Task 1: Sensitivity analysis of DL models towards dwelling ontologies

Pratichhya Sharma

In order to understand the effect in performance for a multiclass segmentation due to several segmentation model I performed an experiment using Kutupalong dataset in bangladesh with 8 classes. They were: no dwellings, blue dwellings, red dwellings, green dwellings, bright dwellings, dark dwellings, iron roofed dwellings & dismantled dwellings.

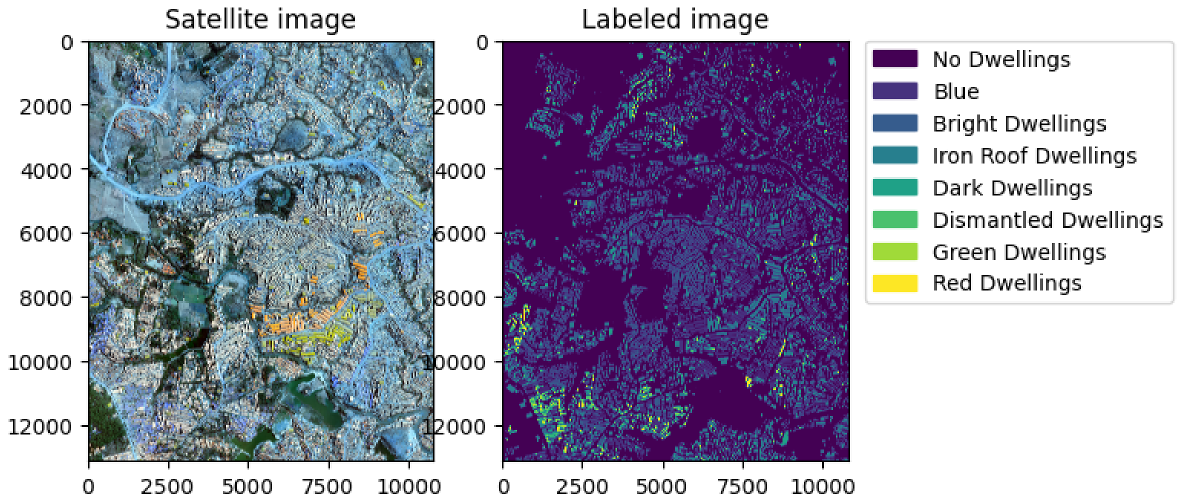
In [1]:
```
# import packages
import rasterio
import matplotlib.pyplot as plt
import numpy as np
from skimage import exposure
import matplotlib.patches as mpatches
```

In [2]:
```
#function to plot
def visualize_data(image,label):
    f, axarr = plt.subplots(1,2)
    image = image[:, :, 0:3]
    _ = image[:, :, 0].copy()
    image[:, :, 0] = image[:, :, 2]
    image[:, :, 2] = _
    image = image.astype(np.float64)
    for i in range(image.shape[2]):
        p2, p98 = np.percentile(image[:, :, i], (2, 98))
        image[:, :, i] = exposure.rescale_intensity(image[:, :, i],
                                                     in_range=(p2, p98))
    axarr[0].imshow(image)
    axarr[0].set_title("Satellite image")

    a=axarr[1]
    values = np.unique(label.ravel())
    im = axarr[1].imshow(label[:,:,0])
    a.set_title("Labeled image")
    colors = [im.cmap(im.norm(value)) for value in values]
    label = ["No Dwellings","Blue Dwellings", "Bright Dwellings","Iron Roof
    patches = [mpatches.Patch(color=colors[i], label=j) for i, j in zip(rang
    plt.legend(handles=patches, bbox_to_anchor=(1.05, 1), loc=2, borderaxesp
```

In [3]:
```
# used dataset
image = rasterio.open("dataloader/image/Kutupalong_13Feb2018_sub.tif").read(
label = rasterio.open("dataloader/label/Multiclass.tif").read()
```

In [4]:
```
visualize_data(np.swapaxes(image,0,2), np.swapaxes(label,0,2))
```



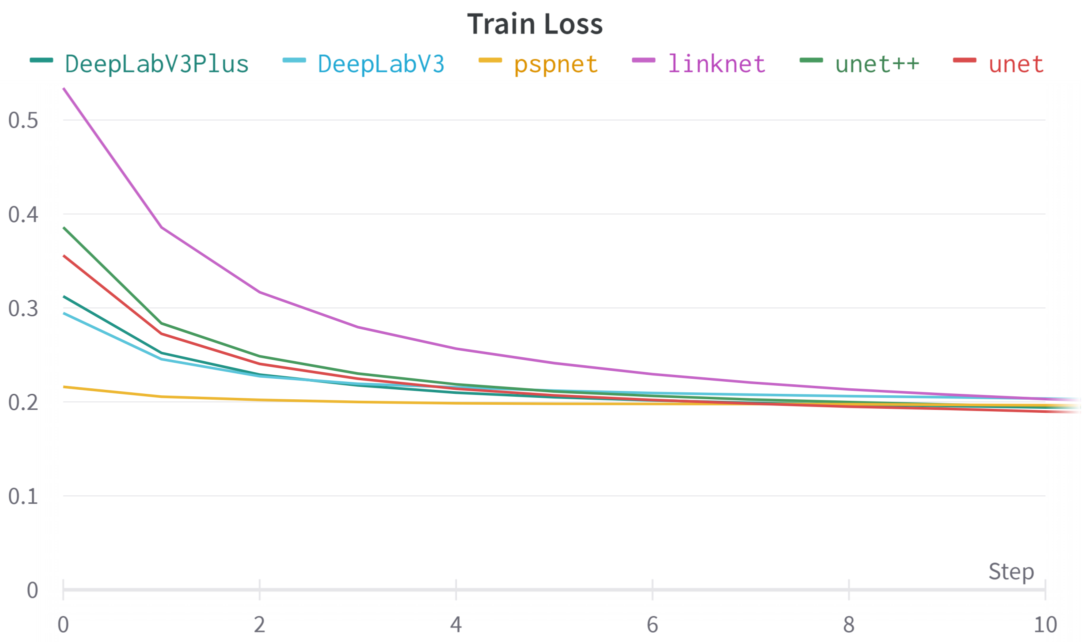
Basic pre-processing steps were completed before performing a multiclass semantic segmentation. The model was only chosen because of its well-known capability. In order to determine how sensitive each DL model was to a dataset with a large number of classes, 6 different DL models were chosen and their performance was assessed.

Due to time limitation, well-known pre-defined model for segmentation based on SoTA was selected from segmentation_models_pytorch python package https://segmentation-modelspytorch.readthedocs.io/en/latest/. Here we have:

1. Unet
2. UNet++
   https://ieeexplore.ieee.org/document/9482266
3. Linknet
   https://dl.acm.org/doi/10.1145/3423323.3423407
4. PSPNet
   https://www.hindawi.com/journals/mpe/2022/8958154/
5. DeepLabV3
   https://arxiv.org/abs/1706.05587
6. DeepLabV3Plus
   https://ieeexplore.ieee.org/document/9513102

Furthermore, these models with resnet34 as backbone were trained and its f1 score was evaluated. Each models were trained for 5 times inorder to compare their obtain their consistency with the change in performace.

Additionally, the loss when the comparative loss function was observed for the model, plot shown below was observed. It shows that PSPnet converged fastest, followed by deeplabv3, deeplabv3+, unet and unet++. whereas Linknet convergence took some time in comparison to the others.

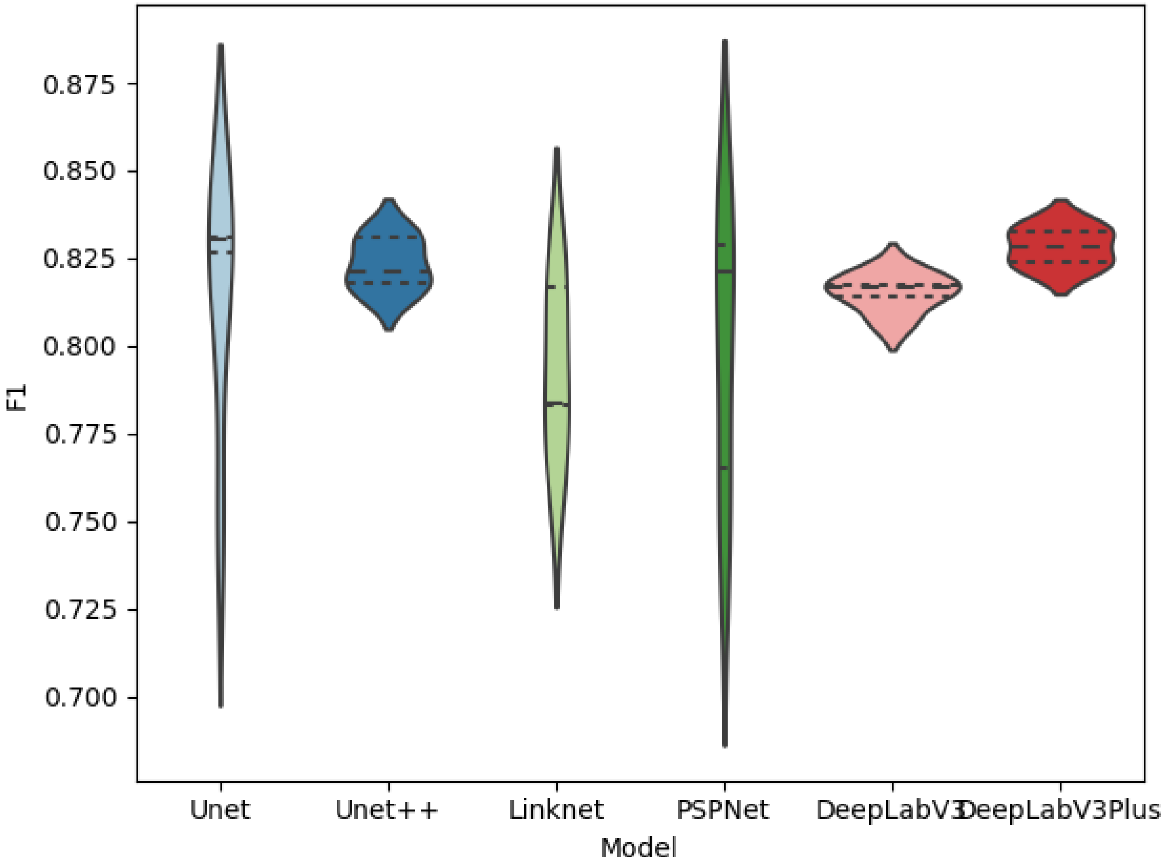


In [3]:
```
import seaborn as sns
from matplotlib import pyplot as plt
import pandas as pd
```

In [4]:
```
df = pd.read_csv (r'trial.csv')
# removing any NAN rows
df = df.dropna(axis=0, how="any")
#rename
df.rename(columns={ df.columns[1]: "F1" }, inplace = True)
print (df)
```

```
            Model      F1
0            Unet  0.8265
1            Unet  0.8336
2            Unet  0.8312
3            Unet  0.7498
4            Unet  0.8306
5          Unet++  0.8154
6          Unet++  0.8179
7          Unet++  0.8214
8          Unet++  0.8313
9          Unet++  0.8308
10        Linknet  0.7616
11        Linknet  0.7835
12        Linknet  0.8168
13        Linknet  0.8203
14        Linknet  0.7828
15         PSPNet  0.8290
16         PSPNet  0.8214
17         PSPNet  0.7442
18         PSPNet  0.8291
19         PSPNet  0.7652
20      DeepLabV3  0.8067
21      DeepLabV3  0.8168
22      DeepLabV3  0.8174
23      DeepLabV3  0.8214
24      DeepLabV3  0.8141
25  DeepLabV3Plus  0.8335
26  DeepLabV3Plus  0.8326
27  DeepLabV3Plus  0.8231
28  DeepLabV3Plus  0.8242
```

In [11]:
```
# sns.violinplot(data=df)
sns.violinplot(x="Model", y="F1", data=df,inner="quartile",palette="Paired",
plt.tight_layout()
```



Thus from the above violin plot, it was seen that Unet, Linknet,PSPNet is very sensitive to change in selection of multi-class dataset combination while Unet++, DeeplabV3 and Deeplabv3+ could be an interesting choice of model for further study on segmentation of multi-class dataset.

Additionaly

The constant values setup for the basic parameters during the data preparation and model training for different segmentation models are:

Patchsize : 256

Number of patches: 2142 (before agumentation) and 6426 (after agumentation)

Data augumentation technique: Flipping and Mirrored (used basic numpy knowledge not any additional package or tools)

Learning rate scheduler: MultiStepLR

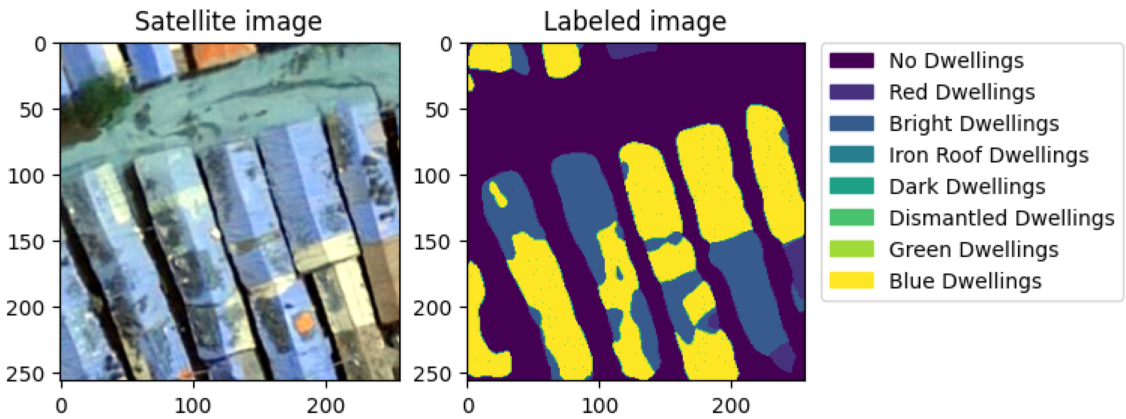
Epochs: 50 epoch for each trial of a model

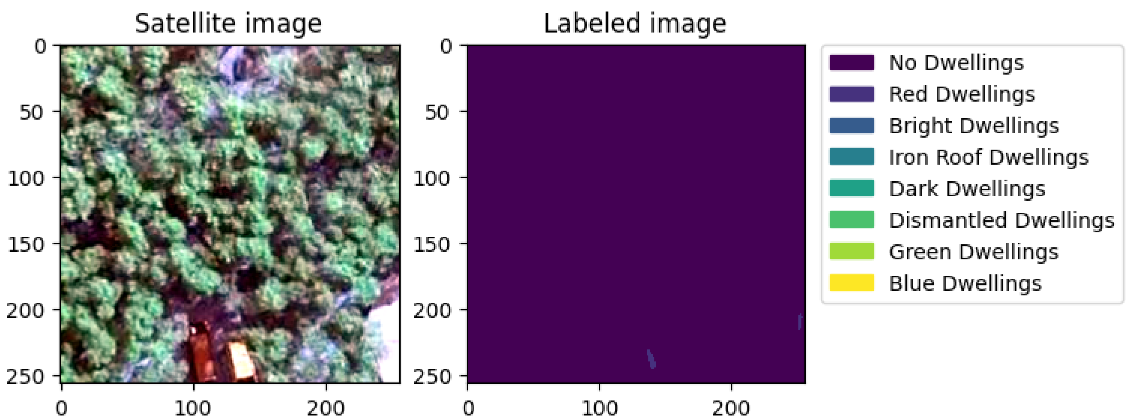
Pretrained weights: no pretrained weights used

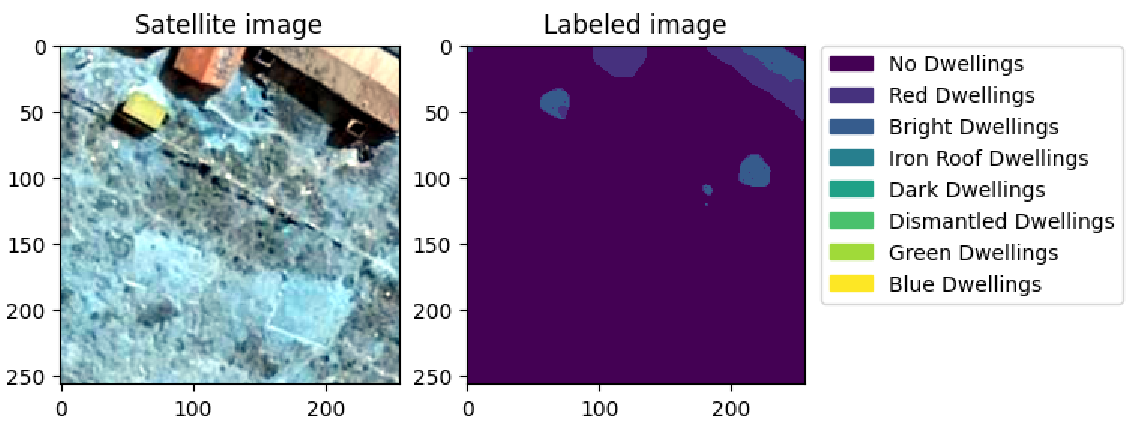
loss function: Diceloss

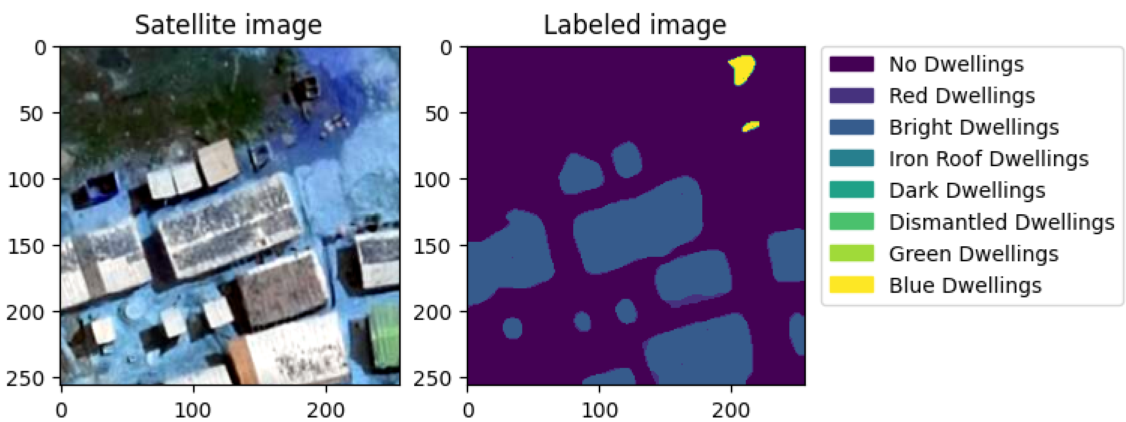
Otimizer: Adam

Furthermore, sample outcomes. (answer in response to question 4 in the comments).

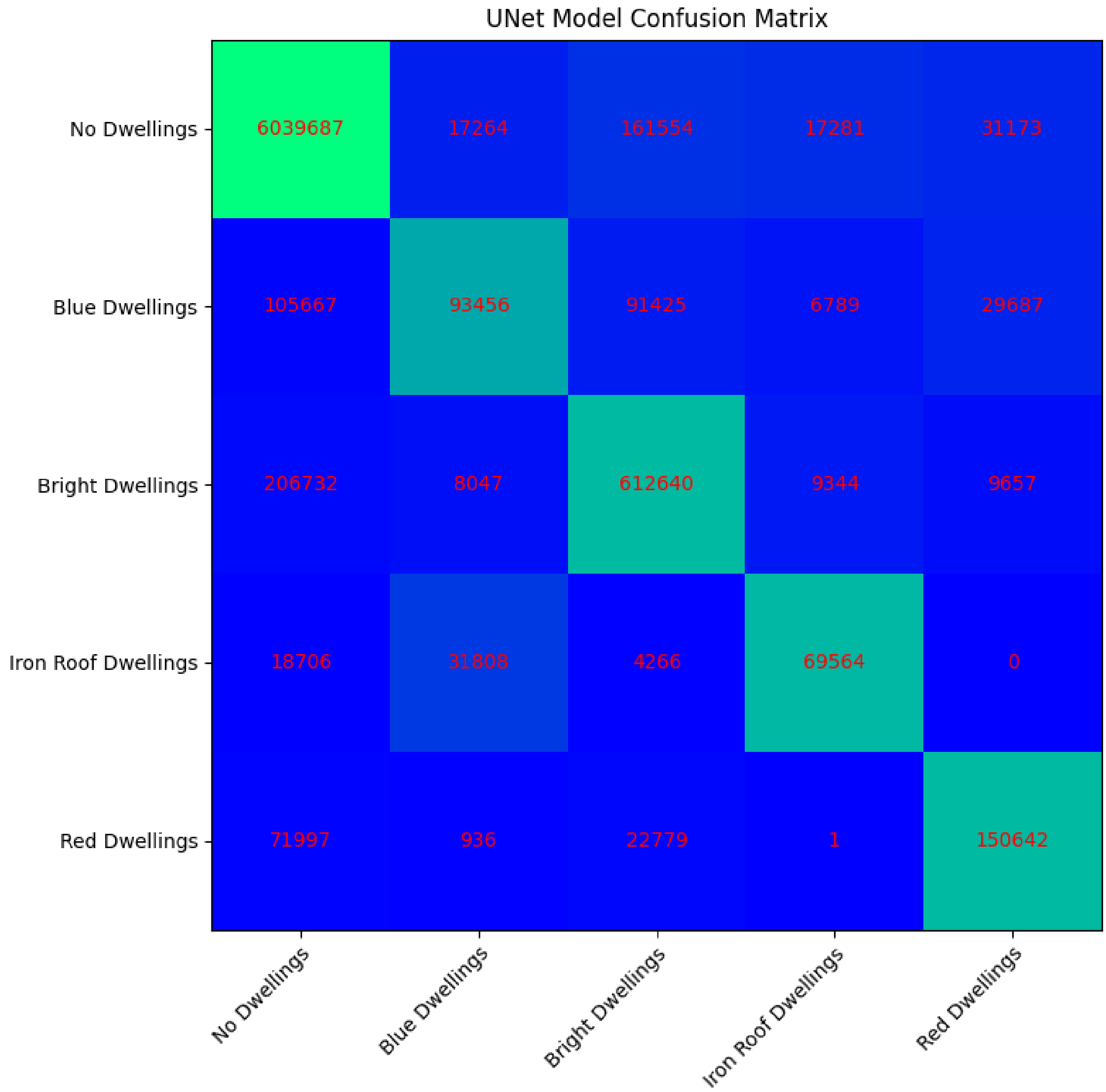




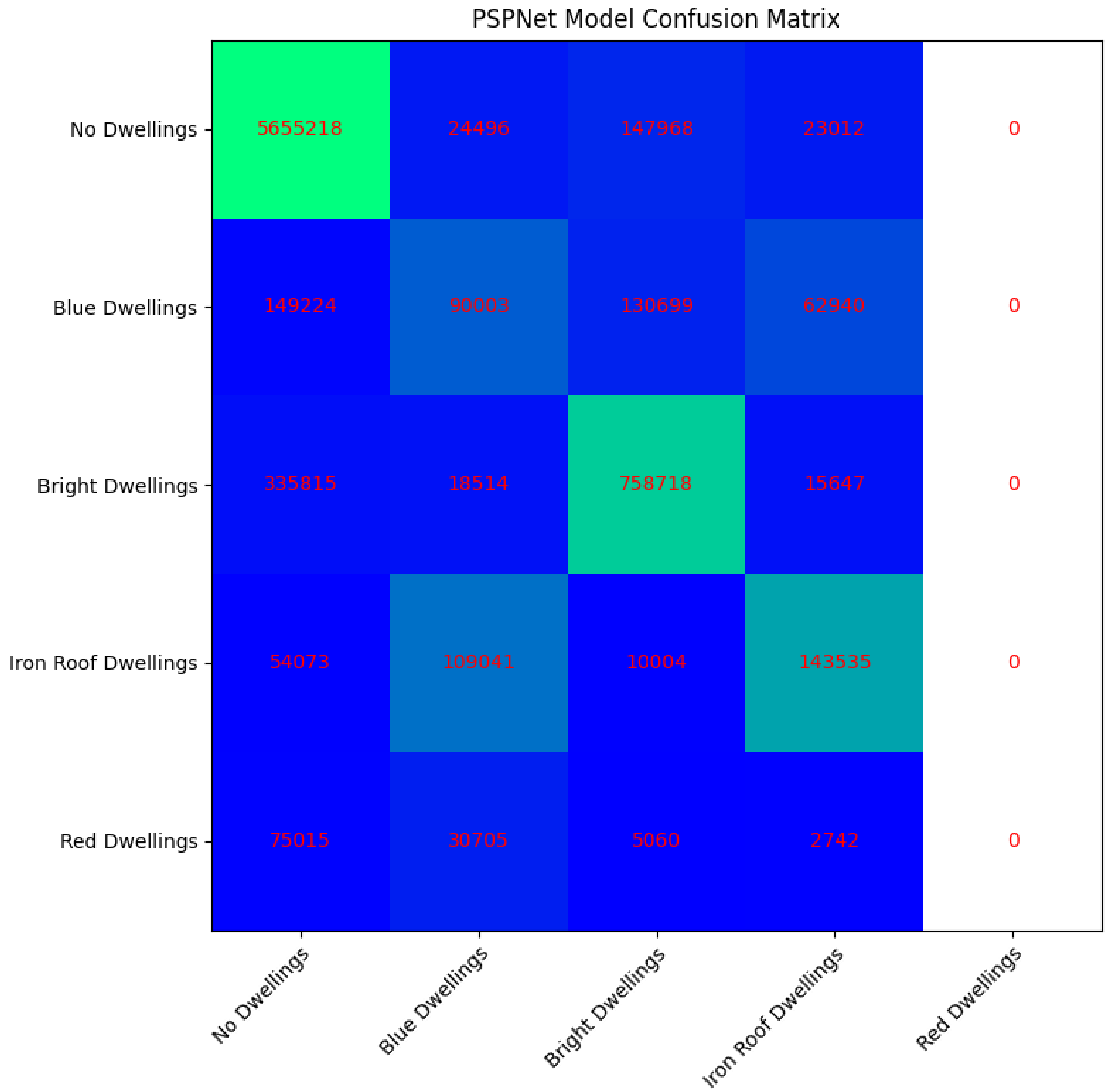




To access the accuracy of individual class, we evaluated all the possible scenarios of the trained model and presented the results of the best model here. To select the best model, we looked at the individual class performance as well as the overall f1 score. The best model with consistent accuracy in all the class is UNET and its Confusion Matrix is shown below. Here only five classess are present because other three classess were very few (around 10-20) in the overall dataset, making it unavailable in the test dataset. Presented Confusion matrix only shows the available classess in the ground truth data (if included, their accuracy will be zero). Overall accuracy per individual class is reported as [0.9637348832184797, 0.2857771906649053, 0.723801422461662, 0.559447983014862, 0.6114834283858659], where we can observe the background class is well predicted but almost all of the class have satisfactory accuracy except for one which have 28% accuracy. This might be due to the unrepresentative dataset where samples of that class is very low. We recommend having all the classess with enough samples or merging them to improve such issues:



Because we have shuffled the training data multiple times, in some of the cases, model did not see any of the samples or very few samples, making that class difficult to predict. For example in PSPNet model, even though it had very good accuracy in all other classes, could not predict very well in the Red Dwellings class. This is because while shuffling the data at random there were very few samples of Red Dwellings. The accuracy per class in this case is : [0.9665892627438728, 0.20792346823266322, 0.6722087651746177, 0.45328798400773085, 0.0]. Here we can also observe that the Blue Dwellings consistently have smaller accuracy compared to others same way as the UNet model because of lower number of samples.



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In [ ]: