

**A Project Report**

**on**

**DETECTION OF UNPLANNED URBAN  
DEVELOPMENT DEVIATION  
USING MULTI-APPROACH ANALYSIS OF  
GOVERNMENT PLAN MAPS AND SATELLITE IMAGERY**

**Bachelor of Technology**

**IN**

**ARTIFICIAL INTELLIGENCE**

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**November 2025**



*Dated.....*

## Declaration

*The work presented in project entitle "DETECTION OF UNPLANNED URBAN DEVELOPMENT DEVIATION USING MULTI-APPROACH ANALYSIS OF GOVERNMENT PLAN MAPS AND SATELLITE IMAGERY" submitted to the Interdisciplinary Centre for Artificial Intelligence, Zakir Husain College of Engineering and Technology, Aligarh Muslim University Aligarh, for the award of the degree of Bachelor of Technology in Artificial Intelligence, during the session 2025-26, is my original work. I have neither plagiarized nor submitted the same work for the award of any degree.*

*Date: 22 November 2025*

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*Dated.....*

## Certificate

*This is to certify that the Project Report entitled "DETECTION OF UNPLANNED URBAN DEVELOPMENT DEVIATION USING MULTI-APPROACH ANALYSIS OF GOVERNMENT PLAN MAPS AND SATELLITE IMAGERY", being submitted by "Aryan Parashar" and "Prakhar Saxena", in partial fulfilment of the requirements for the award of the degree of Bachelor of Technology in Artificial Intelligence, during the session 2025-26, in the Interdisciplinary Centre for Artificial Intelligence, Zakir Husain College of Engineering and Technology, Aligarh Muslim University Aligarh, is a record of candidate's own work carried out by him under my (our) supervision and guidance.*

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# Abstract

Unregulated construction and rapid urban expansion often cause major deviations between approved development plans and the actual built environment. These deviations create challenges such as increased congestion, environmental stress, and difficulty in monitoring compliance using manual inspection methods. This project presents an automated, multi-approach framework to detect and quantify unplanned urban development deviations by comparing government-approved layout maps with satellite imagery.

Three techniques are integrated: (1) K-Means clustering for preprocessing and structural extraction from development plan maps, (2) U-Net-based semantic segmentation for identifying buildings and roads in satellite imagery, and (3) Structural Similarity Index Measure (SSIM) for spatial alignment and deviation quantification. The methodology is applied to several sites across the Aligarh Division, including Atrauli Industrial Area, Ozone City, Talanagari, Sagwan City, and Salempur.

The results indicate clear differences in compliance levels across regions, with some areas showing strong adherence to planned layouts while others demonstrate significant unplanned expansion. The proposed framework offers a scalable, data-driven tool for policymakers and urban planners to monitor development, reduce unauthorized construction, and promote more sustainable city growth.

# Acknowledgements

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We extend our appreciation to the **Interdisciplinary Centre for Artificial Intelligence** and **Zakir Husain College of Engineering and Technology** for providing the necessary infrastructure, assistance, and academic environment to carry out this work.

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# Acronyms

Acronym	Meaning
GIS	Geographic Information System
RS	Remote Sensing
ML	Machine Learning
SSIM	Structural Similarity Index Measure
CNN	Convolutional Neural Network
U-Net	Encoder–Decoder Deep Learning Architecture
ROI	Region of Interest
BCE	Binary Cross Entropy
IoU	Intersection over Union
NIR	Near Infrared Band

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# Chapter 1 – Introduction

Urban environments in rapidly growing regions often expand faster than the ability of planning authorities to regulate them. This leads to large gaps between the intended development described in approved layout plans and the actual construction visible on the ground. Manual monitoring is slow and inefficient, making it difficult to track unauthorized development at scale.

This project proposes an automated system that compares government-approved maps with satellite imagery to identify deviations. Using a combination of image processing techniques and deep learning models, the system extracts structural information from both types of maps and evaluates their similarity.

## 1.1 Motivation

Unplanned construction contributes to traffic congestion, environmental degradation, and inefficient land use. Traditional monitoring methods rely heavily on field surveys, which are time-consuming, error-prone, and difficult to implement over large geographic areas. There is a clear need for an automated, scalable, and objective methodology to evaluate whether urban growth aligns with approved development plans as shown in the following Fig.1.

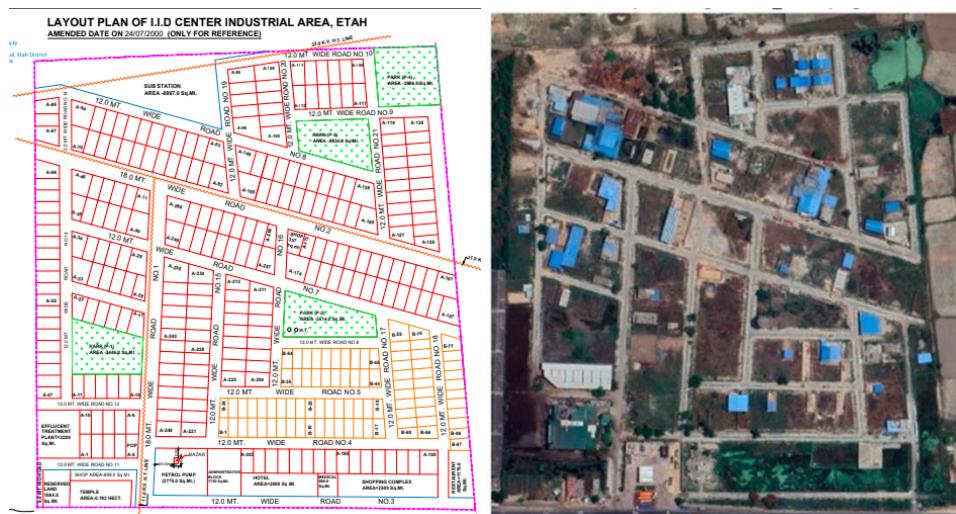


Fig.1: Layout Plan and Satellite image of I.I.D CENTER INDUSTRIAL AREA, Etah

The motivation behind this project is to utilize modern artificial intelligence, satellite imagery, and image analysis techniques to support compliance monitoring and promote more sustainable city planning practices.

## 1.2 Objectives and Scope

The primary objectives of this study are:

1. To preprocess development plan maps using color reduction and text removal so that only structural information remains.
2. To segment buildings and roads from satellite images using a U-Net-based deep learning model.
3. To spatially align the segmented satellite imagery with the processed layout maps.
4. To quantify differences using SSIM and identify areas of deviation.
5. To evaluate compliance levels of selected urban sites across the Aligarh Division.

The project focuses on residential and industrial development sites such as Atrauli Industrial Area, Ozone City, Salempur, Etah IID, and Talanagari.

## 1.3 Organization

The report is structured as follows:

- **Chapter 1** introduces the problem, motivation, and objectives.
- **Chapter 2** reviews relevant literature on change detection, clustering, semantic segmentation, and similarity metrics.
- **Chapter 3** describes the implementation methodology, including preprocessing, segmentation, alignment, and evaluation.
- **Chapter 4** presents the experimental results and deviation findings across study sites.
- **Chapter 5** summarizes the conclusions and outlines areas for future work.

# Chapter 2 – Literature Review

## 2.1 Urban Change Detection

Urban change detection has traditionally relied on techniques such as image differencing and manual on-ground comparison. While these methods offer reasonable accuracy, they often struggle with mixed land-cover regions and high structural complexity. Satellite-based urban analysis has improved significantly with the advent of machine learning and deep learning models capable of learning complex spatial patterns.

## 2.2 K-Means Clustering for Map Preprocessing

K-means clustering is an **unsupervised machine learning algorithm** used for image segmentation to partition an image into K distinct regions or segments. This method effectively groups pixels with similar characteristics, typically **color** or **spectral intensity**, into the same cluster. As mentioned in the research paper [1] “Land cover clustering and classification”.

### Segmentation Process

1. **Data Preparation:** A color image is typically a 3D array (RGB). For K-means, the image is **reshaped** into a 2D array where each row represents a single pixel, and the columns represent its feature vector (e.g., the Red, Green and Blue intensity values ranging from 0 to 255), treating it as a point in a 3D feature space.
2. **Initialization:** The algorithm starts by randomly selecting K initial cluster centers, known as **centroids**, within this feature space. K is a user-defined parameter representing the desired number of segments.
3. **Assignment Step:** Each pixel is assigned to the cluster whose centroid is **closest** to it. The distance is typically calculated using the **squared Euclidean distance** in the feature space.
4. **Update Step:** The centroid of each cluster is **recalculated** by taking the **mean** (average) of all the pixel values (data points) currently assigned to that cluster.
5. **Iteration:** Steps 3 and 4 are repeated iteratively.

The final result is a segmented image where all pixels belonging to the same cluster are assigned the color value of their final cluster centroid, reducing the total number of colors to K and highlighting regions of uniform color/spectral property.

In development maps that contain multiple color zones and annotations, K-Means reduces the color palette to a small set of representative clusters as results in the following image of Ozone City (Fig.2). This makes grayscale conversion and structural extraction more effective.



Fig.2: K means Clustering effect on Ozone City Layout Map  
(original many colors {in left} and after kmeans only 5 colors {in right})

### 2.3 Deep Learning for Building and Road Segmentation

Deep learning has transformed pixel-level segmentation in remote sensing, with U-Net and its variants emerging as the dominant architecture. The U-Net framework uses an encoder–decoder design where the encoder captures hierarchical semantic features and the decoder reconstructs spatial detail through upsampling. Crucially, skip connections bridge the two paths, allowing the model to retain fine-grained boundary information that is typically lost in deeper layers. Inspired from UNet model given in research paper [3] “URBAN CHANGE DETECTION”.

These properties make U-Net highly effective for tasks such as building footprint extraction, road delineation, and broader land-cover classification results are shown in Fig.3. Across numerous satellite datasets, U-Net-based models consistently demonstrate strong segmentation accuracy and robustness, especially in environments with complex urban structures and varying imaging conditions.

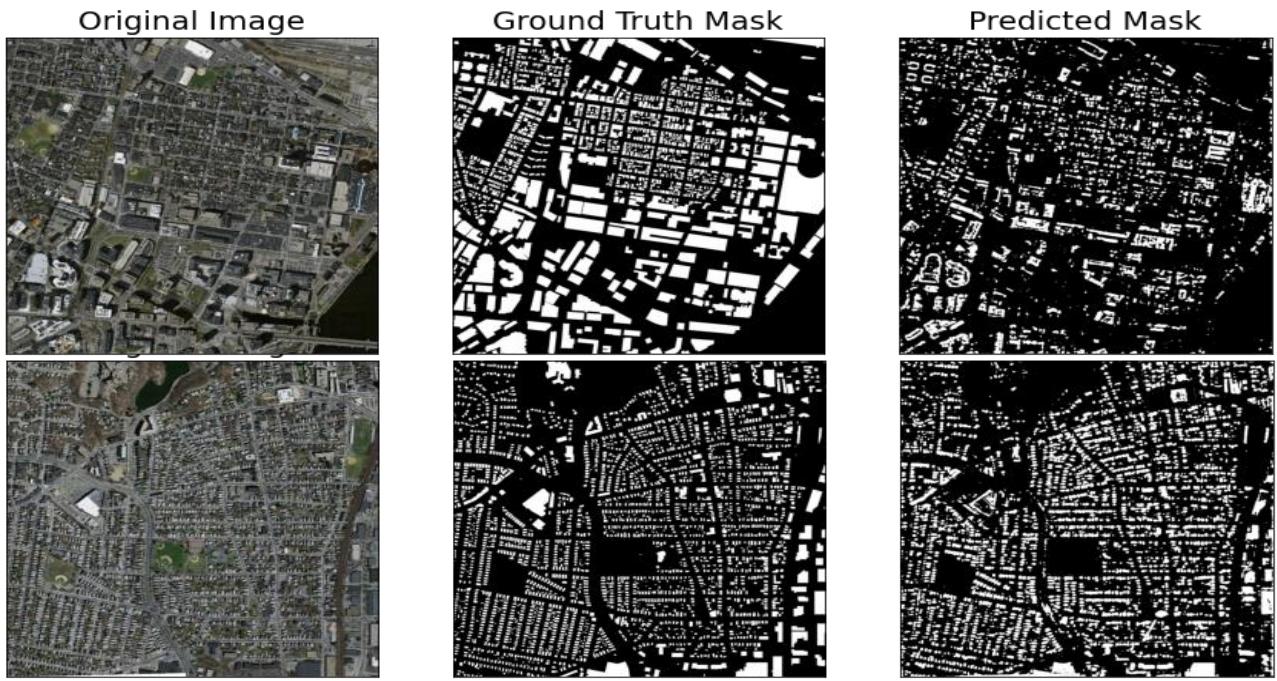


Fig.3: Unet model given in research paper [3] URBAN CHANGE DETECTION

## 2.4 Image Alignment and SSIM-Based Similarity

Image registration ensures spatial correspondence between two maps by aligning key points or intensity patterns. First of all, we need to break the images into same sized tile by Tiling and then calculate Structural Similarity Index Measure (SSIM score). SSIM measures the similarity between aligned images based on luminance, contrast, and structural patterns. The formula is shown in Fig.4. It provides a perceptually meaningful measure of compliance between planned and actual development.

The SSIM for two local windows  $x$  and  $y$  of an image is:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

Here:

- $\mu_x, \mu_y$ : mean luminance of the patches
- $\sigma_x, \sigma_y$ : standard deviations (contrast)
- $\sigma_{xy}$ : covariance (structural correlation)
- $C_1, C_2$ : small constants to avoid division by zero.

A value of 1 means perfect structural similarity, whereas 0 indicates dissimilarity.

Fig.4: Formula used for SSIM, mentioned in research paper [2] "SAR Image Change Detection via Multiple-Window Processing with Structural Similarity."

# Chapter 3 – Implementation

## 3.1 Dataset Description

Two major data sources were used:

### 1. Government-approved plan maps

- Obtained from official sources such as UPSIDA (official UP govt website for industrial maps) and development authority websites.
- Provided in PDF form containing color-coded layouts, textual labels, and zoning boundaries.
- Required extensive preprocessing for machine interpretation.

### 2. Satellite imagery

- High-resolution satellite maps covering the regions of interest.
- 53 manually labelled images from the Aligarh region used for training segmentation models (some of the samples are shown in Fig.5).
- Each image is  $550 \times 550$  pixels representing a  $100m \times 100m$  area.



Fig.5: Alig\_Dataset of 53 satellite images and their respective masks created by us.

### 3.2 Data Preprocessing

Plan maps were processed using the following steps shown in Fig.6:

1. **Text Removal:** Removes labels and symbols to isolate structural components.
2. **Color Reduction:** K-Means clustering reduces colors to 5 representative clusters.
3. **Grayscale Conversion:** Helps highlight boundary lines and zones.

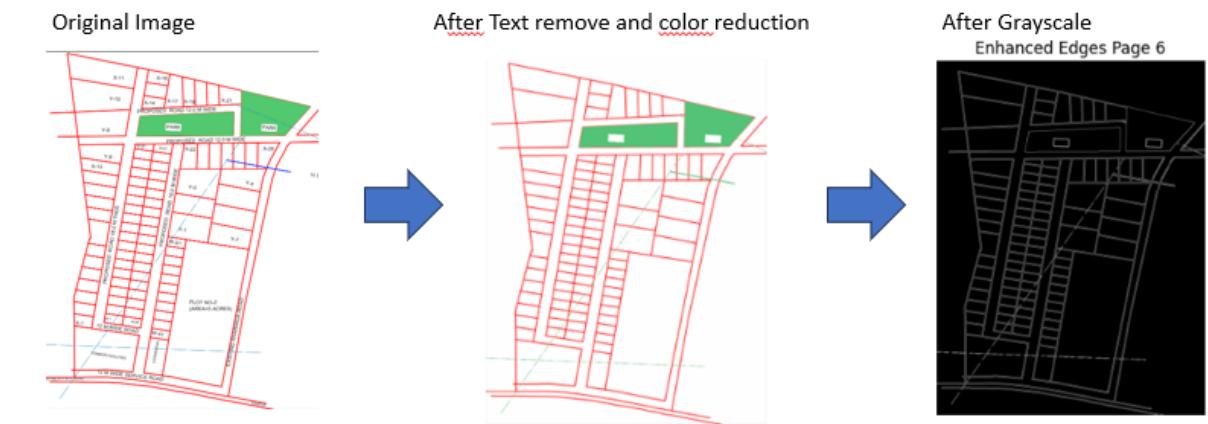


Fig.6: Data Preprocessing on Layout Plan of INDUSTRIAL AREA I, Etah

This process worked effectively on layout maps but performed poorly on satellite images due to noise (such as trees, off-roads, etc) as shown below in Fig.7.



Take aways: Layout are done

Search for appropriate technique for satellite images

Fig. 7: Comparing data preprocessing results in Layout Plan and Satellite image of I.I.D CENTER INDUSTRIAL AREA, Etah

### 3.3 Transfer Learning Setup

For the satellite image segmentation task, transfer learning was applied using a U-Net model integrated with a ResNet-50 encoder. The encoder was initialized with **ImageNet-pretrained weights**, enabling the network to leverage strong low-level and mid-level feature representations such as edges, textures, and structural patterns. The decoder was customized with **U-Net-style skip connections**, allowing the model to merge deep semantic features with fine spatial details.

The final output layer produced a **2-class segmentation mask**, distinguishing background from building and road regions. This configuration allowed the model to simultaneously preserve fine boundary information while capturing high-level contextual features, making it well-suited for urban structure and road extraction from satellite imagery.

### 3.4 Segmentation Model

The segmentation model is a U-Net with a ResNet-50 encoder. The encoder extracts hierarchical deep features while the decoder reconstructs pixel-precise segmentation maps through skip connections.

Training was performed using **Binary Cross-Entropy with Logits (BCEWithLogitsLoss)** and the **Adam optimizer** (learning rate 1e-5).

Data augmentation (random crops, flips, rotations) was applied to increase robustness and reduce overfitting.

Early training showed imbalance between background and foreground classes, leading to biased predictions. Improving annotations and training with balanced samples helped stabilize convergence and improve IoU performance.

### 3.5 Tiling and Deviation detection using SSIM

To compare the plan map and segmented satellite map:

1. Both were tiled into  $n \times n$  segments ('n' is user-defined).
2. SSIM computed similarity for each tile.
3. Tiles below threshold were marked as deviations.

All these steps of implementation are shown in Fig.8.

Thresholds for deviation:

- **<0.3:** High compliance
- **0.4–0.6:** Moderate deviation
- **>0.7:** Significant deviation

Compare each pixel of each tile with respective tile's pixel in other image map.

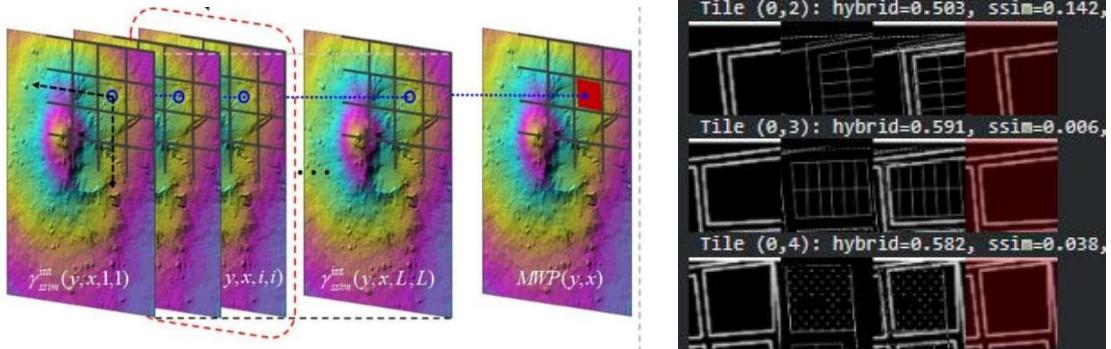


Fig.8: Tiling mention as in research paper [2] (on left) and our implementation (on right)

# Chapter 4 – Results

## 4.1 Segmentation Model Output

The U-Net with ResNet-50 encoder produced satisfactory segmentation masks:

- Building edges were identified (some sample results are shown in Fig.9).
- Road structures were clearly visible in several samples.
- Best results came from training on multiple versions of annotated masks.

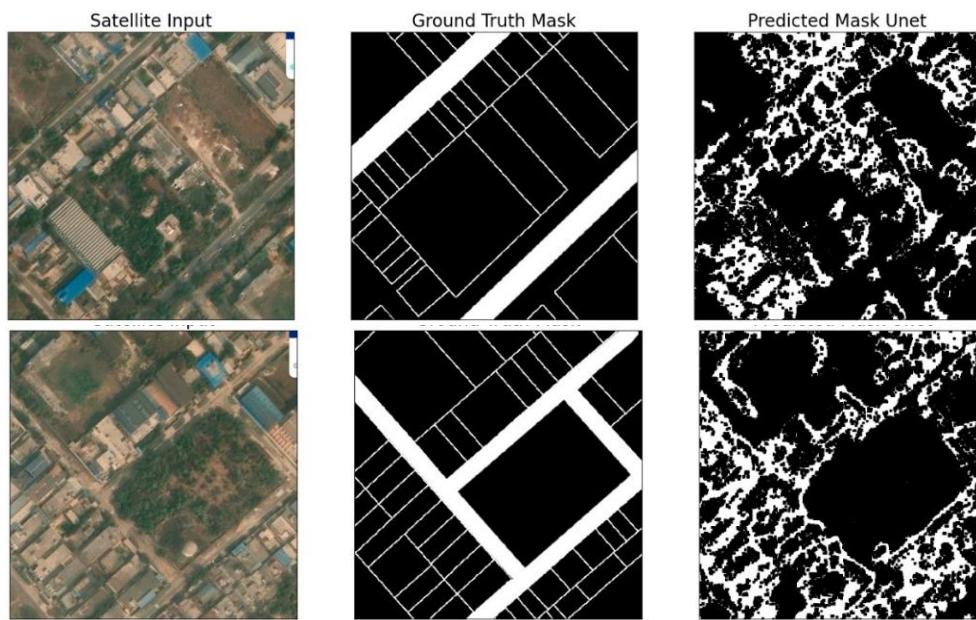


Fig.9: Images generated by U-Net with ResNet-50 encoder after Fine Tuning on our Alig\_Dataset

## 4.2 Deviation Analysis

From the graph in Fig.10, Residential areas show a deviation value of **55**, which is significantly higher than industrial regions (**32**). This finding indicates:

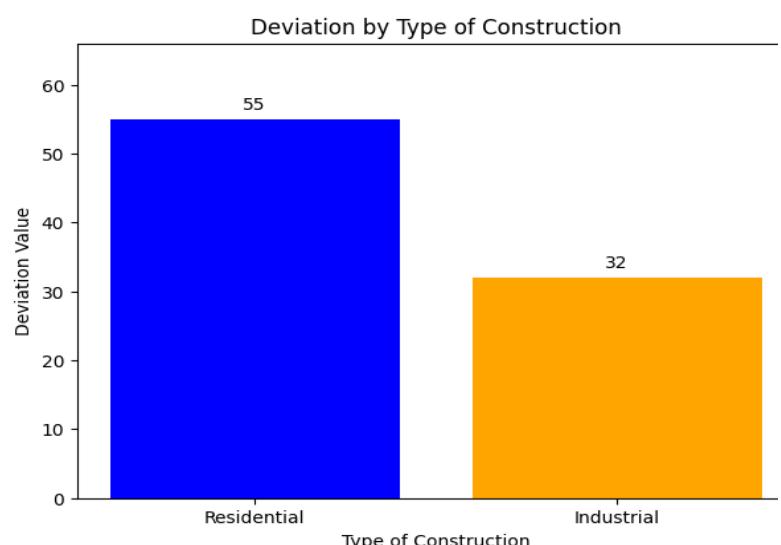


Fig.10: Comparing Avg deviation for Residential and Industrial maps

- **Residential regions undergo continuous transformation** over time by human settlement dynamics i.e. extensions, plot merging, floor additions & other changes in building footprints.
- Frequent redevelopment and boundary modifications **cause planned layouts to deviate** from the approved master plan.
- Conversely, **industrial sites show lower deviation** because construction is typically completed in planned phases and undergoes fewer structural changes post-development.
- Industrial plots also benefit from regulated access, limited boundaries, and fewer unplanned expansions.

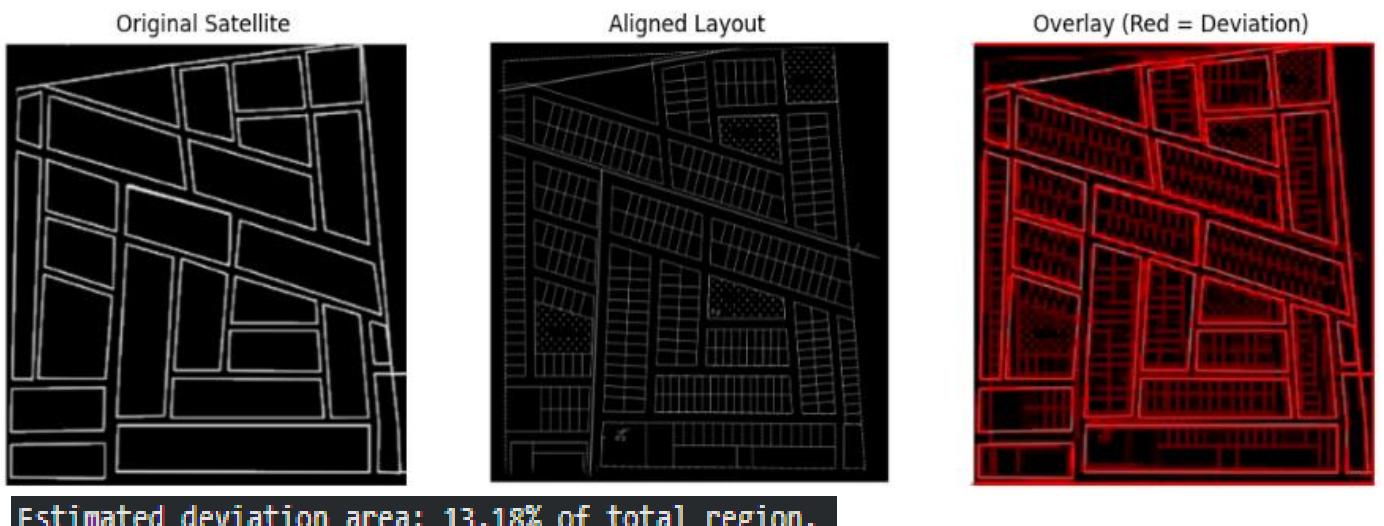


Fig.11: SSIM based deviation of Etah I.I.D CENTER INDUSTRIAL AREA, Etah

Deviation maps highlight mismatched regions and providing a visual interpretation of unplanned growth as shown in Fig.11.

# **Chapter 5 – Conclusion and Future Work**

## **Conclusion**

This study demonstrates the effectiveness of a multi-approach AI framework for detecting unplanned urban development. By combining K-Means preprocessing, U-Net semantic segmentation, and SSIM-based deviation measurement, the system offers a scalable and objective method for compliance monitoring.

It supports city authorities in:

- Identifying unauthorized construction
- Quantifying deviation from approved layouts
- Making informed urban planning decisions

## **Future Work**

- Expand labelled datasets for more accurate segmentation
- Incorporate higher-resolution satellite imagery
- Develop a real-time compliance dashboard
- Standardize threshold metrics across districts
- Automate document parsing directly from government PDFs

## **Bibliography**

### **Research Papers (Journals/Conferences)**

- [1] V. Kharat and S. Khatdeo, "Land cover clustering and classification of satellite images."
- [2] M. Kang and J. Baek, "SAR Image Change Detection via Multiple-Window Processing with Structural Similarity."
- [3] M. Papadomanolaki and M. Vakalopoulou, "URBAN CHANGE DETECTION BASED ON SEMANTIC SEGMENTATION AND FULLY CONVOLUTIONAL LSTM NETWORKS."

### **Datasets (Websites/Online Sources)**

- [4] B. K. (Balraj98), "**Massachusetts Buildings Dataset**," **Kaggle**. [Online]. Available: <https://www.kaggle.com/datasets/balraj98/massachusetts-buildings-dataset>.