

Deep Learning – Based Change Detection For Identifying Illegal Encroachments On Water Bodies

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Abstract: The fast pace of urbanization has resulted in extensive exploitation of natural resources, especially water resources, leading to environmental pollution, flooding hazards, and reduced biological diversity. The traditional monitoring processes that involve field visits, observations, and surveys require lots of efforts, can lead to errors, and are not suitable for wide-range monitoring. In order to overcome the limitations, the current project utilizes satellite imaging and machine learning algorithms to enable automatic identification of any unapproved constructions in water bodies. The presented algorithm uses the lightweight semantic segmentation U-Net neural network model to process satellite images captured by Google Earth Pro from 2010 to 2024. After undergoing the preprocessing stage consisting of image resizing, normalization, and enhancement, the data is used to train the model that detects any newly added construction objects within a specified water body. The approach offers a practical solution for detecting and monitoring any new structures developed in or around water bodies.

Key Words: Satellite Imagery, U-Net, Semantic Segmentation,

I. INTRODUCTION

Water features like lakes, rivers, wetlands, and reservoirs are vital in promoting ecological equilibrium, fostering biological diversity, and meeting various human needs like providing water for consumption, irrigation, and groundwater

replenishment. However, over the last few decades, accelerated urbanization, growing populations, and indiscriminate construction activities have resulted in considerable encroachment on these water bodies. Not only do such practices minimize the water storage capability of these water bodies, but they also cause environmental degradation, higher flood risk levels, and destruction of aquatic life.

Conventional means of tracking water resources include manual surveys, site visits, and government records. Such techniques are laborious, costly, and ineffective because they cannot be done in real-time. Besides, due to the large geographical area and the dynamic nature of urban expansion, it is nearly impossible to detect any form of encroachment using traditional strategies.

Thanks to developments in Geographic Information Systems (GIS) and remote sensing, satellite images have become indispensable tools in environmental assessment. OpenStreetMap platforms offer free geospatial information that can be used to map physical elements like water resources and their surroundings.

Herein lies a great opportunity for Deep Learning technologies, especially semantic segmentation neural networks. For example, the U-Net architecture was specifically designed to segment images by classifying pixels at a particular location and can be effectively utilized in medical imaging, land-use classification, etc. With its help, an image can be split into meaningful classes, like water, vegetation, construction, which

makes it a perfect tool for identifying illegal buildings near water reservoirs.

In this regard, we propose a novel framework combining GIS maps provided by OpenStreetMap with satellite image segmentation based on Deep Learning and more precisely the U-Net model. Our system will automatically analyze satellite images taken over several time periods and find any changes in their use and illegal constructions near water bodies. In addition, there will be a web-based interface that allows visualizing the result of the analysis and performing additional manipulations with it.

Our proposed system will fill the gap in current technology and help people to protect their natural resources with the aid of modern means.

II. LITERATURE SURVEY

U-Net architecture was first introduced by Ronneberger et al. [1] (2015) as a convolutional neural network designed for image segmentation. The model consists of the encoder-decoder paradigm with skip connections, which help locate objects precisely and provide contextual insight. Originally created for biomedical image segmentation purposes, the model proved very efficient even working on a limited data set. Due to its capability of pixel-level classification, U-Net became especially useful for satellite image segmentation into different types of land cover, including water bodies and constructed areas. The use of U-Net for this project becomes obvious at this point.

Fully Convolutional Networks (FCN) were proposed by Long et al. [2] (2015). FCNs were considered a breakthrough in semantic segmentation due to their ability to replace conventional fully connected layers with convolutional layers, enabling the network to deal with inputs of any size while generating spatially coherent outputs. Despite being more efficient and allowing for the end-to-end learning process, FCNs had issues related to coarse output and lack of fine boundary segmentation. For this reason, this type of model became less popular than the one used in this project (U-Net).

The work of Chen et al. [3] (2018) was used to create the DeepLab framework that utilizes atrous convolution and spatial pyramid pooling to provide multiple scales of context learning. High segmentation performance of DeepLab was provided by applying conditional random fields for refining boundaries. The

main drawback of the method is its high computational cost, which makes it impractical to use in lightweight applications. On the other hand, in the proposed research project, U-Net will be used instead, providing comparable accuracy and being less computationally expensive.

The paper written by Badrinarayanan et al. [4] (2017) discusses SegNet, which is an architecture based on encoder-decoder and provides for efficient and fast segmentation. Pooling indices are used in order to perform non-linear upsampling, thus saving the memory needed. SegNet can be successfully used in real-time situations; however, it is inferior in detecting fine spatial details when compared to U-Net, which is the reason why the latter is preferred for the current project.

Zhu et al. [5] (2017) gave an overview of deep learning methods used in remote sensing. The authors showed how convolutional neural networks were able to enhance land-use classification, object detection, and monitoring tasks in remote sensing.

In their research, Singh et al. [6] (2020) examined the possibilities of detecting the land-use and land-cover changes by analyzing multi-temporal satellite images. This paper considered comparing images obtained during specific periods of time as one of the ways to detect urban expansion and environment modifications. In spite of having successfully detected the changes in a big scale, the work did not involve deep learning algorithms and used conventional machine learning approaches.

Ghosh et al. [7] (2019) developed an algorithm for extracting water bodies using spectral indices such as NDWI. This approach allows obtaining high quality in the process of detecting water bodies. Still, in urban areas, this tool faces several difficulties due to the interference of buildings and shadows. The project uses deep learning algorithms and thus, can avoid the problem.

OpenStreetMap Contributors [8] (2024) is a geographic database developed in open sources and used for the creation of maps and other purposes associated with spatial data analysis. The data is gathered from different sources in a process called crowdsourcing and made accessible via APIs, for example, Overpass API.

Goodfellow et al. [9] (2016) provided a detailed review of the fundamentals of deep learning, including convolutional neural networks, optimization methods,

and training processes. The paper represents a theoretical basis that explains how deep learning algorithms behave and perform. Concepts presented in the paper are critical for the implementation and improvement of the U-Net model that will be used in the developed application.

Ji et al. [10] (2018) suggested an algorithm for detecting changes using convolutional neural networks and satellite imagery. The algorithm compares two images taken at various times to detect changes on a per-pixel basis. Although the approach was proven to be effective, the authors needed massive labeled databases and a lot of computing power to conduct experiments. The proposed project is based on the idea of Ji et al. (2018).

III. METHODOLOGY

The methodology of the proposed system will use geospatial data, satellite imagery, and deep learning methods to detect any illegal encroachment of water bodies. This system will follow a pipeline comprising data acquisition, data pre-processing, training of models, segmentation, change detection, and web application layer for visualizing results.

A) Proposed System Architecture

The system architecture involves five layers, which are as follows:

- Data Acquisition Layer
- Preprocessing Layer
- Deep Learning Layer (U-Net Model)
- Change Detection & Analysis Layer
- Web Application Layer

After data acquisition, preprocessing of the same is done in order to train machine learning models on data. The trained models will perform segmentation on the input data. Then change detection algorithm is applied to segmentations done in different time frames. At the end, we have an output visualized using web applications.

1. Data Acquisition

Data sources for the above-mentioned tasks can be classified into two categories:

a) OpenStreetMap (OSM) Data

OpenStreetMap gives real-time data of water bodies, roads, and buildings in the region. Data is collected by Overpass API

Helps in determining the exact locations of lakes and rivers

b) Satellite Imagery

Satellite images are obtained from websites like Google Earth Pro. Different images taken in different years are used to find any change occurred. They act as input to the deep learning model.

2. Data Pre-processing

Before passing data to the deep learning model, a number of pre-processing techniques are carried out:

- i. Image Resizing: All images are resized to be compatible with the model.
- ii. Normalization: Normalizing the pixel values of the image.
- iii. Creation of Annotations / Masks: The masks of ground truth regions like water, land, and built-up region are created.
- iv. Noise Reduction: The artifacts or distortion present in the image is removed.
- v. Data Augmentation: Applying transformations like rotation, flipping, and scaling to generate more data.

3. U-Net Deep Learning Model

At the core of our model lies the U-Net segmentation deep learning model that helps in detecting any sort of encroachment.

Architecture of U-Net

The U-Net model comprises two major components:

Encoder: The encoder helps extract features from the input image.

Decoder: The decoder reconstructs the segmented output using the skip connections that retain spatial information.

Working of U-Net

The satellite image as input to the model passes through several convolutional layers.

It extracts features like edge, shape, and textures.

The network classifies each and every pixel based on their class like:

- Water body
- Land
- Built-up area

Benefits of U-Net Model

- Accurate in performing segmentation
- Good results can be obtained with small amounts of data
- Spatial information retention

4. Model Training Procedure

The model training procedure includes:

- Dataset Preparation
- Input images and corresponding masks are matched.
- Training Settings
- Loss Function: Binary Cross Entropy/Dice Loss
- Optimizer: Adam Optimizer
- Evaluation Metrics: Accuracy, IoU (Intersection Over Union)
- Training Phase
- The model is trained through various epochs.
- Weight adjustments are made to reduce errors.
- Validation
- The model's performance is assessed based on validation data.
- Overfitting is managed through regularization strategies.

5. Image Segmentation

The trained U-Net model is used for image segmentation:

Satellite images are analyzed using the trained model.

The result is an image depicting:

- Water bodies
- Areas with encroachments
- Urban development zones

This segmentation paves the way for subsequent analysis.

6. Change Detection and Encroachment Assessment

For detecting encroachments:

Comparison between segmented images from various times

Detection of changes in urban development zones near water bodies

Expansion in construction zone is viewed as encroachment.

The software computes:

- Change in area
- Percentage of encroachment
- Risk category (low, moderate, severe)

7. Web Application Architecture

The system encompasses a web application interface for users.

Frontend

Designed using advanced web technologies (HTML, CSS, JavaScript)

Features:

- Dashboard
- Mapping
- Analysis and reports

Backend

Deals with:

- Data processing
- API calls
- Model incorporation
- Intermediary between frontend and database/ML components

Database

Stores:

- Geospatial information
- Processed outcomes
- User inputs

8. Visualization and Outputs

Outputs are shown as follows:

- Maps
- Charts
- Statistics
- Alerts for encroachments

Users can check their designated areas and view changes over time.

This aids in identifying changes in real-time.

IV. RESULTS AND DISCUSSION



Fig. 1. System dashboard showing monitored zones, alerts, and encroachment statistics.

A) User Dashboard

The dashboard displays current insights into the process of encroachments within monitored areas. These include different kinds of layers such as statistical insights, trends, warnings about priorities, and system status indications. Such an interface guarantees the possibility of timely identification of the level of violation of environmental conditions.

1. Key Performance Indicators (KPIs)

Monitored Zones (5)

the measure is used to calculate the number of current geographic locations subject to monitoring. It includes water bodies or environmental zones whose satellite images are processed by our system.

Active Alerts (2)

It reflects the number of current alerts on encroachment. They are triggered when there is enough deviation between historical and current satellite images to be considered a serious issue for further investigation.

Critical Risk Areas (1)

It refers to areas determined as critically endangered due to fast growth of encroachments. It is calculated according to changes within detected segments on the base of temporal segmentation and change detection.

Total Encroachment (12,245 m²)

This indicator is calculated according to the total amount of affected areas, which equals to sum of all pixel-based segmented areas from U-Net output.

2. Growth of Encroachments Analysis (2010-2024)

Central Graph shows the evolution of encroachment during the last 14 years:

The red line shows the cumulative area of encroachment in m².

Yellow line illustrates the number of active alerts each year

Main Takeaways:

- Increase in encroachment from 2010 to 2020 is visible.
- Since 2020, there is an abrupt increase, which points to rapid environmental damage.
- The system detects a +920% increase since the initial period.
- The connection between two metrics shows the efficacy of the algorithm used for identification.
- Analysis shows how long-term trends can be detected using continuous monitoring along with deep learning techniques.

3. Priority Zones

According to the dashboard, priority zones for intervention include:

Lake Vihar Buffer Zone — Critical

Mithi River Estuary — High

Priority zones depend on:

- Growth rate of encroachments Distance to sensitive ecosystem areas
- Violation history
- This way, resources will be allocated effectively by authorities.

4. System Status & Model Integration

Current system status: Model Online - U-Net v2

The integration of a deep learning model allows detecting encroached areas in a pixel-by-pixel manner using satellite images.

Data from U-Net model is continuously integrated into the backend system.

5. Additional Features

- Recently Flagged Scans
- Shows recent encroachment detections that require analysis.
- Activity Logs
- Records all activities and changes in the system, allowing for tracking.
- Navigation Pane

Allows the user access to:

- Real-time mapping
- Detailed analysis
- Image model inference
- Datasets used

6. Discussion

It is clear from the above visualization that the dashboard provides a good example of how deep learning-based image segmentation can be used in real-time analytics. The U-Net model plays an important part in detecting encroachment, while the web application presents this information to the user.

By showing spatial and temporal patterns in the data, the tool gives users a better understanding of the situation, which can be used in many applications. For example, the use of alert systems and risk classification in the tool makes it much more valuable for practical uses.

7. Conclusion of Result

Visualization of U-Net image segmentation results

- Real-time analysis and alerts
- Trends of encroachment increase
- Useful for protecting the environment

B) U-Net Segmentation Results



Fig. 2. U-Net segmentation output showing classified regions.

1. Monitor Map User Interface Overview

Monitor Map user interface features several surveillance zones at once, with each one related to a certain geographical zone. Satellite image inputs are analyzed with U-Net segmentation model that identifies the encroachment of zones and marks them accordingly. This UI merges maps with metadata features for efficient analysis of environmental conditions.

2. Zone-Based Monitoring System

Every card in the UI stands for the monitoring zone and includes the following elements:

Geographic Map

- Shows exact location of the monitored area on a map.
- Features latitude and longitude details for geospatial accuracy.
- Enables zooming and navigation for detailed investigation.

Identification of Zone

Sample zones include:

- Lake Vihar Buffer Zone
- Mithi River Estuary
- Coastal Wetland Park

Actual ecological or aquatic areas under surveillance.

Information Pane

Includes descriptions of the region like:

- Its significance for the ecosystem
- Types of risk (illegal settlements/industrial pollution)
- Monitoring purposes

3. Zones' Risk Classification System

Risk levels of encroachments within every zone are classified as:

CRITICAL – In case of severe encroachment detected.

HIGH – Increasing trends of encroachment in a significant way.

MEDIUM – Encroachments within controlled levels.

LOW – No or minimal encroachment detected.

The classification will be generated from the following:

- Output from Segmentation with the U-Net model
- Change rate in encroached area
- Trend analysis historically

Such a multilayered classification will enable the determination of priority regions in terms of the implementation of protective environmental measures.

4. Dynamic Filtering and Search Functionality

Dynamic filtering will be available in the interface:

- Show All Zones (5) – Show all monitored zones
- Critical, High, Medium, Low filters – Filter according to priority
- Search functionality – Help stakeholders search for the relevant zones by name
- This will increase the efficiency of users and assist them in focusing on high-risk areas.

5. Integration with the Deep Learning Model

- The Monitor Map functionality will be closely linked to the deep learning model, the tasks of which are:
- To classify satellite images at pixel level
- Detect regions encroached on by vegetation within water bodies
- Create spatial masks that can be geo-referenced
- Such outputs will then be used to create geospatially visualized risk indicators in terms of zones.

6. Create Custom Zones

Users will have the ability to:

- Add custom zones
- Monitor regions of interest regardless of their location
- Extend the reach of surveillance anywhere around the world

This will ensure that the system is scalable to other geographies.

7. Discussion

The interface of Monitor Map shows how successfully deep learning, geospatial analysis, and web-based visualizations can be combined together. With the help of segmentation results from the U-Net model and

interactive maps, we have managed to develop an efficient solution that will allow us to recognize illegal encroachments in any region.

The utilization of cards per zone allows people to understand spatial information without having any special training in remote sensing. The ability to include filters according to risk categorization improves the process of making decisions considerably.

8. Conclusion of Result

- Geospatial visualization of monitored zones
- U-Net segmentation results with GIS
- Risk classification

C) Encroachment Analysis Report

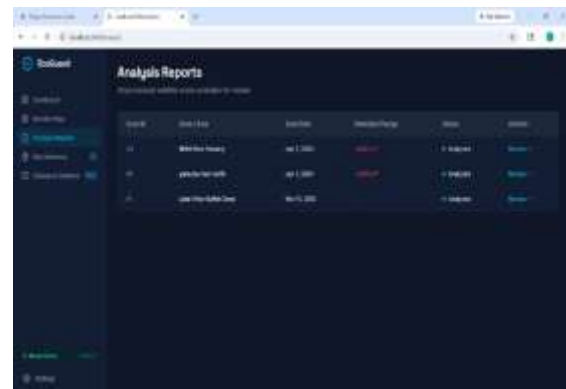


Fig.3 Analysis report demonstrating detected changes in encroachment in monitored zones.

In the Analysis Reports section, a structured report regarding the satellite scans that have been analyzed along with details related to any change in area due to encroachments in monitored zones can be seen. Details provided in each report include Scan ID, zone/area name, date of the scan, detected change in area and status of analysis.

It can be seen from the results that:

- Mithi River Estuary: Increase of +4142 m², demonstrating significant encroachment activity.
- Yamuna River North: An increase of +2403 m², which shows urbanization.
- Lake Vihar Buffer Zone: This acts as reference point without any change in earlier data.

All scans in the list have the status “Analyzed” meaning that the process was successful.

Interpretation

The result indicates that:

- Encroachments can be measured in square meters.
- Rapidly growing urban areas have been identified.
- Changes in various time periods have been recorded.
- Outputs have been generated systematically.
- The increasing trend in the detected change column proves urban growth around the areas near water bodies.

D) U-Net Segmentation Output



Fig. 4. U-Net segmentation interface showing classification of satellite image regions.

The Run Inference module allows users to upload satellite images and conduct real-time segmentation of the images through the U-Net deep learning algorithm. The program offers various file formats including PNG, JPG, and GeoTIFF for users to select their preferred data format.

A user can select custom images for uploading or use sample satellite images provided by the system. These sample images represent urban landscapes, wetlands, and lake areas. Once the user uploads the selected satellite image, the model analyses the image and produces a segmentation result.

The segmentation result includes categorized segments and their percentage values. In the presented case, the model classifies the selected segment into the following categories:

- Built-up area: 27%
- Road area: 17%
- Land area: 56%
- Water and vegetation: 0%

Interpretation

Based on the provided results, the selected segment is mainly an urban landscape with relatively high percentages of built-up and land areas. There is no water or vegetation segment in the selected region. This could mean that the area has been developed or lacks water bodies.

The U-Net model effectively categorizes the land-use segments, making it easier for the model to identify the encroached areas.

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