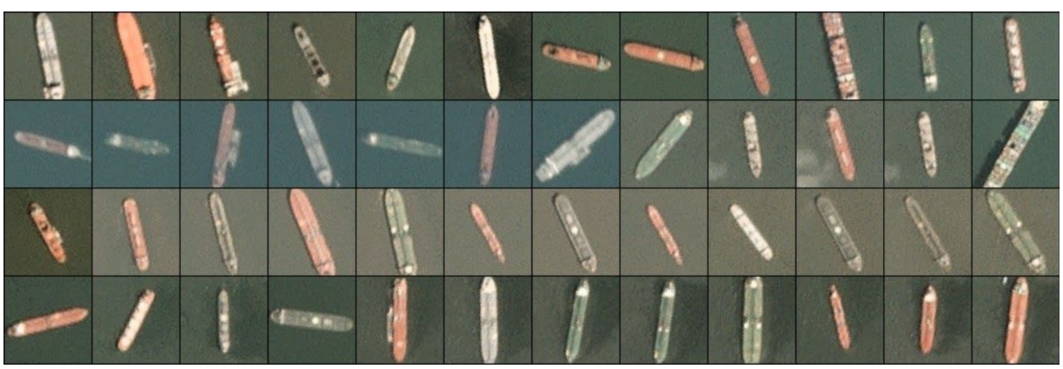
Using Convolutional and Artificial Neural Networks for Object Detection in Satellite Imagery

This article explores the methods, results and accuracies of detecting ships in satellite imagery based on a convolutional neural network (CNN) and an artificial neural network (ANN). Satellite imagery is valuable in the sense that it is capable of providing a broad perspective, is widely accessible, and is in abundance from many previous satellite passes enabling long temporal studies of given areas.[1] With more than 600 imaging specific satellites orbiting the Earth there is an abundance and continuous stream of data to process. However, we need faster procedures than conventional methods in order to adequately and effectively process the data retrieved.[2]

The code can be found at: https://github.com/sjmitche9/ship_detection
While this is a baseline model, there are many avenues to explore for improvement.

The dataset comes from Planet satellite imagery acquired in California. 4000 80x80 colour images comprise the data with labels “ship” or “no-ship.” Spatial resolution is comparatively fairly coarse, at 3 metres. This imagery is easy to obtain and is sufficient for this application, whereas finer spatial resolution images are harder to access and industry leading imagery is usually quite expensive. The spectral resolution (how many reflectance measurement bands are present) of our data is simply red, green, and blue. Different combinations of bands and bands outside the visible spectrum are frequently used for different tasks in remote sensing. These features are not needed in this case, as we are concerned about shapes and edge detection, for which a true colour image is fine. The “ship” class makes up 1000 of the total dataset, with the remaining 3000 being “no-ship.” “No-ship” images consist of land, water, partial ships and objects that are shaped comparably to a ship that were previously misclassified by different models.[3]



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[1] “Deep Learning in Satellite Imagery,” Appsilon | End to End Data Science Solutions, December 4, 2018, https://appsilon.com/deep-learning-in-satellite-imagery/.

[2] “Ships in Satellite Imagery,” accessed March 4, 2021, https://kaggle.com/rhammell/ships-in-satellite-imagery.

[3] “Ships in Satellite Imagery.”

Ship position is important to the maritime industry. Restricted areas exist for a variety of reasons, such as illegal fishing zones and areas reserved for harbour traffic.

Importantly, satellite imagery can provide us with violations of these restrictions.[1]

Before we can build our model, we normalize the data by dividing each pixel in each channel by 255 to set values between 0 and 1. The data is then split into 70% training and 30% testing.

Our neural network consists of 5 layers. The first layer is a convolution layer that applies filtering and consists of 32 output filters, a 3x3 kernel size for the convolution window, and a relu activation function. To break this down, the filters are processing the image to accentuate any edges present which is the basis of our model. The activation function ensures that no values are less than zero – although none should be, as it is not possible to have negative reflectance in an image. After the convolution layer, we add a max pool layer which will cut down the size of our data, enabling it to be processed faster. This also helps to prevent the model from over-fitting to the data because it creates an abstracted version of the image.[2] Using a 2x2 pool size the algorithm takes the highest value from each 2x2 area, moving along the image. Our third layer simply flattens the image and instead of the square image that we passed to our first couple of layers, this third layer provides us with a one dimensional vector which we can then pass to our dense layers. Our model finishes with two dense layers of which the activation functions are relu and sigmoid. The final layer has two neurons and uses the sigmoid function to transform our result between 0 and 1. If the result is less than .5, our model returns 0, and our image does not contain a ship, whereas if the result is .5 or greater, the model returns 1 and our image contains a ship.

Fitting the model we specify 10 epochs, a batch size of 200, and use the adam optimizer and set our loss parameter to binary cross entropy. A test accuracy of .953 and a test loss of .124 are obtained, which is quite positive for such a simple model. This model evidences the vast possibilities for the application of deep learning in satellite remote sensing. If we can automate a significant amount of image processing or classification using deep learning, we can process much more of the available data. Therefore, through the use of deep learning in satellite remote sensing we are both achieving a more effective process of processing data, as well as minimizing time spend sorting images, increasing the efficiency of the entire process.

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[1] “Ships in Satellite Imagery.”

[2] “Max Pooling,” DeepAI, May 17, 2019, https://deepai.org/machine-learning-glossary-and-terms/max-pooling.