Binary Masks and Component Analysis: Following vegetation removal, binary masks are generated to segment various elements in the image. These masks facilitate the identification of connected components, delineating individual structures within the binary images. This process will make sure that each structure is separated for subsequent analysis.

Bounding Boxes and Overlap Elimination: The segmented structures are enclosed within bounding boxes to define their spatial extents. To avoid redundancy, overlapping bounding boxes are eliminated, ensuring each structure is uniquely represented by a single bounding box.

Region Proposals and Building Classification: The next phase involves generating region proposals for potential building sites based on pre-processed data. The proposed regions are subsequently classified using a (CNN), specifically GoogleNet, which sorts the identified regions into various building classes based on the features it has learned.

Building Class Regions and GPS Coordinates: The regions classified as buildings are further processed to determine their exact locations. GPS coordinates for each identified building region are calculated, providing precise spatial data for the structures.

Legality Assessment via Cadastral Map: The final step involves assessing the legality of the identified buildings by comparing their GPS coordinates with cadastral maps. This comparison helps to check whether the buildings are legally constructed according to zoning and regulatory guidelines.

Output - Legal and Illegal Buildings: The entire process culminates in a clear distinction between legal and illegal buildings. The output provides the GPS coordinates of both types of structures, facilitating targeted actions and urban planning efforts.

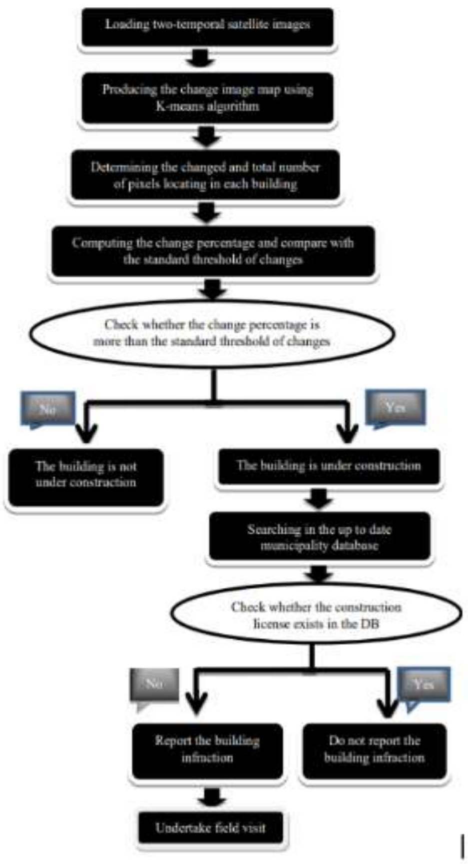

Fig 2: Block Diagram

The block diagram for detecting illegal buildings starts by loading two satellite images taken at different times of the same urban area. These images are then utilized to identify changes in the urban landscape. Using the K-means clustering algorithm, we create a map that shows areas with significant changes between the two time points. The algorithm counts the number of changed pixels for each building, as well as total number of pixels, to measure the extent of the changes. By computing the change percentage and comparing it to a predefined

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threshold, the system assesses whether the observed changes are significant enough to indicate construction activity.

When the change percentage falls below, if the threshold indicating no significant construction activity, the process concludes without further action. However, if the change percentage surpasses the threshold, signalling ongoing construction, the system proceeds to verify the legality of the construction. This verification involves querying the municipality's current database to verify the presence of a valid construction license. If a license is found, no violation is reported, confirming the construction's legality. Conversely, if no license is found, it suggests a potential building violation, prompting the system to report the infraction and initiate a field visit for detailed inspection. This systematic-approach makes sure that is efficient and accurate monitoring of construction activities, supporting the enforcement of building regulations and prevention of unauthorized developments.

III. ALGORITHMS USED

GoogLeNet CNN:

GoogleNet, also known as Inception, is a convolutional-neural-network (CNN) architecture developed by researchers at Google and introduced in 2014. It was designed to ensure the performance and efficiency of DLmodels for image classification. The core innovation of GoogleNet is the inception module, which processes data through multiple layers of parallel convolutional and pooling operations of different sizes. This allows the network to capture features at various scales while maintaining computational efficiency. The architecture includes 22 layers and employs 1x1 convolutions to reduce the number of parameters, auxiliary classifiers to address the vanishing gradient problem, and global average pooling to minimize overfitting. These features make GoogleNet both powerful and efficient for various computer vision tasks.

GoogleNet, also known as Inception, is a deep convolutional neural network (CNN) architecture that uses a variety of layer types. To understand how GoogleNet works, it's essential to grasp the roles of these different layers and how they interact.

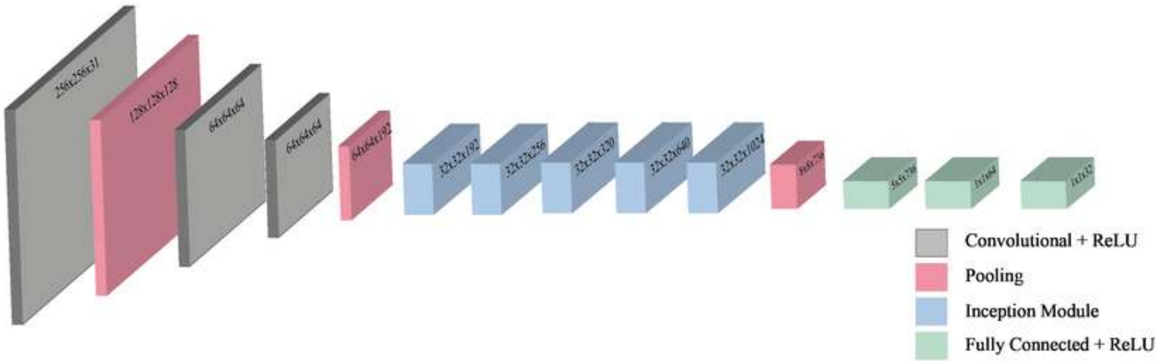

Fig 3: GoogleNet Architecture

K-means Clustering Algorithm:

K-means clustering is a popular and straightforward method to group homogenous data points into distinct clusters. It starts by choosing a group of clusters, and selecting initial centroids, which can be picked randomly or using more refined techniques like K-means++. Each data point is then assigned to the nearest centroid, creating clusters. The centroids are updated by averaging the data points in each cluster, and this process repeats until the centroids no longer change significantly or the assignments stabilize.

The success of K-means clustering hinges on choosing the right group of clusters and good initial centroids. It's known for its simplicity and speed, making it a great choice for large datasets. However, it has its downsides, like needing to know the group of clusters beforehand and being sensitive to initial centroid placement, which can sometimes result in poor clustering. Also, K-means works best when clusters are roughly spherical and of similar size, which isn't always the case in real-world data. Despite these limitations, K-means remains a key technique for exploring and understanding data patterns.

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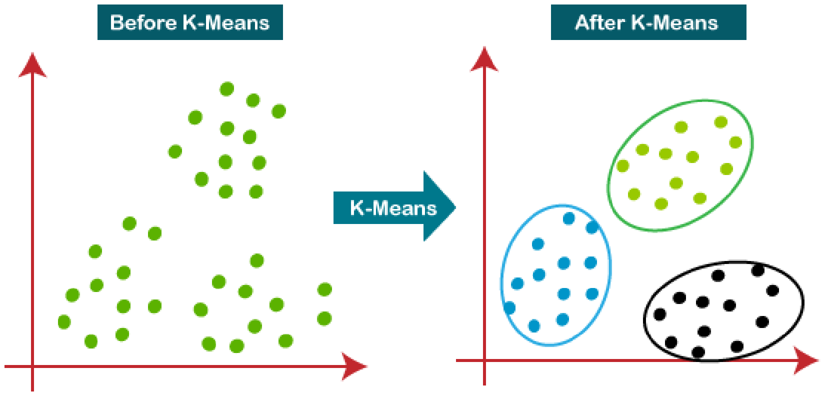

Fig 4: K-means-Clustering Algorithm

IV. RESULTS AND DISCUSSION

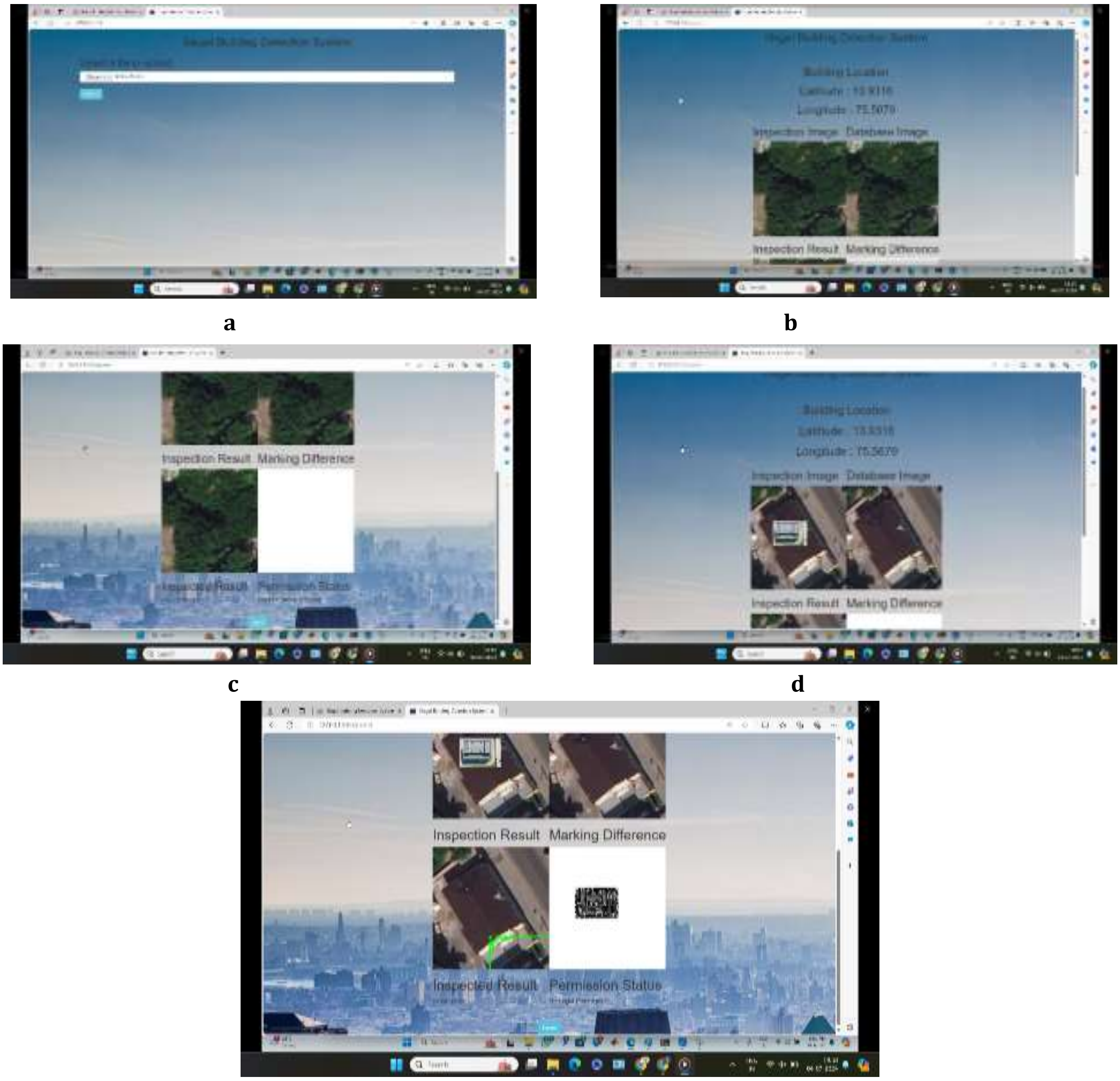

Fig 5: (a) shows the user Interface to select the building images, Fig (b) Shows the Building location depicted in the map, Fig (c) Shows that the Building is legal, Fig (d) Shows that the Building is illegal

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V. CONCLUSION

This paper proposes an automatic method for detecting illegal buildings (IBs) using multi-temporal satellite images, a city map, and a property database for urban areas. While IB detection has primarily focused on suburban areas, this method demonstrates that some IBs in urban settings can be alsoidentified using the city map, municipal database, and field visits. The proposed method's The findings were contrasted with field data, and overall accuracy and kappa coefficient were computed, yielding an 83% accuracy and a kappa coefficient of 55% using the K-means clustering algorithm. The algorithm detected 19 buildings under construction out of 343 total buildings in those images, indicating that approximately 6% of all buildings changed over four months, reflecting rapid construction growth.

The study also compared the detected buildings with municipal statistics, which indicated that 24 buildings were under construction at the time, giving the proposed algorithm a 79% accuracy (19 out of 24) in detecting construction activities. Additionally, out of four unlicensed buildings, the method correctly identified three, achieving a 75% accuracy in detecting unlicensed buildings. From 230,112 total pixels in the images, 9,456 pixels were identified as changed, with 1,577 of those related to buildings. While the method successfully detected most urban IBs, it missed five IBs, necessitating field visits to complete the job. The proposed method accelerates IB detection, aiding municipal inspectors in targeted searches, reducing costs, and saving time to prevent continued unauthorized construction. For more efficient detection, especially given the importance of timely IB identification, satellite-images with shorter intervals should be utilized.

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