Automated Detection of Lineaments on the Surface of Europa using Machine Learning. Das N.[1,*], Nazareth R.[1,*], Mishra S.[1], Thangjam G.[1], [1]National Institute of Science Education and Research Bhubaneswar P.O. Jatni, Khurda 752050, Odisha, India (nishantp.das@niser.ac.in, riong.nazareth@niser.ac.in, thangjam@niser.ac.in, smishra@niser.ac.in), *equal contribution

Introduction: Europa is one of the most interesting planetary bodies in the solar system because of its potential to host life and its complex geologic processes. It has a thoroughly deformed surface that is filled with peculiar features like Lineaments and chaos terrains [1-3] as first revealed by Voyager and Galileo missions. Europa has a global ocean likely composed of saltwater - a curious insight drawn from Galileo's magnetometer and it is considered one of the 'Ocean Worlds' [3]. This ocean likely has bioessential elements, chemical energy, and a stable environment through time which are the ingredients that allow life to emerge.

The Solid State Imaging camera on the Galileo spacecraft has taken high-resolution images of the unique surface morphology of Europa. It is seen that numerous intersecting ridges and dark bands run across Europa's surface which are known as Lineaments or Lineae. According to a model originally proposed by Pappalardo et. al. [4] (which is based on the formation of ridges on the arctic sea ice), the liquid water from the ocean underneath is squeezed onto the surface by the crack formation mechanisms which leads to the formation of these Lineae. Assuming this model, the spectral analysis of the surface restricted to the Lineae, among other surface morphological features, is expected to advance our understanding of the chemical composition of the subsurface ocean.

We thus present a model which can recognise the Lineae in an image of Europa. As the nature of these ridges is quite complex, our model heavily relies on Machine Learning (ML) methods. This model could be helpful to build a global geologic map of all the Lineae on Europa. In addition to this, the spectral data from Galileo/NIMS and Juno/JIRAM focussed on the Lineae and their environment could be analyzed to hunt for prebiotic chemicals and biosignatures [5].

Image Segmentation using ML: ML techniques have been used extensively in recent planetary science studies in an attempt to automate the detection and classification of features of interest in various planetary bodies [6]. Automated Lineae recognition is an instance of a class of computer vision problems known as image segmentation where each pixel is classified into some given class. In our case, the classes we took into account are Lineae and non-Lineae.

Specifications and training of the models: Standard image segmentation models like U-NET [7], do not produce significant results for small data sets. Thus, other models were investigated, built, trained and experimented with. The best model, i.e., the model with the highest mean Intersection over Union (mIoU), extracts features from the images and classifies each pixel using a Random Forest Classifier.

Anomaly detection: Since Lineae are interconnected structures, some misclassifications (false positives) in the predictions could be identified by clustering the predicted Lineae using DBSCAN [8] with a small Eps parameter and some reasonable MinPts parameter. After the Lineae are clustered, the outliers - points which could not be accommodated into any cluster - are likely to be misclassifications and hence, such predictions are dropped.

Dataset: Since we are using supervised learning techniques, a labelled dataset had to be created. An essential criterion to solve any machine learning problem is the availability of labelled data. We have annotated a few images from the Solid State Imaging (SSI) camera of the Galileo mission. From PDS atlas, 0700r and 0713r were annotated and from ASU's website, an image mosaic - E6ESBRTPLN02 - made using five images of the bright plains region was annotated.

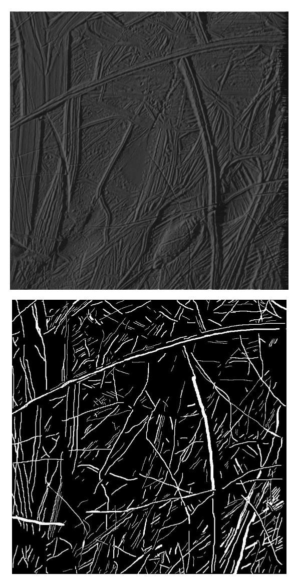

Figure 1: Top - An SSI image, Bottom - Lineae in the image as marked by us.

Preliminary results and Future Work: The highest mIoU achieved is 61.04%.

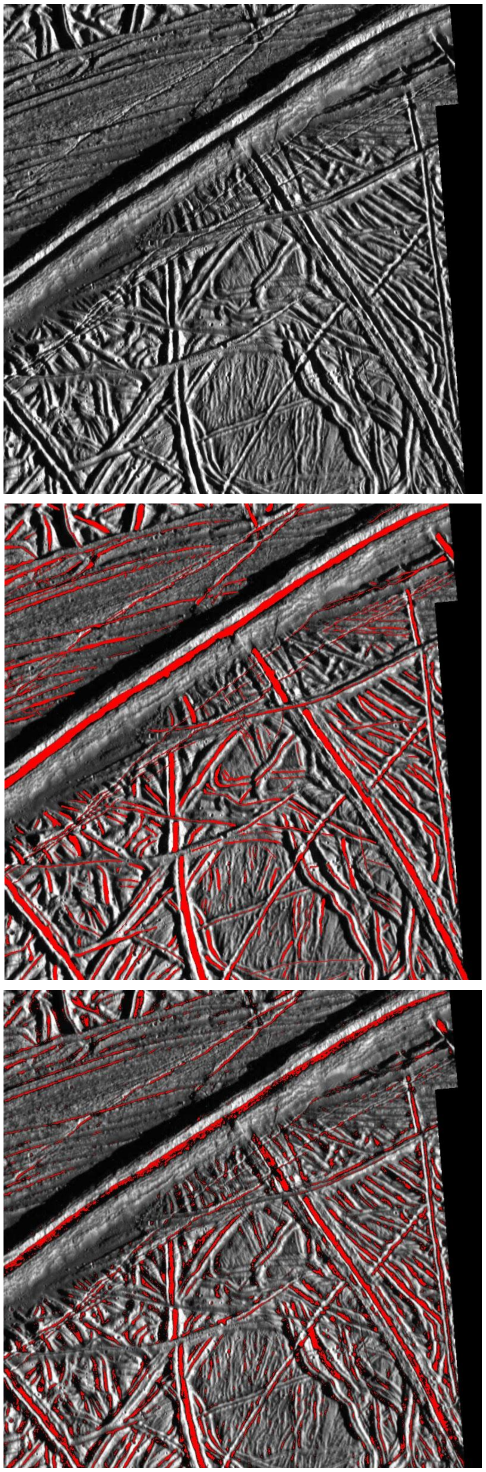

Figure 2: Top - part of an SSI image, Middle - red lines depict the Lineae as marked by us, Bottom - red lines depict the Lineae as marked by our model.

Once this model is ready to be deployed, it will be used to analyse the spectral data of Europa focusing on the Linea. To further improve the mIoU, the following steps have been/are being taken.

Extension of the data-set using Active Learning: Active Learning can be used to extend the data-set efficiently without having to manually annotate each and every pixel in an image.

Use of Inverse Rendering models and Single Image Depth Estimation (SIDE): Using models such as InverseRenderNet++ [9], 3D information about the SSI image is guessed and this information is passed as yet another feature for our model.

Customised loss functions for deep learning models: The Lineae on Europa are inter-connected and multi-episodic geologic events appeared as Linear structures. This piece of information and other structural information could be incorporated into the loss function for deep learning image segmentation models while the model is being trained, by constructing a loss function such that the algorithm penalizes the pixel predictions which are not part of a linear structure. To this end, customised loss functions are being built which will work better with lower training images.

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