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DEFORESTATION DETECTION

Project Report submitted by

Singuluri Ratna Naga Swathi Sri Manogjna ***421257***
Vadla Sreenija ***421268***
Peteti Ram ***421240***

Under the supervision of

Mr.V.D.R.Raghuram Sarma
Adhoc Faculty

Department of Computer Science and Engineering,
National Institute of Technology, Andhra Pradesh

05/05/24

Department of Computer Science and Engineering

NATIONAL INSTITUTE OF TECHNOLOGY, ANDHRA PRADESH

Certificate

It is certified that the thesis entitled “Deforestation Detection” submitted by ”Peteti Ram, bearing Roll No: 421240”, ”Singuluri Ratna Naga Swathi Sri Manogjna, bearing Roll No: 421257”, ”Vadla Sreenija, bearing Roll No: 421268” to National Institute of Technology, Tadepalligudem in partial fulfillment of the requirements for the award of the degree of Master of Technology in Computer Science and Engineering is a record of bonafide research work carried out by him/her under my supervision and guidance. This work has not been submitted elsewhere for the award of any degree

Mr.V.D.R.Raghuram Sarma
Dept. of CSE

Place: Tadepalligudem
Date: May 5, 2024

July 18, 2024

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Chapter 1

Abstract

Deforestation which is primarily caused by human activities affects the ecosystem dangerously. So, detecting deforestation at a place by calculating the difference in deforestation areas at a place at different time stamps using machine learning algorithms helps to take certain measures to avoid the increase in the area of deforestation at a place. The proposed methodology consists of several steps: pretraining the detectron2 model using the chosen dataset, training the chosen dataset, testing the model by considering 2 images at different time stamps of a place and evaluating the model.

Chapter 2

Introduction

Deforestation is the removal of trees by human activities and this causes many climatic changes which will be harmful to living beings. It also increases the carbon dioxide percentage in the atmosphere which causes a threat to the lives of living beings as trees release oxygen by taking carbon dioxide from the atmosphere. Geographic Information System(GIS) is used to examine and visualize the spatial data to detect deforestation. Platforms like LandSat and Sentinel capture high-resolution images daily to detect illegal deforestation.

Machine Learning is used to detect deforestation through various techniques like Classification Algorithms such as Decision trees, random forests, and support vector machines, Convolutional neural networks are used to train the labeled dataset and to recognize the vegetation density, Feature Extraction used to extract the relevant features from the images and send them as input for classification algorithms, Change Detection used to detect the change in land cover in the region, Anomaly Detection used to identify the outliers in the satellite images to detect the illegal logging, Data fusion used to fusion of different data from different sources to increase the accuracy of the model, and Transfer Learning used to enhance the performance of the model by fine-tuning pre-training the dataset.

In this paper, we present the detectron2 model which accurately detects the deforestation area at a place by taking a satellite image as an input using the Roboflow deforestation detection dataset. This model captures the features of the satellite images and gives the annotations to the image to the classes(0-forested area,1-deforested area,2-landslide) and is further implemented to give alerts by comparing the difference of deforested area in images of a place at 2 different time stamps to the specific threshold value.

Chapter 3

Related Work

A model was performed by Hansen et al. in 2018 for detecting deforestation using convolutional neural networks on satellite imagery. The CNN model is trained on large datasets to classify the images into different land covers including forested and deforested areas. It is observed that this model detects deforestation accurately.

A model was performed by Huang et al. in 2019 to monitor tropical deforestation using LandSat time series stack remote sensing imagery. This research investigates the use of Landsat time series stack remote sensing imagery for monitoring tropical deforestation. This study evolve a comprehensive framework for examining temporal changes in landcover and vegetation dynamics, enabling the detection of deforestation over different time stamps and tells about the patterns of deforestation in tropical regions.

A model was performed by Belgiu and Dragut in 2016 to detect deforestation from satellite images using machine learning techniques automatically. This model tells about the use of feature extraction methods, such as spectral indices and texture analysis, combined with supervised classification algorithms, including random forests and support vector machines to detect deforested areas and evaluate their model to know how well their proposed methodology performs in identifying deforestation patterns in the study area.

In summary, the above works demonstrate the effectiveness of various approaches to detect deforestation. Our proposed model illustrates deforestation detection over different time stamps of the study area to give alerts to take required measures to avoid the situation of deforestation increase beyond the threshold value.

Chapter 4

Dataset

In the realm of image processing, we chose the Roboflow deforestation detection dataset which is provided by Prasad NR on the Roboflow dataset. This dataset consists of 3 different sets called train set, valid set, and test set. The train set consists of satellite images of various places and annotations of the respective images. The annotations are in coco-segmented file format in which a category ID is given to each class. The Classes considered are Forested area with category ID 0 representing forest area, Deforested area with category ID 1 representing deforestation area, and landslide with category ID 2 representing area of trees removed naturally due to landslide. The valid set consists of 26 satellite images of various places and annotations as labels to the respective images. The test set consists of satellite images of various places. The satellite images that are in the test set, train set, and valid set are different.

For the analysis of deforestation, we need the images from the dataset in two noted time stamps so that when we compare them we can determine whether some change has occurred between the two images. So we collected some pairs of images which are at two different time stamps among the deforested area and sent as the input to the model in the second step while we are comparing the change.

Chapter 5

Proposed Method

In this model, the deforestation need to be detected from the satellite images.After studying and learning about all possible ways In order to regularize for any kind of satellite image we decided to go with Computer vision techniques in order to identify the deforested area by processing the image.These computer vision techniques should deeply extract the features of the image and then identify the deforested area.The overall computer vision task which can this be categorized as is Image segmentation and RCNN is a suitable one for this task. In the identification of deforested area there is a biggest challenge that an area where the trees were not can also be due to some natural processes like rock movement which should not be termed as deforestation.So the model should be able to differentiate a treeless area whether it is due to human activities i.e deforested area or a area occurred due to some natural i.e landslide area.

So while implementing the R-CNN the brute force approach is that considering windows of all sizes and analyzing them for the objects.This itself takes a lot of time to consider every window.So there is a need of minimizing the windows .So to deal with this we consider starting from a pixel and slowly merge them from a small group based on texture which minimizes the windows number.We take nearly 2000 ROI's for an R-CNN.There is an another challenge here as we need to extract features in every ROI which is expensive this can be minimized by sending the whole image to a feature extractor and features were extracted. Parallelly,the image was the sent into a regional proposal network(RPN) which divides the whole image into ROI's.So when we combine both of them in this way.So making these changes to traditional R-CNN's fast,faster R-CNN's came into the picture.The problem with there models are the proper analysis and highlighting the correct segment is lacking which is very important in the case of deforestation as the tree distribution in not at all uniform.

So after researching all the techniques we have found that the best technique to deal with all these issues is Mask R-CNN due to its efficiency and accuracy.So our proposed method contains two steps. One is processing both the images and segmenting it as a deforested and landslide area using Mask R-CNN. The second step is to compare the deforested area between the two images collected at two timestamps.The final output need to be whether the deforestation occurred or region is safe.

Chapter 6

Methodology Techniques

We have applied the image segmentation on the satellite image using R-CNN initially. We have taken the input satellite images from the dataset as three sets namely train set,valid set and test.So during the training stage we have taken the input train set and preprocessed the data according to our usage. These input images are one by one taken out and are sent into the main part Mask R-CNN architecture.

As a first step the input satellite images are sent to the feature extractor which extracts the features like the tree cover and grass area and resultant feature map of the whole image is obtained.Parallely the image is sent to Regional Proposal network(RPN) which gives more than 2000 ROI's where there each pixel is made into groups smaller to larger depending based on the texture. Later both these ROI's and feature maps are combined to give image maps.Here we get some ROI's (both tree and tree less regions)mapped with respective features.These are now sent to a ROI align for wrapping and the alignment according to the input maps size which gives more accuracy than ROI_Pool where we apply max pooling directly.Now we have equal sized patches where there can be a chance of object each mapped with respective feature maps.

Now these patches are sent to a fully connected layer(a dense neural network) where the patches are trained to classify between deforestation and landslide classes. Also these patches are sent to another fully connected layer i.e linear regressor training different set of parameters for further refining the boundary box for locating the deforested area correctly as the tree distribution will not be uniform in a forest.Due to this we can take a less expensive RPN as we refine the boundaries anyways so we need not take too much effort using RPN which speeds up the process.

We also send patches into the main functionality of Mask R-CNN that is to identify the correct segmentation inside the boundary using detailed analysis as the segmentation need to be sharp edged in the case of treeless area detection as there might be many irregularities in the structure which need to be dealt well.So this Mask R-CNN captures the correct structure of the treeless region and classify them.This happen during training and the model will result in a output image as shown in Figure 1

While testing the image segmentation component we have used binary cross entropy loss for updating the parameters

$$-\frac{1}{m^2}\sum_{1\leq i,j\leq m}\left[y_{ij}\,\log\hat{y}_{ij}^{k}+\left(1-y_{ij}\right)\,\log\left(1-\hat{y}_{ij}^{k}\right)\right]$$

- y_{ij}: is The ground truth .
- $\hat{y}_{ij}$: is The prediction .
- k:is The indicator of a class.
- i: is The index representing specific instances or observations.
- j: is The index representing specific classes.
- m: is The number of classes or categories in the model.

Now after extracting these inputs we considered the area as a measure for deforestation.We have taken the mass of class-wise images and converted into an integer. We have considered these output images tried to find the area of these for both of the images in each pair.We have put certain threshold which indicates the notable area change between the two images collected in timestamp 1 and time stamp 2.We have calculated the difference between the areas and if it is greater than the threshold then it indicates the prone of deforestation or else it is safe.So finally the model outputs the change which it has detected.

6.1 Layers Used

Feature Extractor Layer: To extract the features from the whole satellite image the image is sent as an input to this feature exactor it extract the required features like forest cover,and land cover and grassland.
Regional proposal network: Inoder to divide the image into ROI's based on the object presence we use Regional proposal network which gives nearly 2000 ROI's for an ideal R-CNN

ROI align: In this layer the feature maps and ROI's collectively are sent into ROI align,it wraps the unequal sized images which outputs equal sized images.

Fully connected layers: The equal sized images are sent into fully connected layers(neural networks) which classifies the images into categories and also as the boundary regressor. which refines the boundary.

Convolution layer: This special layer is used to add the detailed analysis on the image segmentation which is very helpful to segment the forest area.

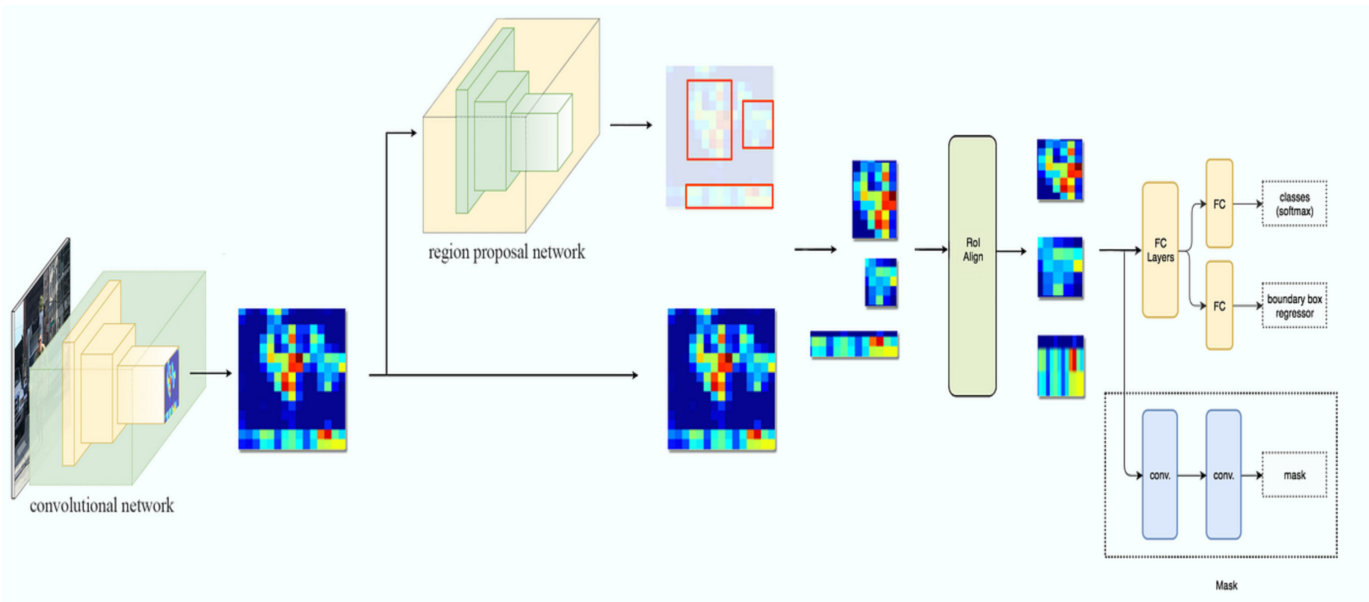

Figure 6.1: Mask RCNN Architecture

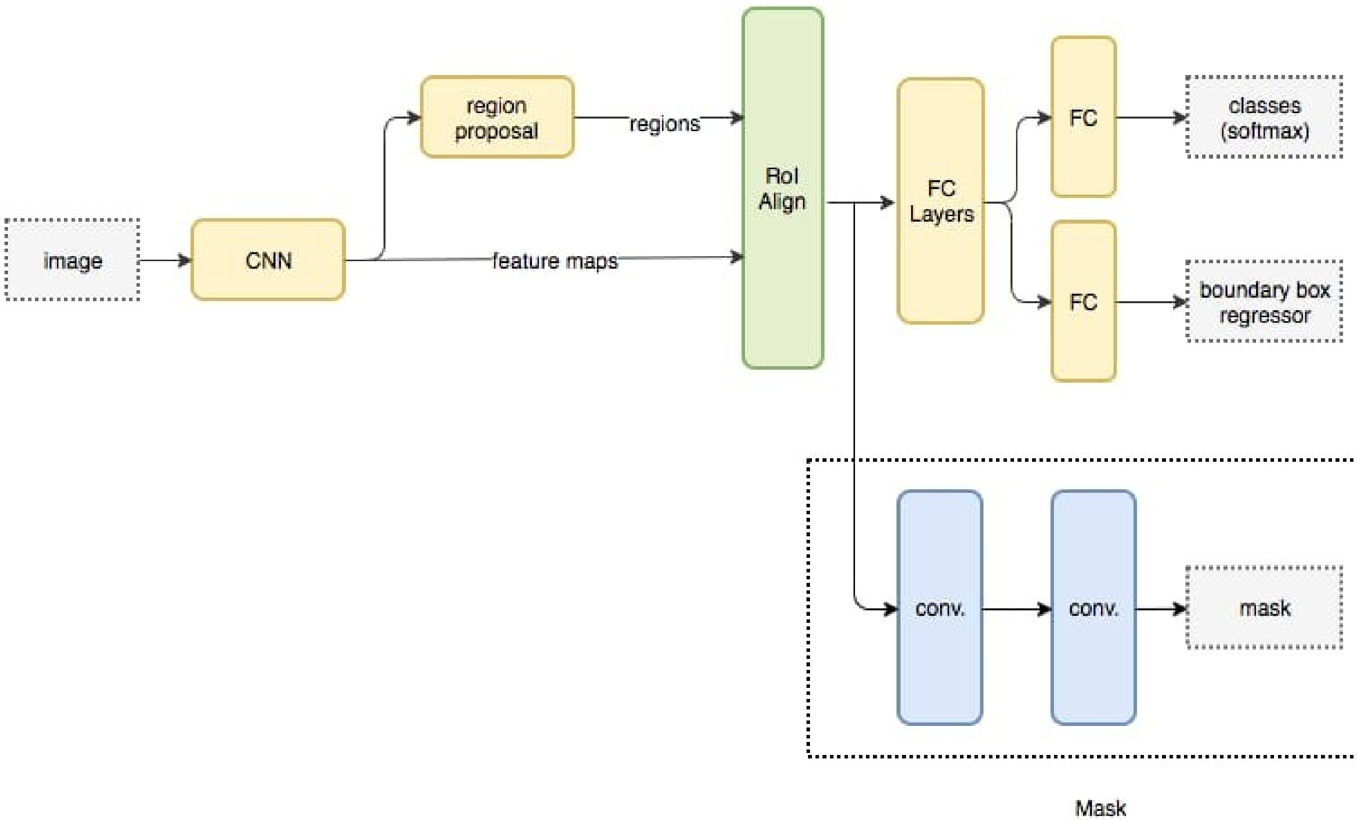

Figure 6.2: Work flow of mask RCNN

Chapter 7

Experimental Result And Analysis

To experiment with the proposed model, we considered 2 cases of examples, one that shows there is an alert message regarding an increase in deforestation at a place and another that shows there is no alert message regarding an increase in deforestation at a place.

Case 1: Here 2 images of a place at different time stamps are given as input and we got the deforestation areas of 2 images after going through the segmentation. Now we will call the check_deforestation_btw_time_stamps to check whether the deforestation area of a place has increased beyond the threshold value or not. In this case, we got the result as the deforestation area increased beyond the threshold value and it prints the alert message saying that deforestation is happening, take correct measures.

Case 2: Here also 2 images of a place at different time stamps are given as input and we got the deforestation areas of 2 images after going through the segmentation. Now we will call the check_deforestation_btw_time_stamps to check whether the deforestation area of a place has increased beyond the threshold value or not. In this case, we got the result as the deforestation area increased but not beyond the threshold value and it prints the message saying the place is safe from deforestation.

Analysis:
The model is evaluated on COCO dataset(Roboflow deforestation detection dataset). The evaluation metrics used Average precision and Average Recall calculated at different thresholds.

Bounding Box Evaluation('bbox'): Average Precision(AP) represents the area under the precision recall curve. AP50 is the Average Precision at IoU(Intersection over union) threshold of 0.5. AP75 is the Average Precision at IoU(Intersection over union) threshold of 0.75. AP-Forest, AP-Deforest, and AP-landslide are the Average Precision for specific categories like Forest, Deforest, and landslide.

Table 7.1: Evaluation Results for bbox

AP	AP50	AP75	APS	APm	AP1
60.073	85.718	61.907	90.000	68.086	60.998

Table 7.2: Per-Category bbox AP

Category	AP	Category	AP	Category	AP
Forest	nan	Deforest	76.174	Landslide	43.972

Segmentation Evaluation ('segm'): we got similar metrics for segmentation evaluation, including AP, AP50, AP75, APs, Apm, API, and category-specific metrics.

Table 7.3: Evaluation Results for Segmentation (segm)

AP	AP50	AP75	APS	APm	AP1
54.868	89.542	55.591	80.000	75.908	54.051

Table 7.4: Per-Category Segmentation AP

Category	AP	Category	AP	Category	AP
Forest	nan	Deforest	69.355	Landslide	40.380

Chapter 8

Conclusion

8.1 Conclusion

In conclusion, the proposed model detects the deforested area and then can also find whether increase in deforested area at a place over 2 different timestamps exceeds the threshold value or not with 69.35 as Average Precision.

8.1.1 Limitations

The spatial resolution might not be high enough to detect small-scale deforestation. Detecting deforestation in high-vegetative forest areas will be difficult.Also the forest area is not a regular surfaces there are different kind if Processing large amounts of satellite images demands high computational resources and expertise in remote sensing techniques.

8.1.2 Future Work

- We can design a website that monitors an area to detect deforestation by locating any region.
- We can use the proposed model to give alerts to the forest department.
- This model can monitor an area using satellite images and compare the deforestation area from day to day.

Chapter 9

Acknowledgement

The satisfaction and euphoria that accompany the successful completion of any task would be incomplete without the mention of people who made it possible, whose constant guidance and encouragement crowned our efforts with success. It is a pleasant aspect that we now have the opportunity to express our gratitude for all of them. We owe our sincere gratitude to our project guide Mr.V.D.R.Raghuram Sarma, Department of Computer Science and Engineering, National Institute of Technology Andhra Pradesh, who took keen interest and guided us all along, till the completion of our project work by providing all the necessary information. We avail ourselves of this proud privilege to express our gratitude to all the faculty of the department of Computer Science and Engineering at NIT Andhra Pradesh for emphasizing and providing us with all the necessary facilities throughout the work. We offer our sincere thanks to all our friends, fellow mates and other persons who knowingly or unknowingly helped us to complete this project.

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