Understanding Clouds from Satellite Images

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1. Abstract

Climate change is one of the greatest threat that the humanity is dealing with today. It has put a question mark on our future survival and we have proceeded in a direction to be extinct. It has been found that climate change can be determined by shallow clouds. And to understand the clouds we need to understand their organisation, the different organisations they form in the sky. There are three different shapes the clouds form, Flower, Gravel, Sugar and Fish. There is a human annotated data available by Max Planck Institute about the clouds and their organisations. The boundary between different organisations is murky, so we are aiming to use deep learning models to get the boundaries between these shapes and correctly identify which cloud organisation shapes are present in an image. Through this project, we are automating the pattern detection of clouds to learn global climatologies for these four patterns. We have used two state of the art image segmentation models for this task. U-net and Res-net. This understanding of cloud structure might help researchers to understand the climate change better, which further with political involvement can be resulted in policy implementations to help save the climate.

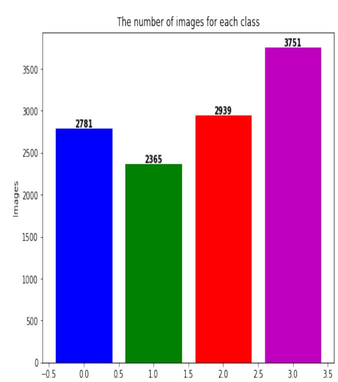
2. Introduction

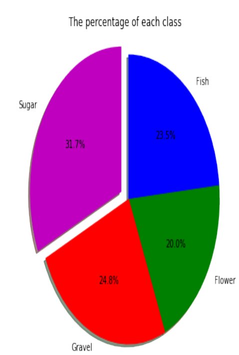
Climate change is one of the most important problem that we are facing in the 21st century. It has been found by the researchers that shallow clouds can play a huge role in determining the Earth's climate. But they are difficult to understand and represent in climate models. Clouds can organize in various ways, but the boundary between different organisations is very murky.So, we are trying to efficiently recognize various cloud formations. If we are able to classify these organisations successfully, we'll help scientists better understand how cloud organisations shape the climate. This research will guide the development of next-generation models which could reduce uncertainties in climate projections and enable scientists to build better climate models.

2.1. Dataset exploration

The data consists of images of certain cloud formations downloaded from NASA Worldview. The images have been captured by 2 polar orbiting satellites TERRA and AQUA each of which pass a specific region once a day. The cloud formations in each image have been given four labels: Flower, Fish, Gravel and Sugar. An image may contain multiple cloud formations, which even may overlap.

- The training data contains 5546 satellite images each of size 1400 x 2100 pixels.
- A csv file contains the class label and the image name along with the region of the image which contains the corresponding cloud formation in a run length encoding format.
- The training data has shape Fish in 2781 images, Flower in 2365 images, Gravel in 2939 images and Sugar in 3751 images.

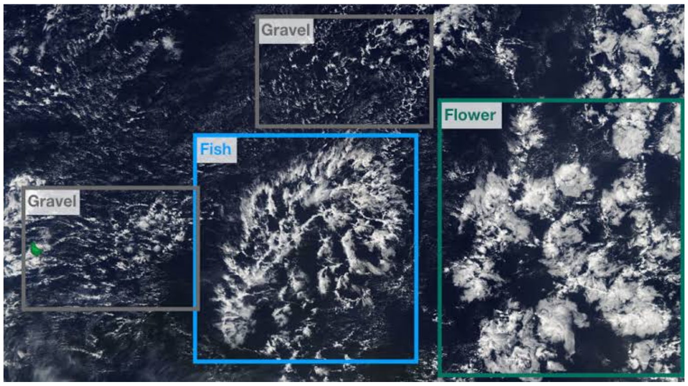




- The test set contains 3698 images of the same size.

3. Related Work

Understanding climate change through shallow clouds organisation is quite a new area which the researchers are now exploring. To understand this, there have been attempt to gather dataset for clouds. In a recently published article, the researchers of Max Planck institute have explained



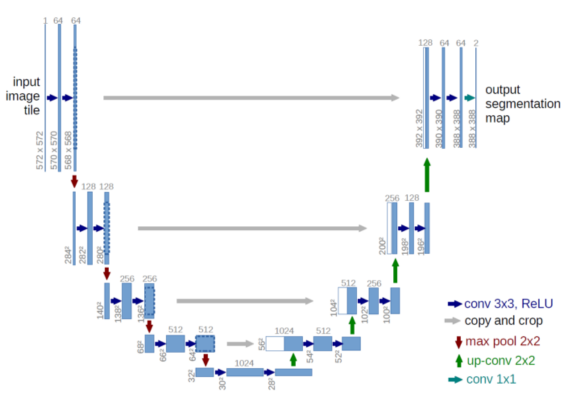
how crowd sourcing and deep learning are combined to explore the meso-scale organization of shallow clouds in the subtropics.

4. Methodolgy

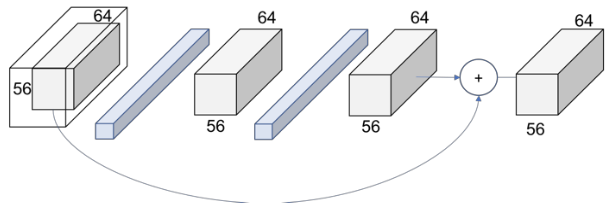
We have used two state of the art models that are generally used for image segmentation, UNET with ResNet34 encoder and MaskRCNN. Let us discuss each of the model in detail.

4.1. UNET with ResNet34

- **UNET:** It was developed by Olaf Ronneberger et al. for Bio Medical Image Segmentation. The architecture contains two parts. First path is the compression path or the encoder which is utilised to capture the context in the image. The encoder is a stack of convolution and max-pooling layers. The subsequent path is the expansion path or the decoder which is used to enable precise localization using fractionally strided convolution. Along these lines, the network, from start to end, is a **fully convolutional network (FCN)** as it does not contain any dense layers.



- **ResNet encoder:** When working with deep neural networks the most common notion is *'the deeper, the better'*. However, it has been noticed that after some depth the performance degrades as these networks start suffering from a problem known as the **Vanishing Gradient problem**. This is because when the networks are too deep, the gradients from the loss function shrink to 0 after successive applications of the chain rule. Hence, the update value becomes 0 and thus no learning happens. With ResNet we add skip connections from the previous layers to layers ahead. The gradients flow from the initial layers to later layers where they are added to prevent the gradients from shrinking to 0.



Some information about the model:

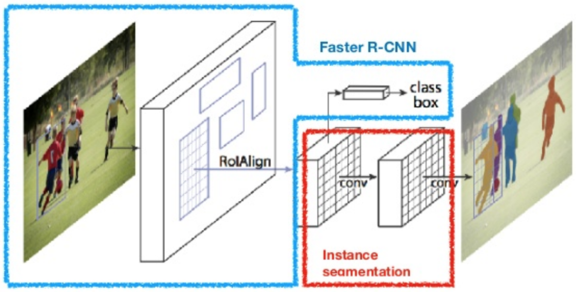
- The model is compiled with Nadam optimiser with learning rate=0.0002.
- Dice loss was used as the loss function.
- In all intermediate layers, ReLU was used as the activation function and sigmoid activation was used at the last layer as the model outputs a 320x480 mask image with each pixel having a value between 0 and 1. Thus the model classifies each pixel individually.
- To make the model generalise better, images were augmented.
- An 80-20 train-test split was performed on the data.
- A batch size of 32 was used.
- The model was trained for 10 epochs.

Note that there could be a lot of scope to tune these hyperparameters and further improve the model performance.

4.2. MaskRCNN

MaskRCNN is extension of faster RCNN as it adds a mask along with the box of image segmentation.We used an Implementation of MaskRCNN from a github repo matterport/Mask_RCNN built on FPN and ResNet101 and trained the model after loading pretrained weights of the same model on the coco dataset.

- Learning rate : 1e-4
- Total Epochs : 9



- Trained on the total training data available and tested on for visualising masks on a few samples of the test data.

We used the Dice coefficient to evaluate the models. It was given by Sorensen, is a statistic to measure the similarity of two samples.

$$\frac{2 * |X \cap Y|}{|X| + |Y|}$$

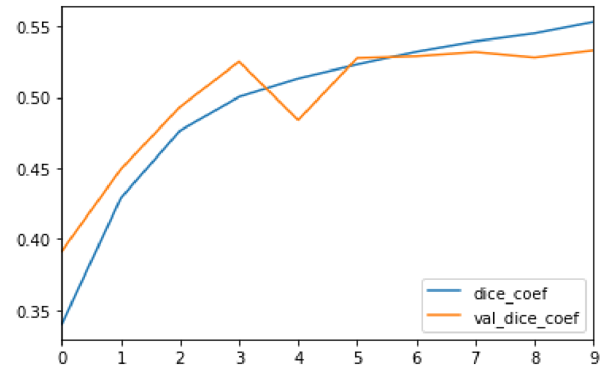
where $|X|$ and $|Y|$ are the cardinalities of the two sets (i.e. the number of elements in each set).

When applied to boolean data, using the definitions of True Positive (TP), False Positive (FP) and False Negative (FN), it can be written as

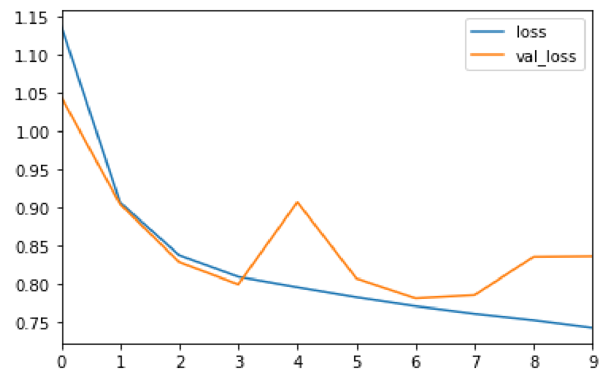
$$Dice = \frac{2 \times TP}{(TP + FP) + (TP + FN)}$$

5. Results

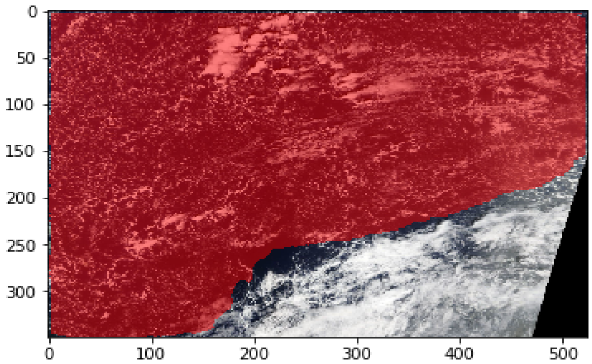
5.1. UNET with ResNet34 encoder



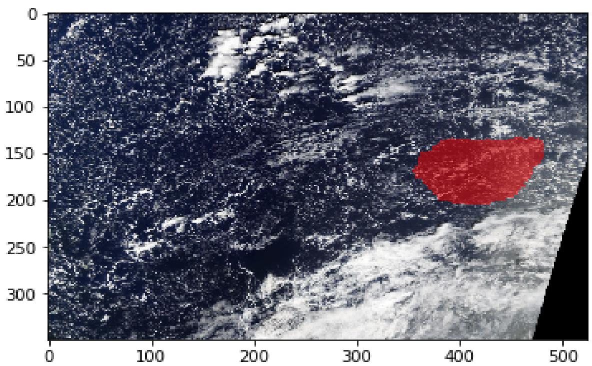
Dice coefficient vs Epochs



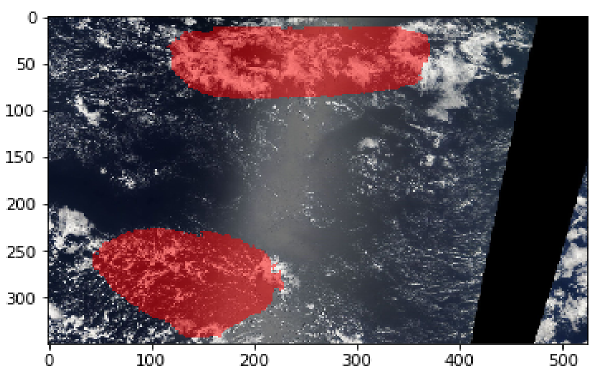
Loss vs Epochs



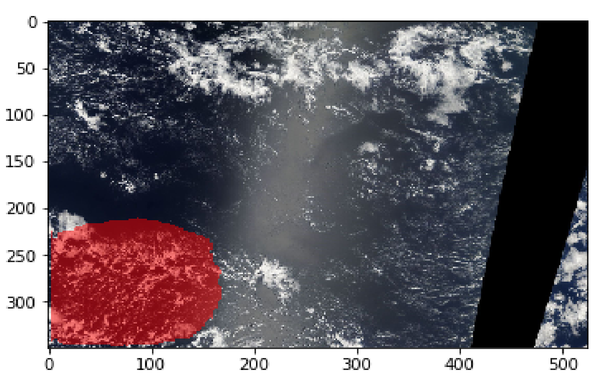
Gravel



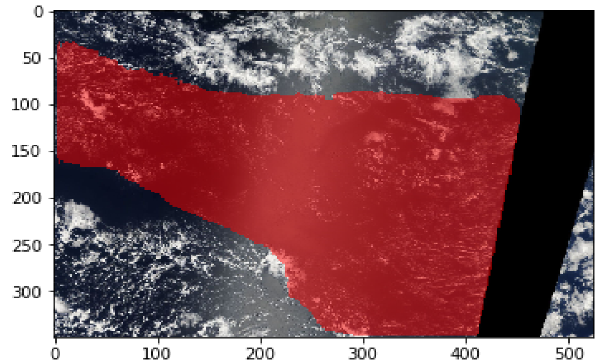
Sugar



Fish



Gravel



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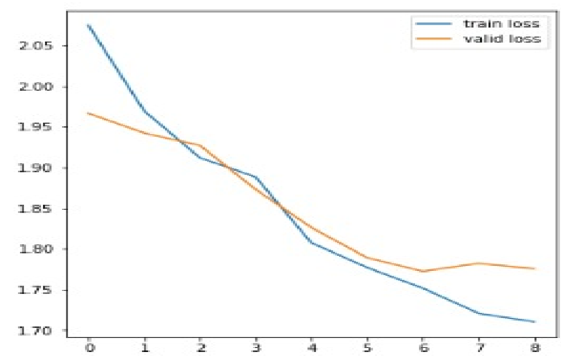
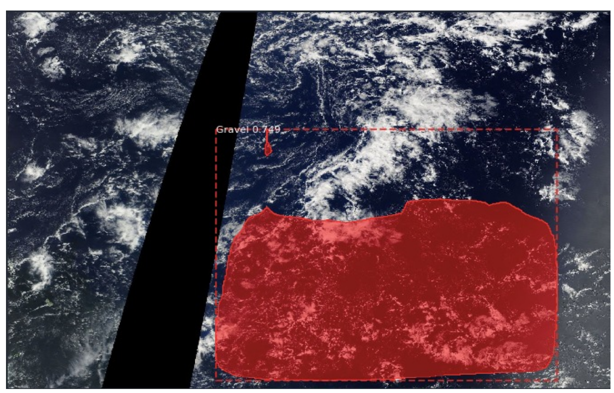
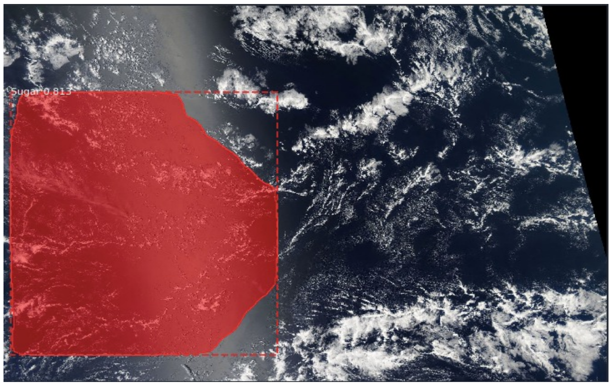
5.2. MaskRCNN



Loss vs Epochs



Gravel



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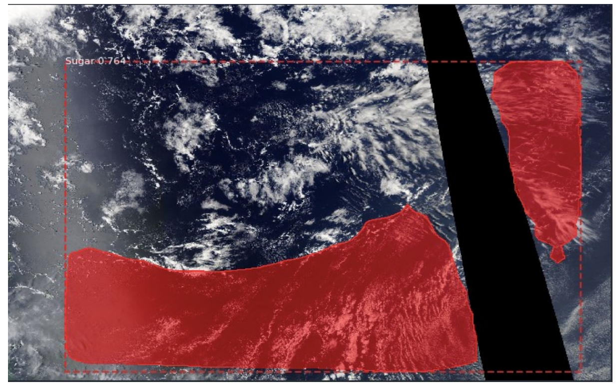

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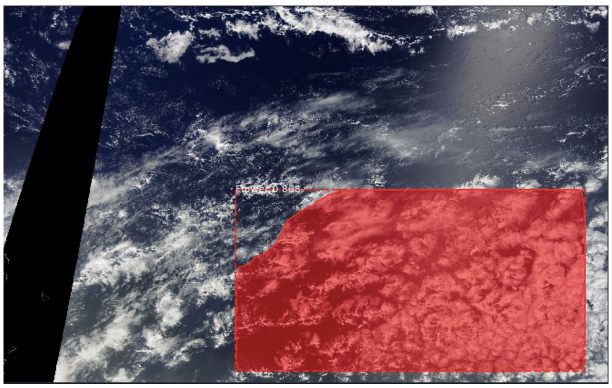
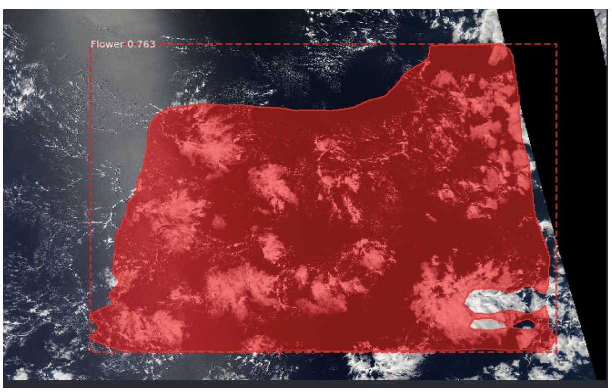
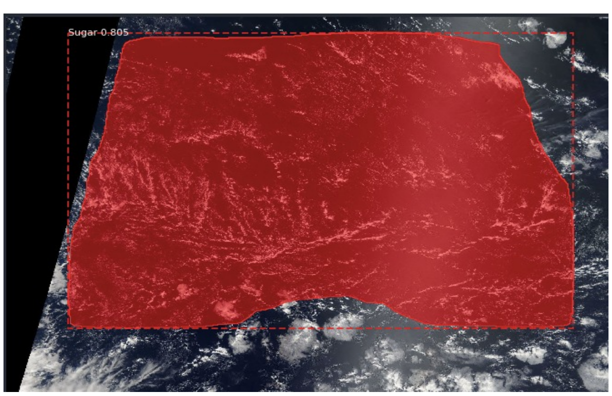


Flower



Flower



Sugar

6. Conclusions

We found out the Dice coefficient for both of these models which is metric generally used a evaluation metric for image segmentation tasks. The **dice coefficient** calculated on Kaggle portal for UNET with ResNet34 and MaskR-CNN was 0.58659 and 0.58689 respectively. The metric was quite decent and could be used for furthering the research on detecting the cloud patterns which further can help in understanding climate change through the cloud patterns.

7. References

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