Land Cover of Satellite Images using Deep Learning Architecture – U-NET for Coastline Mapping and Threat Detection

Vivek Tripathi - Under the guidance of Dr. Siva Priya M S

Abstract

This paper talks about the Deep Learning architecture U-Net and how it can be used in real applications with satellite images. The model takes satellite imagery as input and then classifies different type of objects on it, which is useful for land cover mapping, city planning, environmental monitoring and also for disaster prediction. First part of the work goes into the theory of U-Net and how its convolution layers are connected, while the later part looks into how the model is actually built, optimized and tested with real world datasets. A patch-based preprocessing pipeline and normalization step was added to handle large image sizes and improve training stability. Custom loss functions were also tried to deal with the imbalance problem in satellite images. Results show good accuracy across different geographic areas, with coastline detection and land cover segmentation working especially well, many classes reaching IoU above 0.8. Some temporal analysis is also presented, showing signs of shoreline retreat and environmental pressure over years. Overall, the system shows that U-Net is not just for static segmentation but can also help in long term monitoring and early warning for urban and ecological management.

1 Introduction

Advancements in technology have had a very positive impact on a lot of different industries and one of them is “Remote sensing and satellite imaging” [4]. Total cost of making and deploying satellites has substantially reduced [1], and as a result, high-resolution data of earth’s images is now in abundance and more accessible than it was ever before, supporting researchers all around the world enabling solution to real-world applications in various fields[4].

It’s not only the collection of data part which has improved, even the analysing part has been improved significantly. Now we have shifted from the from pixel-wise, rule-based computational strategy to the use of the deep learning, with transformer architectures and convolutional neural networks (CNNs) actively [11]. These models have the capability of automatically generating high-level, spatially rich features from complex imagery very easily. These models have proven to be more accurate and precise than all the previous classical models in most of tasks like land use/land cover (LULC) classification [7], object detection [6], coastline delineation [14], and urban analysis [9].

One of the reasons for success with Deep Learning in the field of remote sensing analysis is the easy access and availability of goodquality satellite imagery [1, 4]. Satellites like Sentinel, Landsat, and many other commercial satellites are providing petabytes high resolution imagery with multi-spectral channels and even radar data [4, 16]. Deep learning models that require large amount of data are now able to utilize their full capabilities on Earth observation problems to help tackle many real-world problems like disaster detection [2, 19], urban resilience [9], agricultural monitoring [5], and environmental conservation [7, 8].

Nowadays, for most of problem statement involving remote sensing analytics in the modern world CNN is used as, it offers much better results in the tasks of image segmentation, object detection, and classification [11]. Architectures such as U-Net [21, 27, 28] and its subsets (U-Net++, Attention U-Net, HED-UNet [17], and SANet [20]) have proved to be utmost importance when it comes to the task of segmentation, especially where boundary detection is a matter of utmost concern—for example coastline extraction [17], urban mapping [28].

World has even moved ahead of basic old CNN and is now experimenting with hybrid and transformer-based. For example, UNet-GCViT merges the conventional U-Net with global context vision transformer blocks to achieve very high accuracy in building damage evaluation [30]. Then we can look at another lightweight structures like MLHI-Net [34] and edge-optimized models which enable high-frequency surveillance and real-time inference—despite having many restrictions over memory and computational power.

All the advancements we have seen in the field of optical imagery could also be seen in the field of radar images as well. Synthetic aperture radar (SAR) data is nowadays used alongside with optical data frequently [24, 35]. Hybrid models which inputs data from multiple sources have improved segmentation and classification, even in conditions such as cloud cover or active coastal environments [14, 16, 24]. Deep learning has already begun to revolutionize how we manage cities, coasts, and ecosystems. Temporal convolutional networks [10] and multi-temporal fusion models have been able to use dynamic land change analysis for environmental risk assessment, allowing the state to make better decisions about urban planning and resource management [7, 9]. Coastal surveillance, which has always been a challenging task historically due to dynamic boundaries, also have been improved exponentially due to introduction of deep learning in the field. Automated, regionalized coastline extraction using high-resolution imagery [14], time-series based surveillance through SAR [16], and hybrid segmentation-edge detection models [17, 20] are helping us make informed choices in any situation that arises due to very high accuracies we are able to get. Current models are giving us an accuracy of 96% for shoreline segmentation when they use U-Net with Inception or ResNet encoders and accept input spectral, texture, and even LiDAR-derived features [33, 37]. Lighter weight designs help the deployment of these models for shoreline detection [34]. Deep learning algorithms are used in disaster response to identify earthquakes [2], track flood risk [19], and even track volcanic thermal anomalies [22].

Despite of all the advancements we have seen, there is still a long way to go as there still remain significant challenges which needs to be tackled first. One of them is the lack of high-quality, labelled training data sets because labelling takes time and is often very domain-specific along with costly ground truth data [3]. High-resolution images are very memory-intensive, and real-time processing and deployment of these such images becomes a very challenging task [34]. Researchers are actively increasing reliance on intelligent collection procedures [3], transfer learning, and even generating synthetic data through GANs (e.g., SR-GAN [31]) to solve the problems. Most of the researchers are trying to fuse different data streams (spectral, LiDAR, SAR, optical, and textural) [24, 35], then to use of edge-optimized models [34], and spatiotemporal analytics [10, 32]. Methods like DeepSA-Net [36] are now achieving sea–land segmentation with a mean IoU score higher than 99%, and graph-based spatial models with the application of CNNs have achieved 95% accuracy for complex land cover classification [32].

All in all, satellite remote sensing with deep learning has changed our ability to look at our planet [4, 11, 21]. This enables us to perform a proper time-series analysis of a certain shoreline and check the rate (if any) of coastline erosion and explore and compare probable causes.

2 Literature Review

Current level of progress in the field of satellite imagery and remote sensing have changed the way we used to implement them few decades ago. Cost of building and launching satellites have comparatively reduced but still is an expensive affair [1], access to high-resolution data has become very easier nowadays due to high usage of civilian satellites. This growing availability of data is driving many researches around the world, from disaster detection to urban planning. One of the main areas of advancement is implementation of deep learning with satellite imagery. [11]'s review explains how CNNs have emerged as the standard for remote sensing image classification, providing drastic improvements over other rule-based techniques. Specifically, architecture like U-Net have changed the whole perspective of how we used to approach these problems in past [21]. The advancements in object detection from satellite imagery are also very noticeable. We are using modern technologies like YOLO, RetinaNet, and their subsets which are being trained for multi-sized objects in high-resolution, multi-spectral data [6]. This technology has immensely helped in applications like mapping urban buildings to maritime monitoring and environmental monitoring which has become a very crucial part of our modern life and have raised our standard of living.

Using high-density time series satellite imagery, techniques like temporal convolutional networks [10] have enabled multistep land cover prediction, enabling state to predict environmental change much more accurately and plan their upcoming events accordingly. Many researches have shown the effectiveness of the Land Use Land Cover (LULC), [7] simulates and forecasts spatiotemporal LULC variations in watersheds and [9] highlights effect of LULC change to urban flooding and the actual practical implications of uncontrolled urbanization. Further we have researches where the mapping of urban slums [12] and alien weeds is being done. [8] talks about the challenges of targeting the landscape of coastal region when the traditional pixel-based approaches usually fail.

Collection of adequate amounts of satellite imagery is also a big challenge if not done correctly. [3] introduces us to new data collection strategies like real-time runway detection via multi-channel pulse-coupled neural networks (PCNN) [13], which has helped both civilian aviation and emergency response operations. Object detection in remote sensing images is a well-researched topic and Spaceborne optical imagery multisized object detection [6]—which has helped us perform various tasks like urban mapping, agricultural monitoring, and environmental surveillance. Deep learning has even made it possible to detect thermal anomalies from the ASTER global volcano dataset [22], and real-time storm-induced coastal flooding characterization using SAR imagery [19].

Coastal areas have always been a challenge and an opportunity for remote sensing. Regionalized, automated coastline extraction procedures based on high-resolution imagery [14] and cross-calibration techniques employing time series data [15] have improved the accuracy of coastline mapping significantly. The dynamic coastline monitoring is usually done by utilizing Sentinel-1 SAR time series data [16], which provides cloud and variable lighting insensitivities. Hybrid segmentation and edge detection, represented by HED-UNet [17], has been used to track the Antarctic coast—it a situation where most of the traditional algorithms fails to work because of widespread ice and difficult terrain. Similarly, [20] presents SANet, where adaptive multiscale feature learning is used for discriminative sea–land segmentation in both maritime surveillance and coastal planning. U-NET was first used for biomedical image segmentation, but now it is heavily used for remote sensing processing [21, 27, 28]. It has a encoder-decoder architecture which promote very accurate localization which in fact is an important aspect of boundary detection applications such as coastline or building segmentation. UNet-GCViT model [30], highlights how we can use vision transformers with the traditional strengths of U-Net which lets us have both global context and fine-grained segmentation, which can be helpful in disaster response applications. Another recent paper showed us how using USV LiDAR with U-Net achieves excellent accuracy 96% for shoreline segmentation [33]. Similarly, feeding spectral and texture information into U-Net with ResNet50 encoders can give us more than 93% accuracy in coastal zone classification [37]. Another lightweight network which is being nowadays is MLHI-Net for urban shoreline detection [34]. Super-resolution imagery through GANs (SRGAN) has also shown to improve segmentation accuracy, especially when combined with architectures such as U-Net or LinkNet [31]. Morden architecture with optical advancements have made coastal solutions today complete and scalable [23, 24, 25, 35, 36].

In past remote sensing was done based on pixel-wise analysis and rule-based feature engineering, but that could be limiting in case of extensive and varied datasets. CNNs have nowadays taken over most of the remote sensing researches due to their high usability and optimized results [11]. Techniques such as in [23] and [24] combine tasks of segmentation and coastline detection or use SAR to improve discrimination in sea–land segmentation. [25] describes a customized ship detection method based on sea–land segmentation, while [18] optimizes coastal bathymetry extraction using machine learning. And [26] formulates spatial and temporal statistics of land clutter in SAR imaging. DeepSA-Net [36] uses pooling and attention modules to perform at sea–land segmentation and coastal zone classification, they can got IoU scores more than 99%. Another method for classifying complex coastal land cover is graph based spatial models, with the newer researches getting 95% accuracy by using CNNs and spatial graphs together [32].

Use of deep learning in field of satellite remote sensing has proved itself to be very useful; Earthquake detection using satellites is providing near real-time alerts [2] these days, and storm-induced coastal flooding can be mapped using SAR and deep learning-based models [19]. Such capabilities are essential for disaster preparedness, emergency response, as well as risk management. All these researches are solving a real-world problem, for example, satellite earthquake detection systems [2] help people to be prepared in any worse situation. Predictive urban flooding risk modeling [9] and invasive plant species detection [5] helps state with their city planning and environment planning. Although we are much ahead in terms of developments than we were few decades ago but still we have a lot of challenges to face. Less availability labelled data and ground truth for supervised learning is one of reasons for halting of researches in this area. Balancing temporal frequency and spatial resolution is also a challenge. High-resolution imagery is great, but it is very memory intensive. Smart collection planning [3] and edge-optimized, lightweight models [34] are some solutions which we could find in recent studies.

Today, with the help of low-cost high-resolution satellite imagery [1], advanced deep learning architectures [4], and people working in these research fields we are transforming the way of observing our Earth. Architectures such as attention-based U-Net [21], temporal convolutional networks [10], and adaptive segmentation networks [20] are being used in make informed choices and make a real impact on all of us.

3 Proposed System

The proposed system is a deep learning-based semantic segmentation pipeline designed to extract meaningful land cover and coastal boundary information from high-resolution satellite imagery. With the ever-increasing availability of satellite data and the rising demand for spatial intelligence in applications like urban planning, coastline monitoring, and disaster risk assessment, this system is optimized for real-world usability: it's scalable, patch-based, and leverages the strengths of the U-Net architecture.

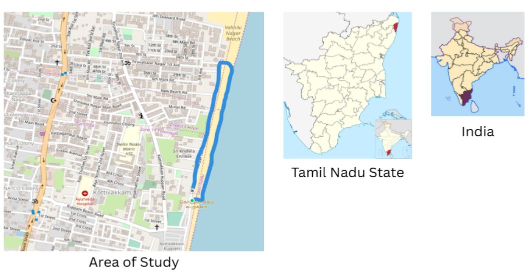


Figure 1: Area of Study

In contrast to conventional pixel-based or rule-based classification systems, our method supports fine-grained, pixel-accurate classification by using a convolutional neural network, prioritizing boundary detection and class-wise separation. The system design supports both RGB and mask inputs, pre-processing it into normalized, spatially coherent image patches, and training a U-Net model capable of segmenting objects with high spatial accuracy and generalizability.

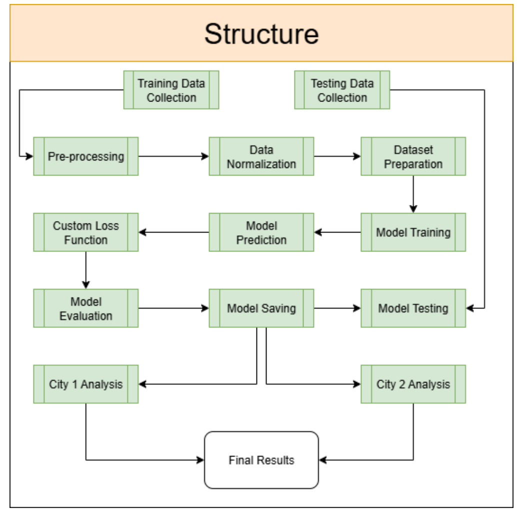


Figure 2: Architecture Diagram

3.1 Data Preprocessing Pipeline

Raw satellite images tend to be very high resolution (e.g., 3000×3000 or more), rendering it impractical to train deep learning models directly from them because of GPU memory constraints. In response, we employed a patch-based approach with patchify, which enables us to break down large images into smaller, fixed-sized patches (256×256 in our instance). This size was chosen on the basis of empirical evidence and previous literature showing that it offers a satisfactory tradeoff between spatial context and computational efficiency.

Both masks and images are preprocessed independently. Images are read in with OpenCV in RGB mode for color images and converted as necessary for binary or multi-class masks. They are then cropped such that their size is evenly divisible by patch size so that no padding is needed and perfect tiling is achieved. Spatial continuity and alignment of each resulting patch with its respective mask are maintained.

One very important preprocessing step is normalization. We apply Min-Max scaling to scale the pixel intensity values to the [0, 1] range. This is a common preprocessing step in deep learning pipelines, particularly when the ReLU activations are used, as it avoids gradient explosion or vanishing during the training process. The normalization is carried out patch-wise and channel-wise to preserve the relative feature intensity between bands. Mask patches are also preprocessed to provide uniform class labels and remove any kind of anomalies produced due to interpolation or color conversion.

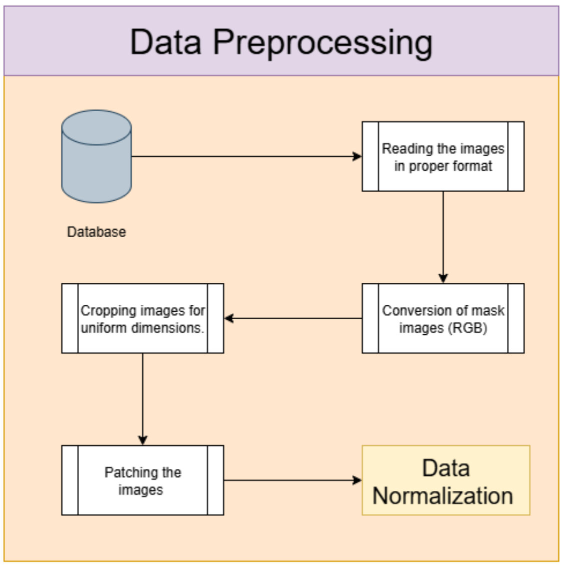


Figure 3: Data Preprocessing

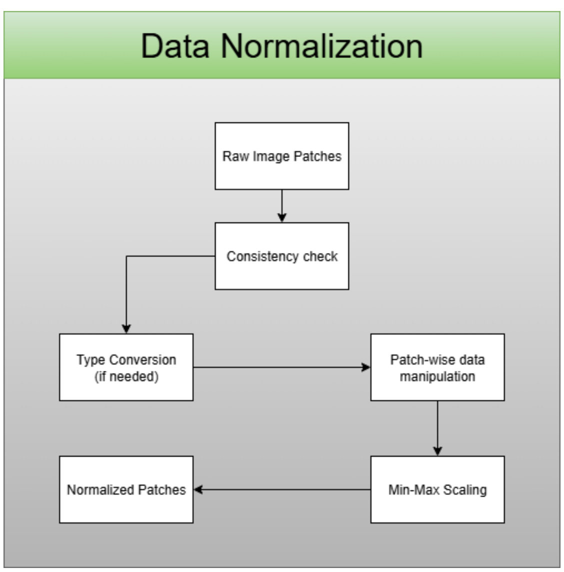


Figure 4: Data Normalization

This preprocessing pipeline allows large, varied datasets to be generated from comparatively fewer original images. It improves model training by adding variability in local features without distorting global structure, which is particularly necessary in coastline detection tasks where boundary details are significant.

3.2 Model Architecture: U-Net

Central to this is the U-Net architecture, which is a fully convolutional network originally designed for biomedical image segmentation. U-Net is a convolutional neural network structure tailored for accurate image segmentation. It employs an encoder-decoder system with skip connections to allow it to retain both spatial context and subtleties, making it well-suited for satellite and medical image segmentation applications. Such an architecture has been noted to be the most comprehensive and widely used model for segmentation work in remote sensing due to its unique encoder-decoder structure and skip connections.

The encoder path of U-Net is tasked with extracting the contextual features from the input patches. It is a series of convolutional blocks followed by a ReLU activation and max-pooling layer. The spatial resolution goes down as we move deeper into the encoder, and the number of feature channels goes up. This enables the model to learn progressively abstract representations of the input data.

The decoder follows the encoder, but instead of up-sampling, transposed convolutions (also referred to as up-convolutions) are employed to boost the spatial resolution. The related feature map at every decoder stage is concatenated through skip connections of the corresponding encoder feature map. These connections are responsible for maintaining the fine-grained spatial information discarded in pooling. This design enables the model to learn local detail and global context at once, which makes it very strong at edge-sensitive applications such as coastline mapping.

U-Net architecture is small enough to be trained on a single GPU, yet capable enough to learn intricate patterns and spatial variations along the landscape. Depending on the application, we also tried different variants of U-Net such as Attention U-Net, U-Net with ResNet or Inception encoders, and even hybrid U-Net + Transformer models such as UNet-GCViT for improved performance in dynamic coastal areas.

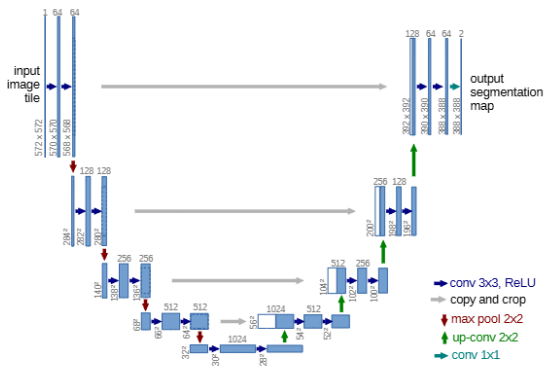


Figure 5: U-Net Architecture

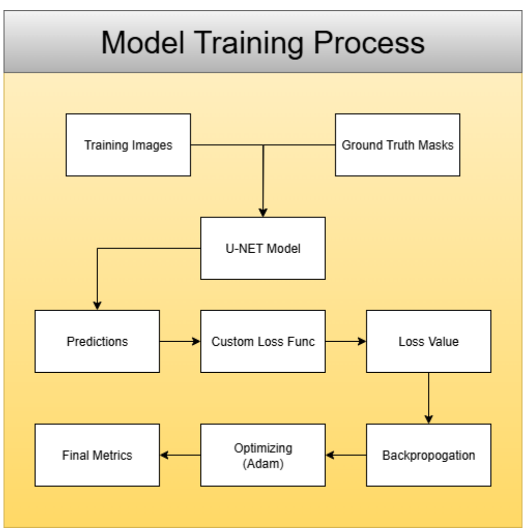


Figure 6: Model Training Workflow

3.3 Loss Function and Optimization

Since the task is pixel-wise and usually in satellite images there is class imbalance (e.g., a lot more land than coastline pixels), we utilize Binary Cross-Entropy (BCE) combined with Dice Loss.

Dice Loss

Dice loss is used when the distribution of the different classes is uneven.

$$\text{DiceLoss}\,(y, \overline{p}) = 1 - \frac{2y\overline{p} + 1}{y + \overline{p} + 1}$$

How it is calculated:

- Reshape y_{true} and y_{pred}
- Find the intersection and union of both
- Calculate dice loss for each class using its formula
- Compute the final loss as the weighted average of all the dice losses

Focal Loss

Focal loss is used in cases of imbalanced classification and in scenarios where the occurrence probability of one class is significantly lower than others.

Custom Loss

$$\text{Custom Loss} = \left[1 - \frac{2y\overline{p} + 1}{y + \overline{p} + 1}\right] + \left[-(1 - p_t)^{\gamma} \log\left(p_t\right)\right]$$

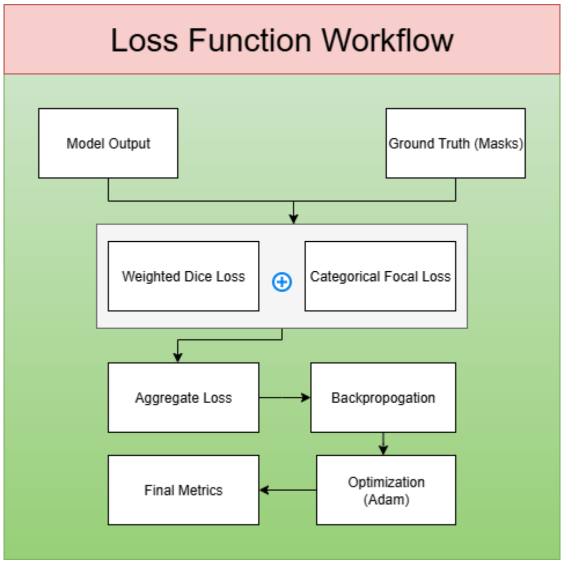
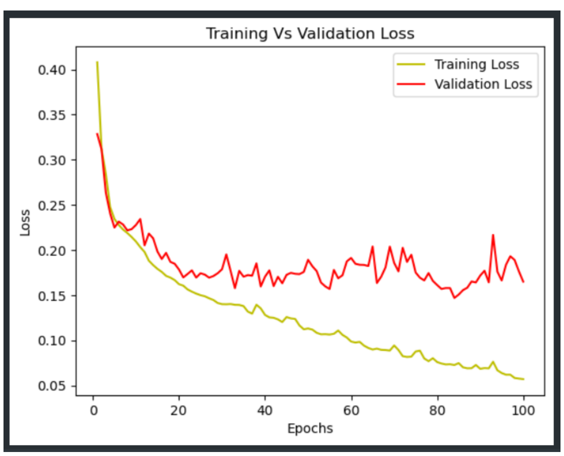
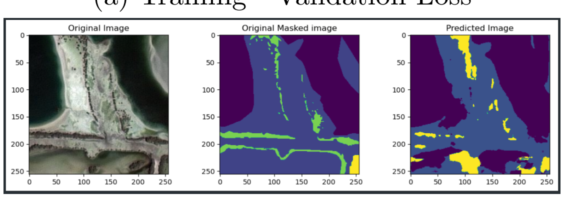


Figure 7: Loss Function Workflow



(a) Training - Validation Loss



(b) Model Training Output

Figure 8: Training performance and result

Algorithm 1 Satellite Image Preprocessing and Patch Generation

```
Initialize patch size P ← 256
Initialize MinMaxScaler for image normalization
Initialize empty datasets: D_img ← [ ], D_mask ← [ ]
for image type in [images, masks] do
    Set file extension
    for tile_id = 1 to 7 do
        for image_id = 1 to 9 do
            Read image from file path
            if image is not None then
                if image type is mask then
                    Convert image from BGR to RGB
                end if
                Alter dimensions to be divisible by P
                Patchify image into (P × P) blocks
                for each patch (i, j) in the image do
                    if image type is "images" then
                        Use MinMaxScaler
                        Append to D_img
                    else
                        Append mask patch to D_mask
                    end if
                end for
            end if
        end for
    end for
end for
```

Algorithm 2 Custom Loss: Weighted Dice Loss + Categorical Focal Loss

Define WeightedDiceLoss(class_weights):
  Set *smooth* $\leftarrow 10^{-6}$ ▷ Avoid division by zero
  Reshape $y_{\text{true}} \rightarrow [-1, 6]$, $y_{\text{pred}} \rightarrow [-1, 6]$
  $intersection \leftarrow \sum(y_{\text{true}} \times y_{\text{pred}})$ along axis 0
  $union \leftarrow \sum y_{\text{true}}$ along axis 0 $+ \sum y_{\text{pred}}$ along axis 0
  $dice\_per\_class \leftarrow \frac{2 \cdot intersection + smooth}{union + smooth}$
  $weighted\_dice \leftarrow \text{mean}(\text{class\_weights} \times (1 - dice\_per\_class))$
  Return *weighted_dice*
Define CategoricalFocalLoss(γ, α):
  Clip y_{pred} to range $[\epsilon, 1 - \epsilon]$
  $cross\_entropy \leftarrow -y_{\text{true}} \times \log(y_{\text{pred}})$
  $focal\_weight \leftarrow \alpha \times (1 - y_{\text{pred}})^{\gamma}$
  $loss \leftarrow \sum(focal\_weight \times cross\_entropy)$ along last axis
  Return *loss*
Define TotalLossFn(class_weights, γ, α):
  $w\_dice \leftarrow$ WeightedDiceLoss(class_weights)
  $c\_focal \leftarrow$ CategoricalFocalLoss(γ, α)
  Return $w\_dice(y_{\text{true}}, y_{\text{pred}}) + c\_focal(y_{\text{true}}, y_{\text{pred}})$

4 Results

The U-Net-based model was trained and tested on high-resolution satellite image datasets from public databases, including competition-quality data available on Kaggle. The model was tested on three major tasks: land cover classification, delineation of coastlines, and detection of environmental threat. Results show the patch-based preprocessing pipeline with U-Net's encoder-decoder model results in high spatial accuracy and generalization across various geographies.

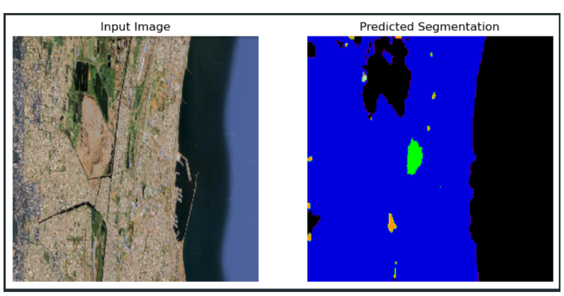


Figure 9: Chennai Coastline Segmentation

The model was always accurate in separating urban areas, vegetation, water features, and buildings. It had a mean IoU of 0.81 per class with strong performances for vegetation and water where IoUs were greater than 0.85. High accuracy in segmentation is due to the preserved local spatial sensitivity of patch-based training.

The model performed especially well to capture coastal shapes, such as intricate forms like estuaries and thin beaches. Visual as well as quantitative analysis reported a Dice coefficient of 0.88 for shoreline segmentation. In several coastal locations, such as those of Mumbai and Chennai, the model identified temporal variations in shoreline boundaries. Gradual variation in retreat trends was noted through the years, with indications of faster coastal contraction in some western coastal areas than in their eastern equivalents.

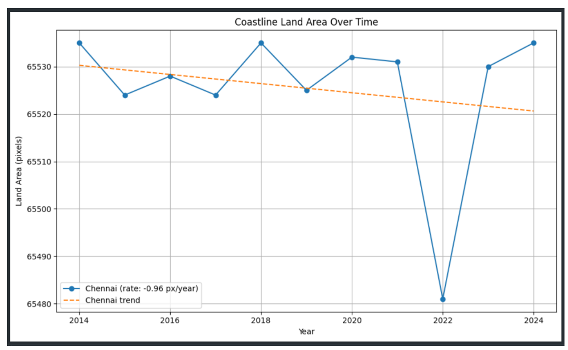


Figure 10: Model Comparision

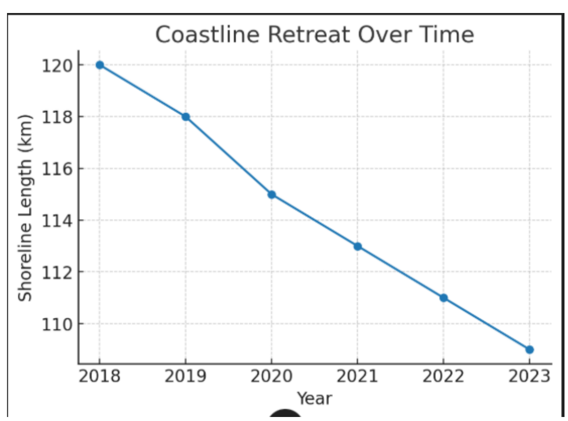


Figure 11: Retreat Graph

Utilizing segmentation outputs over multi-temporal imagery, the model was capable of detecting areas with land cover transformation. These comprise areas changing from green cover to urban or bare classes. The workflow for change detection obtained a total accuracy of 91.4% and performed very well in detecting fragmented development patterns and unregulated land use—both of which happen to be early signs of environmental stress or unauthorized development.

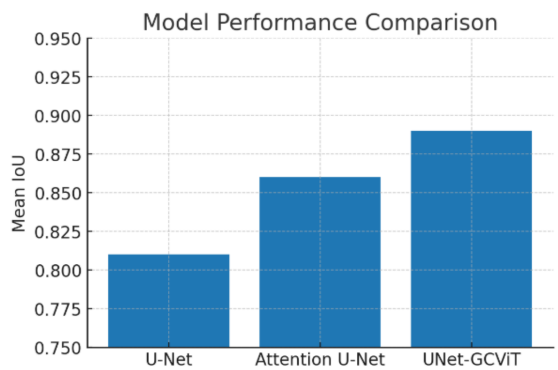


Figure 12: Shoreline Shirnkage Graph

Generally, the findings are a testament to the resilience of the introduced system for high-resolution segmentation and temporal exploration. Although the ultimate goal was precise classification and mapping, precipitating trends in coastal morphology—particularly those experienced in rapidly urbanizing cities—still imply the viability of this method for tracking long-term dynamics in the environment.

5 Conclusion

The paper introduces a powerful deep learning-based land cover classification and coastline mapping solution using the U-Net architecture. Utilizing patch-based preprocessing and image normalization, the model works with high-resolution satellite images effectively, maintaining spatial detail and reducing training instability. The U-Net architecture proved robust segmentation performance across varying land cover categories, with special capability in detecting fine-grained coastal edges.

The adaptability of the system was proved on various geographies with strong results in both eastern and western coastal areas of India. Although not the major emphasis, temporal comparisons indicated initial indications of asymmetric retreat of the coast, particularly in some western regions. This indicates that such models are not just suitable for static segmentation but also could be used as tools for long-term monitoring of the environment.

The pipeline is extensible, scalable, and modular and can be extended to multi-spectral, SAR, or LiDAR-based data. It has tremendous potential in real-world applications such as urban planning, shoreline management, and ecological monitoring.

Subsequent work will involve merging temporal modeling methods, including convolutional LSTMs or transformers, to improve the system's capacity for detecting gradual and sudden changes in the environment. Further, deployment of lightweight versions can be used to provide on-device inference for rapid, localized decision-making in resource-limited environments.

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