"Semantic Segmentation of Satellite Images using Modified U-Net"

Bachelor of Engineering
in
Computer Engineering

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(Affiliated to University of Mumbai)

April 2022

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B.E. Project Report

Submitted in partial fulfillment of the requirements

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CERTIFICATE

This is to certify that, the project 'B' titled

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is a bonafide work done by

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and is submitted in the partial fulfillment of the requirement for the degree of

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University of Mumbai

Supervisor	Co-Supervisor
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Project Co-ordinator	Head of Department	Principal
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Project Report Approval for B.E

This is to certify that the project ‘B’ entitled ***“ Semantic Segmentation of Satellite Images using Modified U-Net ”*** is a bonafide work done by ***Ms. Dhanishtha Patil***, ***Ms. Komal Patil***, and ***Ms. Rutuja Nale*** under the supervision of ***Dr. Sangita S. Chaudhari***. This dissertation has been approved for the award of ***Bachelor’s Degree in Computer Engineering, University of Mumbai***.

Examiners :

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Date : . . . /. . . /. . . . . .

Place : . . . .

Declaration

We declare that this written submission represents my ideas in my own words and where other's ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

Ms. Dhanishtha Patil	**Roll No. 1**	____________________
Ms. Komal Patil	**Roll No. 2**	____________________
Ms. Rutuja Nale	**Roll No. 3**	____________________

Date : . . . /. . . /. . . . . .

Abstract

Detecting roads, regions, vegetation-flora, and evidence of water resources in regions is essential for the long-term development and enhancement of remote areas around the world. Despite the fact that deep neural networks have made tremendous progress in the semantic segmentation of satellite pictures, the majority of present techniques yield unsatisfactory results. The challenge of retaining the quality of semantic segmented pictures is addressed in this study by presenting a unique combination of architecture. The segmentation model offers a solution for generating automatic area segmentation and shows high accuracy for six classes: Building, land, road, vegetation, water, and miscellaneous. The model is trained on Dubai Satellite imagery dataset of MBRSC. For achieving the best performance we augmented the dataset and trained the augmented data where Shift, scale, and rotate transformations were applied to the satellite images and segmentation masks. This baseline U net model modifies U-Net's encoder by employing the Inception ResNet V2 model to have enhanced mathematical and structural complexity. The model is further evaluated using the Dice coefficient and pixel accuracy which came out to be 82 percent and 87 percent respectively in validation samples.

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Chapter 1

Introduction

1.1 Overview

One of the most effective and significant resources is satellite imagery. These photos reassure forecasters about the behaviour of the environment because they show how events are occurring in a straightforward, succinct, and precise manner. Rather than classifying an entire image based on a label, image segmentation includes detecting and classifying individual objects within the image. In addition, semantic segmentation varies from object detection as in that it determines the contours of objects within an image at the pixel level whereas in object detection only an object is detected with a boundary outline to the object. Image segmentation allows us to decompose an image into meaningful parts and understand a scene at a more granular level. Satellite image semantic segmentation is a pixel- wise classification task for a satellite image. In Semantic segmentation expresses the way of identifying each pixel of a particular image along with a class label, such as road, building, river, or trees. Satellite image segmentation, used to locate objects and boundaries in images (straight lines, curves, etc.), refers to the division of a digital image into multiple pixel sets. In this project we have proposed the modified U-Net model. UNet employs a very unique loss weighting scheme for each pixel, with a higher weight at the segmented object's boundary. U-Nets can learn in environments with small to medium amounts of training data. This fundamental U-Net model improves the mathematical and structural complexity of U-Net's encoder by using the Inception ResNet V2 model.

1.2 Objective

As the processing of the entire image is not successful image segmentation segments an image into sub regions of our interest and then those areas can be analyzed individually. For this, there are several techniques that partition an image into segments based on certain features such as color, texture, strength of pixels etc. The categorization of techniques is carried out and depending on the mechanism used. The problem statement here in this case is that the images obtained from the satellite are segmented and the roads, buildings and natural resources present in the image need to be detected.

1.3 Motivation

Satellite image semantic segmentation, including extracting roads, detecting buildings, and identifying trees, crops, rivers, is essential for sustainable development, agricultural development, forest reservation, urban planning, We are thus motivated into building a model which is useful for sustainable development and urbanization. Our goal is to use modified U-Net model and semantic segmentation techniques and build a predictive model that can detect the five classes that we are working on that are buildings, trees, rivers, roads, crops.

1.4 Organization of report

The remainder of this report is organized as follows. Chapter 2 will provide a brief review of related works. Chapter 3 will elaborate details of the proposed system. Chapter 4 provides the schedule of the project and detail plan of execution. Chapter 6 and 7 will conclude our work.

Chapter 2

Literature Survey

2.1 Survey of Existing System

A survey of the research done for the image segmentation of satellite images, give the following results.

1. “Understanding Convolution for Semantic Segmentation” [1]
   In this research paper, Convolutional neural networks (CNNs), have resulted in variant gains over previous developed systems. They have demonstrated the enhance pixel-wise semantic segmentation by understanding theoretical and realistic convolution-related methods. Also, they created dense upsampling so as to make a pixel-by-pixel projection, this is capable of capturing and decoding more comprehensive statistics than bilinear upsampling. While, in the encoding process, they have proposed a hybrid dilated convolution (HDC). The architecture done in this paper has two features firstly, the model, for one, effectively expands the network’s receptive fields (RF) to aggregate global data, and for another, it eliminates the ”gridding problem” caused by the standard DC activity.

2. “Semantic Segmentation based Building Extraction Method using Multi-source GIS Map Datasets and Satellite Imagery” [2]
   In this paper they have executed building extraction process. For high-resolution satellite images, they have made use of semantic segmentation and ensemble learning-based building extraction process. To upgrade the extraction performance, they used public GIS map datasets which were combined with multispectral WorldView-3 satellite datasets. They have achieved an average estimation score of 0.701 on the test datasets. For the training phase, provided annotation files are transformed into pixel labels so as to conduct

supervised learning process.

3. “Super-Resolution Integrated Building Semantic Segmentation for Multi-Source Remote Sensing Imagery” [4]
   In this paper, they proposed a set for creating semantic segmentation using multi-source spatial data imagery. They have proposed to incorporate SR techniques with the current system to improve segmentation efficiency, as opposed to previous works that primarily concentrated on improving the model, which did not allow significant issues resulting from misaligned resolution between training and testing sets to be substantially resolved. Rather than simply segmenting buildings from LR imagery using the model trained on HR imagery, the deep learning-based super-resolution (SR) model was first utilized to super-resolve LR imagery. It resolved it into SR space, minimizing the impact of the resolution mismatch between training sets and testing sets.

4. “Attention Guided Encoder-Decoder Network With Multi-Scale Context Aggregation for Land Cover” [6]
   This paper covers about the difficult task of Land cover segmentation as it is important in the remote sensing field. The other merit models in remote sensing photos, it’s challenging to capture global information and long-range interdependence, despite the fact that convolutional neural networks (CNNs) provide excellent hold up for semantic segmentation. So, they have gave an idea of attention driven encoder-decoder network with variational background aggregation to overcome these limitations and achieve more accurate land cover segmentation. They have also added a variational function fusion module with two attention modules to the top of the encoder based on the configuration of the encoder-decoder network. The multi-scale feature fusion module is used to combine multi-scale features and capture global correlations. The attention modules are utilized to take benefit of the long-range dependencies and interdependencies between channels from a perspective standpoint.

5. “Segmentation of Satellite Imagery using U-Net Models for Land Cover Classification” [7]
   This work investigates a modified U-Net convolutional machine learning model. Convolutional models for autonomous land/area cover mapping were trained and tested. Also, to see how effective they are at improving land/area cover mapping accuracy and change detection. The dataset was created and the model was trained for classification of land or area cover and segmentation of satellite pictures using semantics. As one of two main

datasets Big-Earth-Net satellite image was used in this paper. The results of the models showed a possibility of enhancing the accuracy of existing system of land classification maps and in land cover detection.

6. ”Towards Accurate High Resolution Satellite Image Semantic Segmentation” [8]
In this paper, they have explored the attention dilation-LinkNet (AD-LinkNet) neural network. For semantic segmentation, it uses an encoder-decoder architecture, serial-parallel combination dilated convolution, channel-wise attention mechanism, and a pretrained encoder. The outcome on road detection and surface categorizing datasets have proven that the AD-LinkNet that the segmentation accuracy has a significant effect on improving it. They’ve also devised a data processing and transfer learning strategy to minimise the picture semantic segmentation task’s semantic label needs in the satellite zone. They used LinkNet as the basis model for refined semantic segmentation and use already trained ResNet so as to encode and execute transfer learning. They also created a combined module AD-LinkNet, by using the useful properties to perform easy and effective semantic segmentation of satellite images.

7. ”Hybrid first and second order attention U-Net for building segmentation in remote sensing images” [9]
The paper explores the hybrid first and second order attention network (HFSA). To adaptively rescale intermediate features HFSA explores both the global mean and the inner-product among different channels. HFSA completely utilizes of first order statistics, and it also incorporates the next order feature statistics, which guides to additional expressive, understandable and discriminative features. The method proposed in this paper gives the idea of developed HFSA network which is not only efficient but it also achieves better segmentation performance than base model for building segmentation.

8. ”Application of U-Net fully convolutional neural network to impervious surface segmentation in urban environment from high resolution satellite image” [10]
The paper explores the image classification algorithms which are used to map impervious surfaces from remotely sensed imagery. The surface type is complicated because it is made up of several different materials, so image classification and aggregation techniques are commonly used to map it. This research investigates the use of fully convolutional layers (FCNN), particularly U-Net, to map these complicated features at the pixel level from high quality satellite data. When compared to automated goods, the preliminary findings are positive in both qualitative and quantitative assessments. This study demon-

strates the effective outcome of a UNet FCNN to spatial and spectral landsite images in an urban scenario for mapping impermeable surface characteristics. The FCNN will account for the meaningful and subtle spectrum connections of such functions using the method described in this paper, not at the maximum spectrum level of the raw data.

9. ”Inception-v4, inception- ResNet and the impact of residual connections on learning.” [11]
   They have compared the two pure Inception variations, Inception-v3 and v4, with similarly priced hybrid Inception-ResNet versions in this study. Those models were chosen haphazardly, with the key limitation being that the parameters and computational complexity of the models should be comparable to the cost of the non-residual models. They also showed many new streamlined Inception network topologies, both residual and non-residual. On the ILSVRC 2012 classification challenge, these modifications considerably improve single-frame identification performance. This also indicated how correct activation scaling helps to stabilise the training of very large residual Inception networks. On the test set of the ImageNet classification (CLS) challenge, they achieved 3.08 percent top-5 error with an ensemble of three residual and one Inception-v4 networks.

2.2 Limitations of Existing System

1. Because the resolution is quite high, satellite databases are large, and image processing (generating meaningful images from raw data) is time-consuming, the dataset must be pre-processed.

2. Another constraint is that methods for effective data utilization and extraction of meaningful information from remote sensing data are still limited, as no one sensor combines the best spectral, spatial, and temporal resolution.

3. In remote sensing, there are currently a lack of software tools for extracting usable insights from remote sensing data.

4. To make the best use of remote sensors and extract the most usable information, new and improved data fusion methodologies are required.

2.3 Problem Statement

Semantic segmentation using the modified U-Net model is a deep learning based idea. The aim of our project is to find a solution for semantic segmentation of water resources like river, sea; land resources like buildings, trees, etc. from satellite images by applying semantic segmentation. The approach of semantic image segmentation is to label every pixel of a particular image with a appropriate class of what is being depicted. Since we are predicting each pixel in the image, dense prediction is the term used to describe this task. The output is a high-resolution image (usually the same size as the input image) with each pixel categorised into a different class. As a result, it is a pixel-by-pixel image description.

2.4 Scope

Analysing any satellite image without the help of any software is tricky. Also it is difficult to breakdown the satellite images into various pixels so as to analyse it. Semantic segmentation technique gives us the ability to do it quickly and using appropriate model with proper layers helps one to analyze the geographical area present in the satellite image. By analysing this it will be helpful to detect whether there is need for urbanization or not, or whether water resources in a particular geographical land is present or not.

Chapter 3

Project Proposal

3.1 Proposed Work

The encoded/decode architecture is proposed, in which we reduce the spatial resolution to lessen computing complexity, the network learns lower resolution features, and it appears to be efficient. Finally, the architecture generates a full-resolution segmentation map by upsampling the feature representations. Most research projects end up choosing U-Net design after going through many architectures. The U-Net architecture is considered mentioned in figure 1 to be intended for semantic segmentation. The segmentation model Modified U-Net, was built using

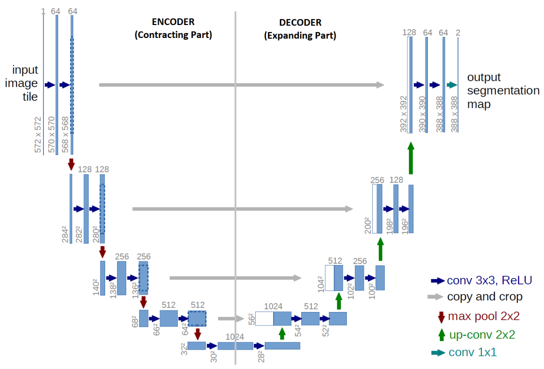

Figure 3.1: U-Net Architecture

the U-Net architecture with Inception-ResNet-v2 blocks integrated. The inception-Resnet-v2 architecture was utilized as a contracting path of U-Net in the U-Net Inception-Resnet-v2 design. Multiple sized convolutions are blended utilizing residual connections in the Inception-

Resnet block. The deterioration problem was avoided, and the training time was shortened due to the residual connections. In Modified U-Net Inception Resnet v2 replaces the contracting section of U-Net architecture, with the stem block as the major component, followed by five inception Resnet A layers and a reduction A layer.

3.2 Proposed Methodology

To classify the five classes with good accuracy we proposed a modified model of U-Net architecture. This modified U-Net model consists of U-Net as well as Inception ResNet-v2. As mentioned above, there are five inception Resnet A layers and a reduction layer. 10 layers of Inception Resnet B and reduction B layer is included and concluded with 5 layers of inception Resnet C. The Residual connection and the Inception framework have been combined to create Inception Resnet-v2. The ResNet-v2 model has been adapted into the Inception-ResNet-v2 model.It features linkages from an encoder to a decoder in the middle, as well as a concatenation of feature maps that aid in providing more localization information. The former employs the latter's convolution 3x3 and convolution 1x1 techniques, as well as a variety of inception blocks. This approach is intended to replace a single high-convolution dimensional filter with numerous lower-convolution blocks while maintaining the data's dimension. The expanding pathway entails repeated upsampling of feature maps via up convolution of clipped feature map concatenation from the contracting channel. Two 3x3 convolutions and a rectified linear function are then applied. For categorization, the end is later joined to a fully connected layer combining the whole as Modified U-Net. The predictions are encoded and decoded using one hot encoding across the model corresponding to RGB Labels used for representing classes. Figure 2 represents steps for network exploration used in model.

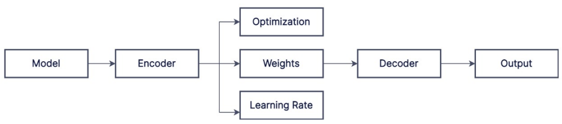

Figure 3.2: Network Parameters

3.3 Details of Hardware/Software Requirement

3.3.1 Colab

Colab is a web-based Python editor that allows anyone to write and run arbitrary Python code. It's notably useful for machine learning, data analysis, and education.

3.3.2 Dataset

The dataset is made up of MBRSC satellite imagery of Dubai that has been annotated with pixel-by-pixel semantic segmentation. It's a high-resolution data collection with 72 distinct images evenly distributed over six different classes. Each image has been masked into 6 different classes Building, land, road, vegetation, water, and miscellaneous which represents different color codes for various classes.

3.3.3 Training GPU

The model was trained for 50 epochs using 16 picture batches for each epoch. After each period of training, the networks were evaluated to see how much of a difference there was between training and validation performance, in order to look into over-fitting owing to a lack of variation.

Chapter 4

Planning And Formulation

4.1 Schedule for Project

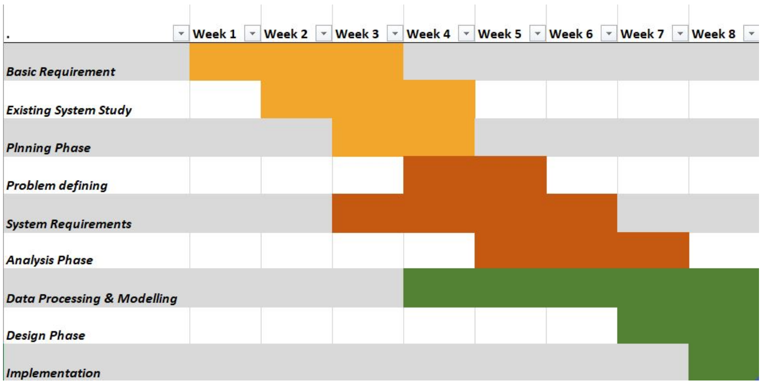

Figure 4.1: Ghantt Chart

4.2 Detail Plan of Execution

- **Basic Requirement**: In March, we gathered basic requirements that will be needed for this project.
- **Existing System Study**: We went through previously worked models so as to analyze which model works better and what difficulties they went through while developing the model.
- **Planning Phase**: Project's functionalities and how to implement it was decided in this phase.

- **Problem Defining**: We formulated the necessary things that we will be working on in whilst defining our problem(problem statement).
- **System requirements**: Hardware and Software requirements of the system were analyzed.
- **Analysis Phase**: We analysed our problem statement and system requirements status, the RAM space and GPU analysis was done.
- **Data Processing Modelling**: We were working side by side on our data, data preprocessing and building the modified U-NET model was done during this phase.
- **Design Phase**: The designing of the model i.e adding additional layers and down-sampling was done.
- **Implementation**: This is the final stage where we implemented the whole model. The model is further evaluated using the Dice coefficient and pixel accuracy which came out to be 82 percent and 87 percent respectively in validation samples.

Chapter 5

Design of System

5.1 Design Diagram with Explanation

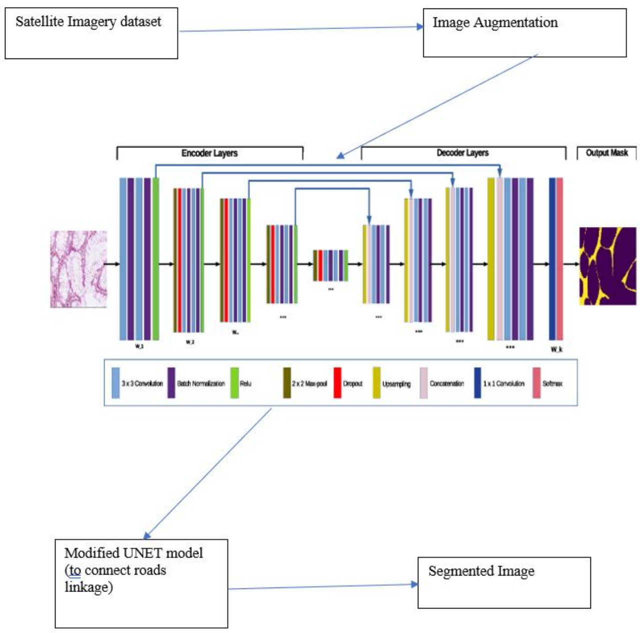

Figure 5.1: Design of System

Chapter 6

Results And Discussion

6.1 Implementation Details

6.1.1 Dataset and Data Augmentation

The dataset is made up of MBRSC satellite imagery of Dubai that has been annotated with pixel-by-pixel semantic segmentation. It's a high-resolution data collection with 72 distinct images evenly distributed over six different classes. Massive numbers of trainable parameters, in the tens of millions, characterize state-of-the-art deep learning architectures. Optimizing the performance of such complicated models is difficult, and if the number of training instances is insufficient, model overfitting to the training data set might occur. The performance of each of the basic augmentation approaches was first assessed individually and then compared to the no augmentation condition. The network may learn feature categorization without consideration to feature orientation via augmentation. Image orientations generate mirrored replicas of a seed image on both the horizontal and vertical axes. The seed and transposed photos are then rotated to increase the amount of training data available. Individual scene photos are used as data samples for classification, which increases intra-class data variety while avoiding inter-class ambiguity. The dataset is made up of 72 images separated into two sets: train (58 images) and validation (14 images). Further, augmented the training data up to 10 times resulting in 580 training images comprising of 58 original and 522 enhanced images.

6.1.2 Model

The initial model utilized was a basic U-Net architecture, which was trained using 50 epochs and eight batches. The learning rate was 0.001 and the loss function was categorical cross entropy. Futher the result were compared with modified U-Net model. The model was trained for 50 epochs using 16 picture batches for each epoch. An Adam optimizer is one of the most often used optimizers in terms of semantic segmentation, with applications in hyperspectral pictures as well due to its high classification accuracy. With learning rate of 0.001 was used to minimize a categorical cross-entropy loss function for optimization. While image augmentation attempts to increase the quantity and diversity of training pictures, the number of training samples remains constant, whereas the image augmentation objective was to increase the variety of training samples solely. This was done to guarantee that each condition was compared fairly and to exclude the number of training photos as a confounding factor. After each period of training, the networks were evaluated to see how much of a difference there was between training and validation performance, in order to look into over-fitting owing to a lack of variation. A commonly established way for accelerating deep learning training is to use ImageNet weights to initiate pre-training. By a large margin, ImageNet surpasses random initialization. As a result, for the base setup, we'll use this weight initialization approach. The ReLU activation function, as well as hidden layers and a softmax function, are employed in the input. To minimize overfitting during training the model, a dropout of 0.3 has been implemented.

6.2 Result Analysis

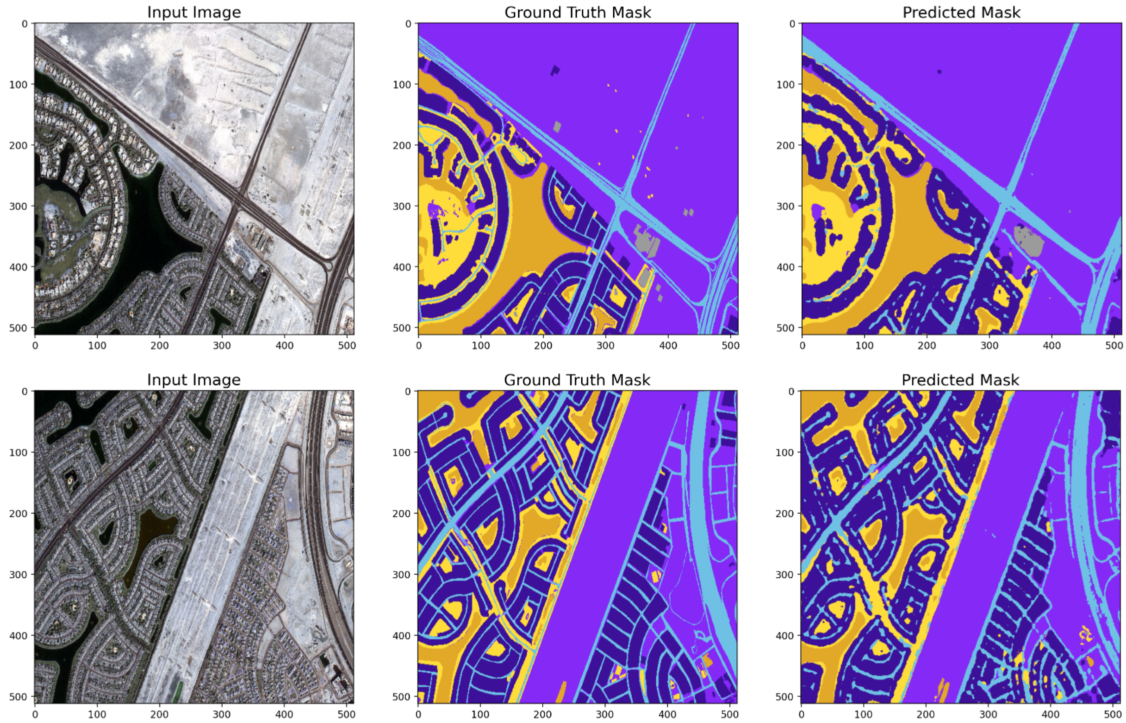

Figure 6.1: Predictions

Chapter 7

Conclusion And Future Work

In this paper, we focused on the improvement of satellite image semantic segmentation. Through unique model design and combination, the segmentation result is more refined and accurate. In addition, the modified U-Net model demonstrated the ability to improve on the present poor resolution of segmentation masks. These modern and unique models, U-Net and Inception ResNet V2 encoder yield more accurate results when paired together. Experiments on a variety of satellite images show that our proposed approach and has excelled the segmentation accuracy and processing time. The current study can aid other research areas concerning policy development, urban planning, forest, and agricultural monitoring, etc. We intend to build on this study by expanding our multi-task approach to include a more in-depth examination of the impact of the number of classes.

The results obtained proved that the proposed approach is very precise and effective in comparison with other approaches reported in the literature. This work can be extended further to obtain the Detection Percentage as maximum as possible but keeping Branch Factor much less.

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Appendices

Appendix A

Weekly Progress Report

Appendix B

Plagiarism Report

Appendix C

Paper Publication

Appendix D

Project Competition

Acknowledgement

We take this opportunity to express my profound gratitude and deep regards to our guide **Dr. Sangita S. Chaudhari** for her exemplary guidance, monitoring and constant encouragement throughout the completion of this report. We truly grateful to her efforts to improve our understanding towards various concepts and technical skills required in our project. The blessing, help and guidance given by her time to time shall carry us a long way in the journey of life on which we are about to embark.

We take this privilege to express our sincere thanks to **Dr. Mukesh D. Patil**, Principal, RAIT for providing the much necessary facilities. We are also thankful to **Dr. Amarsinh V. Vidhate**, Head of Department of Computer Engineering, Project Co-ordinator **Mrs. Smita Bharne** and Project Co-coordinator **Mrs. Bhavana Alte**, Department of Computer Engineering, RAIT, Nerul Navi Mumbai for their generous support.

Last but not the least we would also like to thank all those who have directly or indirectly helped us in completion of this thesis.

Ms. Dhanishtha Patil
Ms. Komal Patil
Ms. Rutuja Nale