U-Net Based Machine Learning for Identification of Auroras in Space-Based Images

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Summary

- Using a Semantic Segmentation based U-Net model we predict the presence of different classifications of aurora in images captured from the Fast Auroral Imager (FAI) on Swarm-E.
- Trained on ~5000 images, the model achieves an accuracy of 74% for unseen data on a pixel-by-pixel basis.
- Tags for individual ~10-20 minute satellite passes are created that act as a search filter for fast and simple discovery of aurora in space-based images.

1. The Swarm-E Fast Auroral Imager

The Swarm-Echo Fast Auroral Imager(1) (FAI), is a dual-CCD camera designed to image the nightside aurora in the near infrared (NIR, 650-1100 nm) and the visible (VIS, 630 nm) wavelengths. This project uses images from the NIR camera.

The NIR camera captures images with 0.1 second exposures at 1 Hz with spatial resolution dependent upon its mode and altitude, up to 0.6 km/pixel at perigee.

2. Semantic Segmentation and U-Net

Semantic segmentation is a deep learning algorithm that associates every pixel in an image with a classification and produces a segmentation mask dividing the image into different classes.

The U-Net(2) model belongs to the semantic segmentation category of machine learning and uses an encoder-decoder architecture to create segmentation masks of images with the features it detects.

The encoder is the first part of the architecture and works like a traditional image classification network like VGG16/ResNet-50. Convolutional blocks combined with down-sampling pooling layers encode the input image into feature representations at multiple levels.

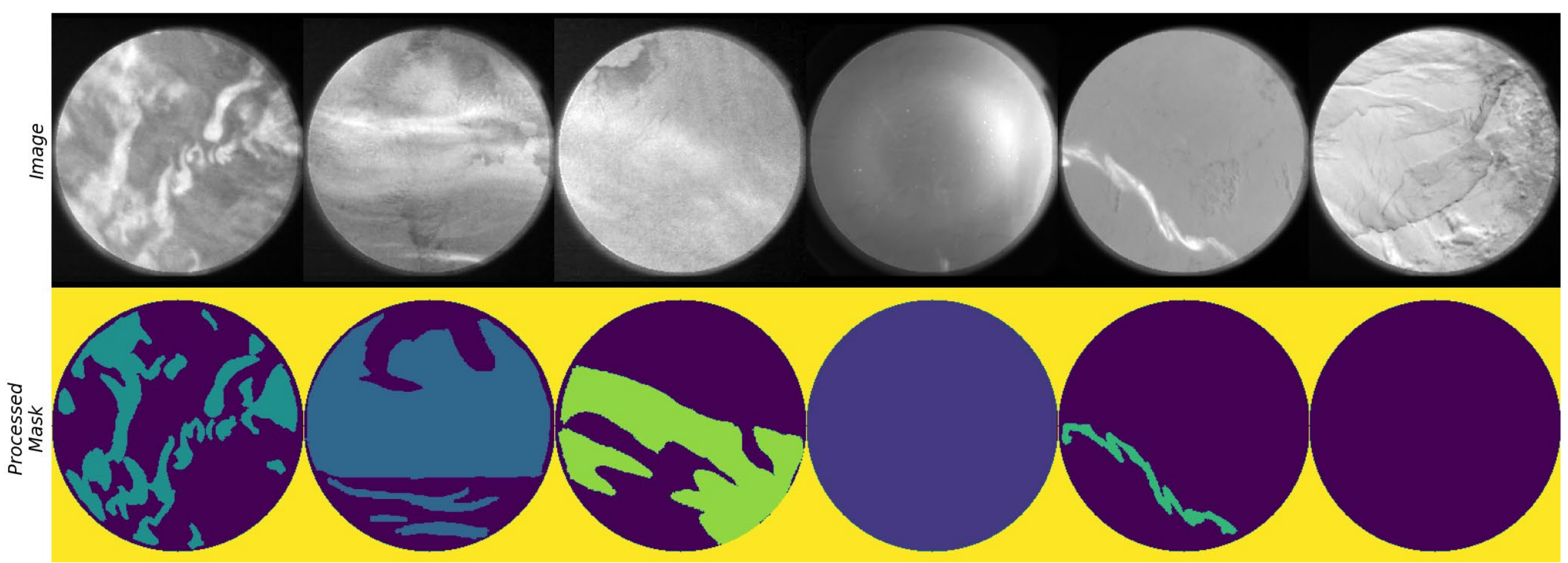
The decoder portion creates segmentation masks by projecting the features learned by the encoder at lower resolution to pixel space at higher resolution. The decoder consists of up-sampling and concatenation layers followed by regular convolution operations.

Parameter	Value
x_train shape	(4983, 280, 256)
x_test shape	(1246, 280, 256)
Classifications	7
Model Input	(280, 256, 1)
Dropout Rate	0.35
Padding	Same
Activation Functions	Leaking Rectified Linear Unit (a = 0.3)
Activation function	SoftMax
Kernel Initializer	*he_uniform*
Loss function	Weighted Sparse Categorical Cross Entropy (W-SCCE)
Optimizer	Adaptive Moment Estimation (*adam*)
Metric	Mean Intersection-over-Union
Learning Rate	10^{-4}
Batch Size	8
Epochs	150

3. Data Preprocessing and Training

An individual FAI image pixel could belong to one of 7 classes, namely, *no aurora*, *contaminated*, *diffuse*, *discrete*, *arc*, *ambiguous* and *vignette*, similar to Clausen et al. (2018)(3). Each classification was given a unique color with a different RGB value for labelling.

Due to the architecture of semantic segmentation, we were not limited to having only one class output for an image. The resulting image masks were provided as target labels for machine learning.

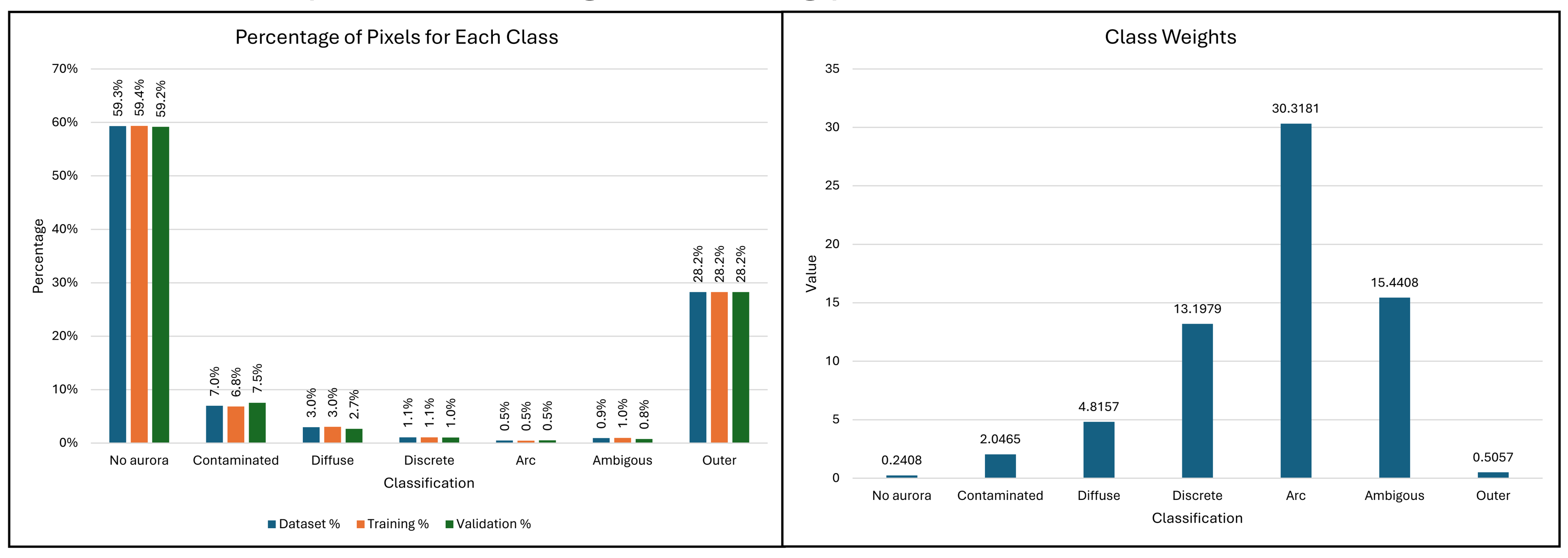


Some sample FAI images with their processed masks

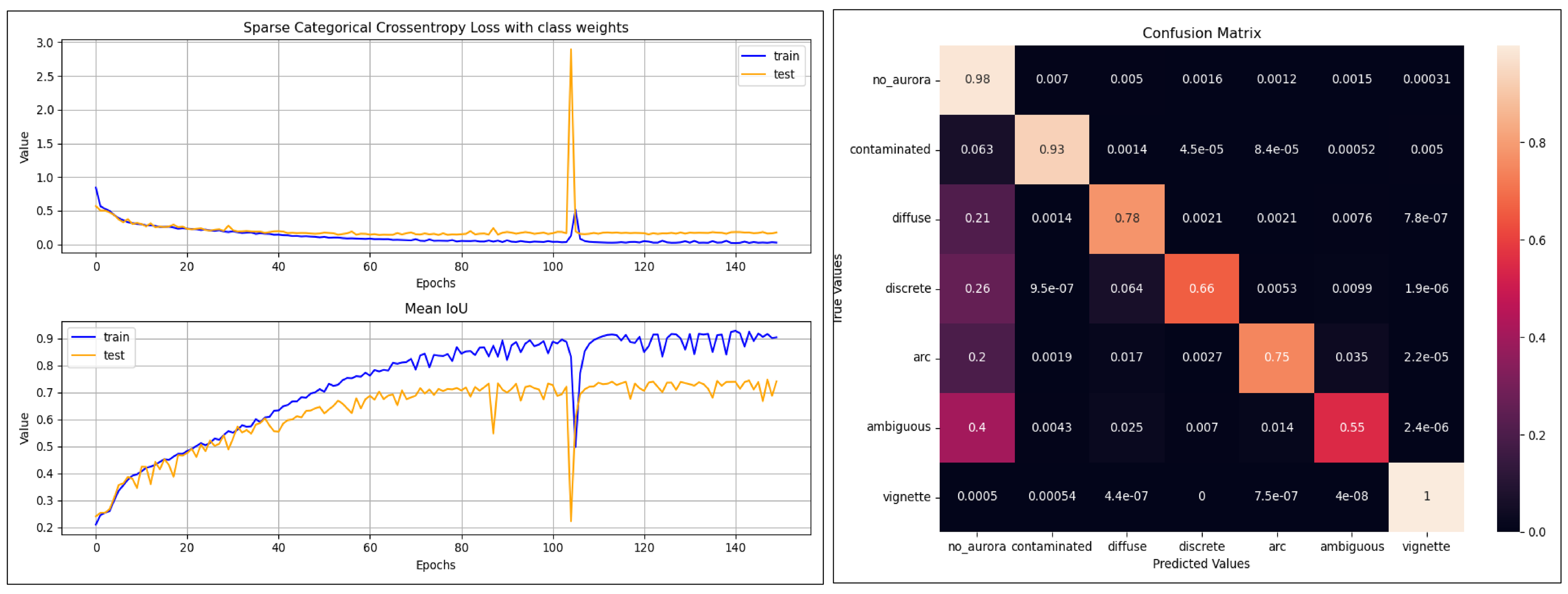
Approximately 5000 individual images with their corresponding masks were chosen primarily from January 2017 – September 2017.

With the help of random image augmentation (vertical/horizontal flips) the number of images were increased to 6229 and 80% of these were used to train the model and the remaining 20% were used for testing.

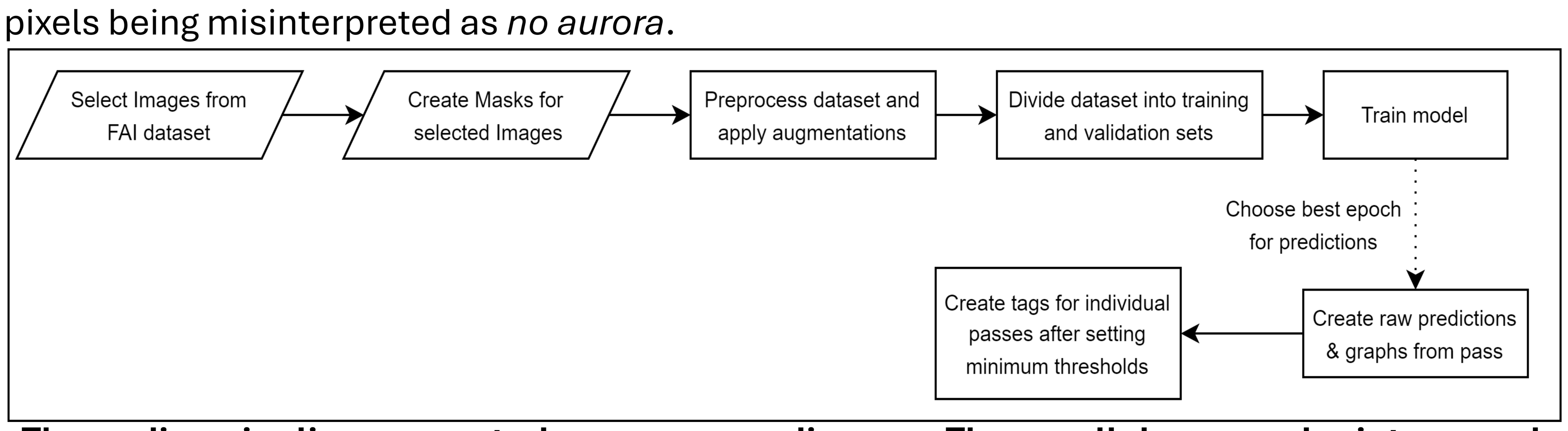
The aurora often represents only a small portion of the image. To address this, class weights were calculated and provided during the training process.



4. Results



Top Left: Model loss (Sparse Categorical Cross Entropy) as a function of epochs. For the training set the model was able to minimize loss to an approximate value of 0.02, and 0.1 for the testing set.
Bottom Left: Model metric (Mean IoU) as a function of epochs. For the training set the best model prediction overlapped with target labels (image masks) with an average value of ~91%. For the testing set the value was ~74%. Considering the difference between the plateauing stage for loss and Mean IoU, the model was able to detect features from an image by the 70th epoch but was not able to correctly classify them into different categories until the 115th epoch.
Right: The confusion matrix shows that the model was able to correctly predict all non auroral classes i.e., *no aurora*, *contaminated* and *vignette*, likely due to their high representation in the dataset. For auroral classes, *diffuse* had the highest score followed by *arc* and *discrete*. *Ambiguous* aurora was the worst performing class with about 40% of its pixels being misinterpreted as *no aurora*.

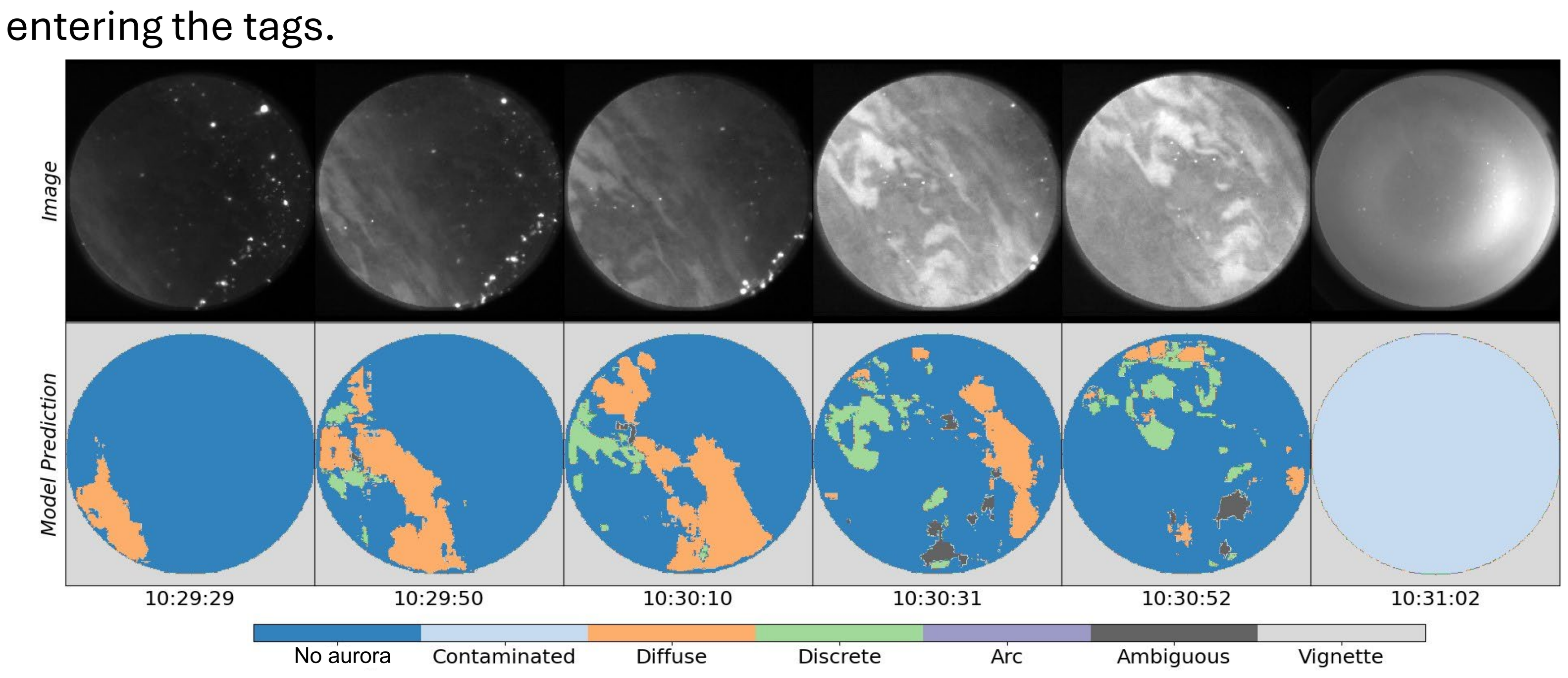


The coding pipeline presented as a process diagram. The parallelograms depict manual inputs and rectangles show determined processes

5. Post Processing and Batch Tags

The trained model provides predictions for individual images and has no dependence on time. To create tags for individual satellite passes some post processing techniques were used.

1. Segmentation masks for all images from the pass were produced and class probabilities with a value lower than 70% were labelled as *no aurora*.
2. Thresholds were set for segmentation masks to remove many of the false positives from entering the tags.



Segmentation masks from a series of FAI images on February 3, 2016, using the trained model

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References

[1] Cogger, L., Howarth, A, Yau, A. et. al. Fast Auroral imager (FAI) for the e-POP Mission, *Space Sci Rev*, 2015, 189:15-25
[2] Ronneberger, O.; Fischer, P.; Brox, T. U-Net: Convolutional Networks for Biomedical Image Segmentation, *Medical Image Computing and Computer-Assisted Intervention*, 2015, Springer
[3] Clausen, L. B. N., & Nickisch, H. Automatic classification of auroral images from the Oslo Auroral THEMIS (OATH) data set using machine learning, *Journal of Geophysical Research: Space Physics*, 2018, 123:5640–5647