Deep Learning for Wave Height Classification in Satellite Images for Offshore Wind Access

Ryan J. Spick and James A. Walker

The School of Engineering and Computer Science, University of Hull, Cottingham Road, Hull, Yorkshire HU6 7RX
https://www.hull.ac.uk/Home.aspx
ryan.spick@hotmail.co.uk

Abstract. Measuring sea height has traditionally been associated with physical buoy tools that aim to measure and average multiple wave heights over a period of time. With our method, we demonstrate a process of utilizing large-scale satellite images to classify a sea height with a continuous output using a corresponding input for close shore sea. We generated and trained a convolutional neural network model that achieved an average loss of 0.17 meters (Fig 6). Providing an inexpensive and scalable approach for uses in multiple sectors, with practical applications for offshore wind farms.

Keywords: Convolutional Neural Networks · Deep Learning · Satellite Images · Off-Shore Wind.

1 Introduction

The most common form of sea height detection uses buoy data instruments. They are by far the most robust and simple to use with transmissions occurring wireless; however suffer from time and cost related issues. Techniques have been generated for use of radar and microwaves to measure sea height [1], however very little has been investigated into the use of RGB satellite data partially due to its inability to measure through clouds. Nonetheless, we aimed to determine a method of generating, using the vast available open source satellite data, a neural network that can learn representations of satellite data.

Satellite images provide a robust and high-resolution view of our world. Large amounts of work have been completed regarding the application of Deep Learning to land satellite data such as predicting poverty [4], however very little has been investigated on the uses for offshore applicability. Using the Copernicus API we can access Sentinel-2 satellite data for any region of the planet producing a vast data set which proves to be crucial for training neural networks that can generalize well.

Sentinel-2 satellite data provide multiple spectrum data ranging from 10m to 100m spatial resolution across a 100KM^2 region. The RGB channel, however, offers a 10m pixel resolution which is paramount for the learning of the CNN model, by persevering as much of the visual features as possible.

Supervised Deep Learning requires an input and a corresponding label for that class, the network then attempts to learn a representation of the input data usually as a discrete class. Once a network has been trained the learned representation can be used for future classification problems [7]. Combining this method with a single dense final layer gives the ability to output continuous values, in this case corresponding to the wave height.

The scope of this work is to provide an alternative way of discovering the sea state on a given day, providing higher detailed information for the sea that is within several hundred kilometres of the shoreline and away from other measuring tools. Specifically aiming at the access to offshore wind farms.

For safe offshore wind farm access, there are varying levels of acceptable sea height ranging from 1.2 - 2.5 meter wave height [2] with larger and more expensive vessels required to tackle the rough waves.

Table 1 shows sea heights and their meanings, red highlighted values prove dangerous to smaller vessels. We made sure to classify and train data between these values, where values past the point of 4 meters would be considered extremely dangerous.

Wave Height	Characteristics
0 metres	Calm (glassy)
0 to 0.1 metres	Calm (rippled)
0.1 to 0.5 metres	Smooth (wavelets)
0.5 to 1.25 metres	Slight
1.25 to 2.5 metres	Moderate
2.5 to 4 metres	Rough

As sizes of offshore wind farms increase in size we require so does the cost of maintenance and therefore the need to access at a moments notice a wind farm. The ability to extract data of the sea height in a large area would prove extremely useful with the potential of removing buoys altogether.

2 Processing Data

The creation of a framework was necessary due to a number of steps that needed to be taken before the data could be learned by a CNN. Using Python and the SNAP (Sentinel Application Platform) library for the automated downloading and processing of the data into RGB format. Further processing was then required for the removal of anomalous extremities in the image; such as cloud or land. Leaving a clean data set which would be labelled with a backlog of buoy data that was located at the centre of our training region east of the Humber Estuary (Dowsing buoy).

For the purpose of training the neural network to classify sea height, each satellite image (10,800 x 10,800 pixel resolution) should be subdivided into 244x244 sections leaving a maximum of 2025 sub-sectioned images per input minus those sections removed from the data set due to cloud/land contamination.

2.1 Satellite Image Cleaning

Satellite images are very rarely captured with no anomalous data, be it cloud, land or even aeroplane interference. The removal of atmospheric anomalies in satellite imaging is a key part in most pre-processing steps for the use of satellite images. Most methods are not robust enough for the level of accuracy required or depend on large levels of manual interaction [8], and so a method using deep learning was devised to remove unwanted data.

To construct the data set needed we first took 30 input satellite images from various positions, each image was divided into a sub-sampled set leaving a substantial data set of 60,750 images.

For these images, we used a manual filtering approach in order to construct a labelled database of two classes, one for images we want the model to remove/throw away and one for the pure sea images that we wish to keep. A method of adaptive thresholding [5] between neighbouring pixel values was chosen, leaving similar neighbouring pixel colours white, whereas the massively different cloud and land pixels will be set to black.

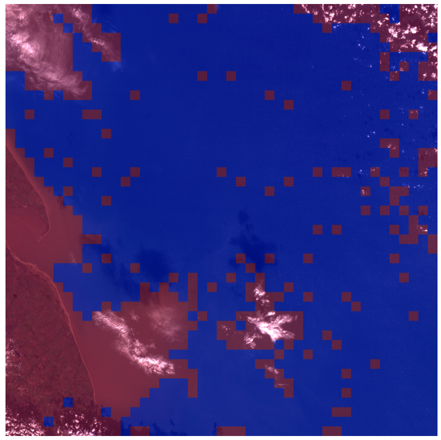
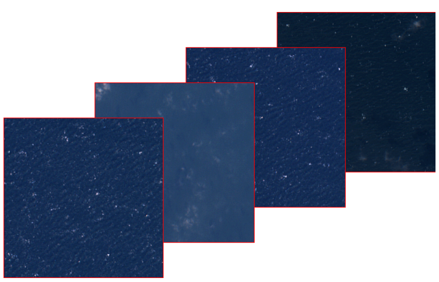


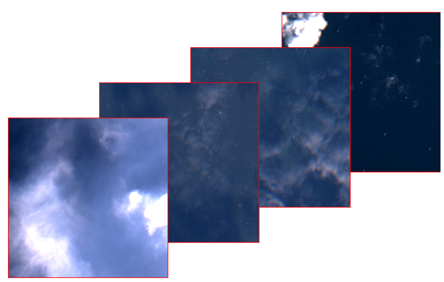
Fig. 1: RGB Image that has been classified using our neural network. Red representing anomolous data and Blue representing pure sea data.

These manually split images were fed into a Deep Convolutional Neural Network [6] which learned a representation of the two classes to 91% accuracy, this allowed the future use of this model instead of the manual based approach. Figure 1 shows the analysis and output of one trained image.

The slight amount of false negatives that will be transferred to the learning of sea tiles that may contain some noise is not necessarily bad when the network is tested on unseen data the noise can contribute to a reduced over fit representation.



(a) Sea Class



(b) Cloud/Land Class

Fig. 2: Example of a set of images from the two classes that have been separated

3 Learning the Sea Height

Given the previous processing steps, we are left with a collection of clean sea images of 244x244 resolution accompanied with the date and time they were taken. Figure 3 shows a collection of sea images from different days, notice it's fairly easy to distinguish between the rough "wavey" images against the fairly smooth "flat" images, this is an important step for the practice of using visionary deep learning, too complex patterns can result in low levels of understanding, and thus accuracy, from the network.

To label our data, which is required by the supervised learning network, we mapped the buoy sea height data values to the time that the satellite image was taken. These values were rounded to 1 decimal point, leaving 17 data points of varying sea height ranging from 0.5 meters to 2.9 meters.

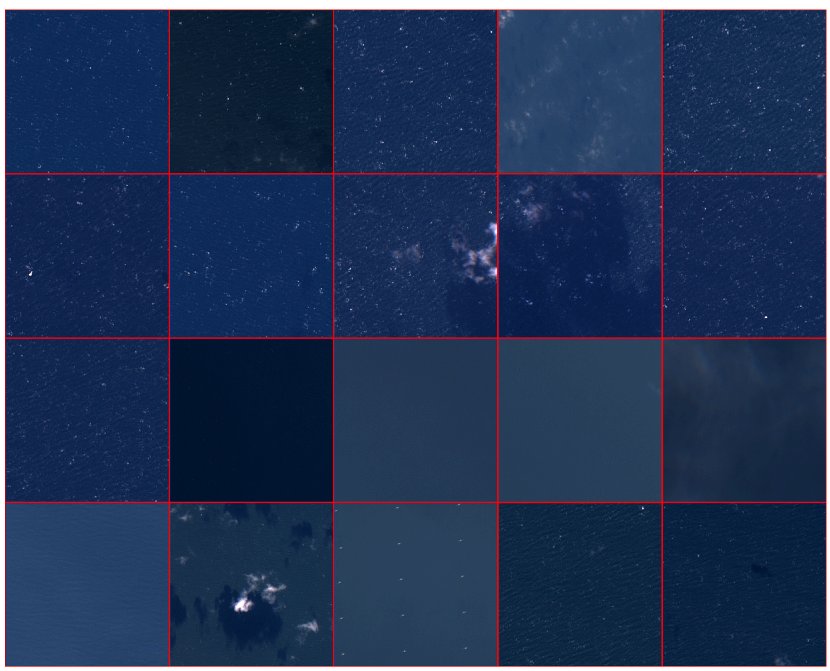


Fig. 3: 20 244x244x3 random samples of varying sea state training data. Showing only slight cloud interference.

Deep convolutional neural networks [6] usually classify images into a discrete output, however since a continuous output is required we simply remove the final activation layer (softmax) and replace it with a dense layer with 1 output [3].

The architecture of the network consisted of a pre-trained VGG16 [9] with two additional dense layers replacing the final output layer. The network was then fine-tuned [11] on the data set, while the VGG16 section was frozen. Figure 4 shows a visual representation of the network that was chosen.

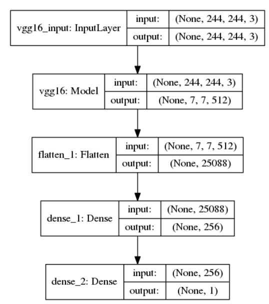


Fig. 4: Network architecture with one dense final layer for continuous output. VGG16 model is frozen.

The 15K preprocessed sea state images were then fed with their corresponding label outputs into the deep network (figure 4). Over a course of 20 epochs, we saw a gradual reduction in loss to a plateau at 0.07 meter loss for the training set.

4 Results

Initial results were run to determine if we could use a neural network to classify sea height using banded data, where we rounded each sea height into 3 classes; 1,2,3 meters. We attempted to train the model to classify each input into either of the three classes. Since this method provided a promising start, classifying 92% of the images into the correct three classes, we proceeded to swap out the classes for continuous outputs/regression.

The methods devised compare to some of the most accurate techniques used currently. With an average of 5% different between true and predicted values for sea height for values between 0.5 meters and 3.0 meters. Whereas buoy data can be seen to vary its accuracy between 0-20% [10] but cover a greater range of sea height values.

Similarly comparing the results to radar methods of sea height detection we can see that techniques currently used range around 0.21m difference across inputs between true and predicted, so on average we perform slightly better using our technique with a gain of 0.04m accuracy.

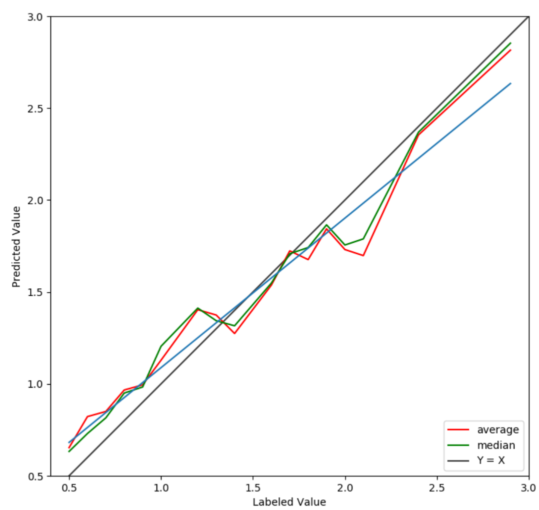


Fig. 5: Learned representation of input data, True vs Predicted labels values. Plotted median and mean for comparison with blue line of best fit for both curves against black Y=X (True=Pred) perfect data representation

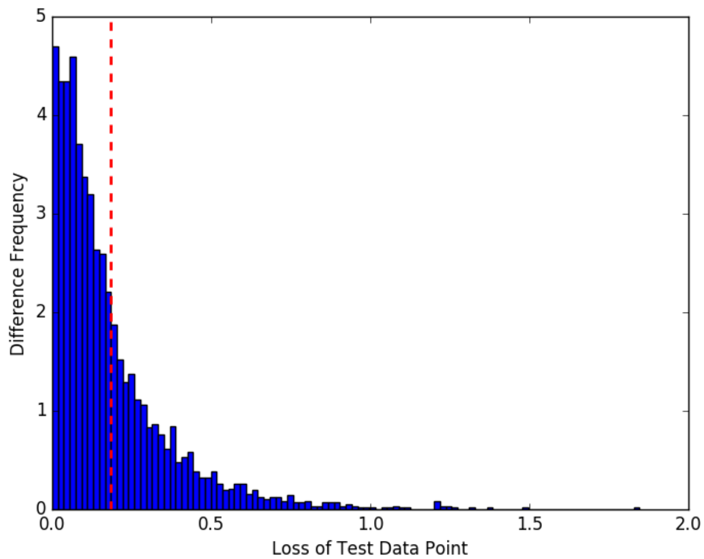


Fig. 6: Difference in classified test data between true and predicted. Average line plotted (red) for expected loss in meters

Since a neural network is inherently difficult to understand the underlying representations we opted to plot test data to determine the accuracy of the model. Using figure 5 we can visualize and understand the average results of the output test set. This method of analysis was our main indicator that the network was learning over time, achieving as close to the Y=X (True = Learned) line as possible.

Note at two points on figure 5, roughly at 1.4m and 2.3m, we experienced a large drop in loss, this was caused by a smaller than usual amount of images in these data points, with more data alleviating this issue.

5 Discussion

The techniques used proved crucial to the building of the training data, when using other methods of clouds and land removal we saw a greater disparity between clean and "dirty" images being separated.

During collection of satellite image data, it was found that a small portion of satellite data had been corrupt, this was via transmission from the satellite to the receiver. After manually scrolling through each image is was determined that the data corruption only affected a small portion of images on a specific data.

The size of the input images was also an important factor, if we lowered the image size, and subsequently obtained more data, the convolutional neural network would struggle to find patterns in the small feature data. On the opposite side, with a larger input image, we struggled to both train the network and generalize due a to smaller data set.

There are certain considerations in that since we are using RGB images, large cloud coverage proves to be an impassable problem. It was noticed that in the test set anywhere over 80% cloud coverage was simply too much to generalise on given the small amount of data remaining, which presents one large drawback of this method. Though it seems rare that the level of cloud in a satellite image exceeds this limit.

6 Conclusion

There has been presented a rigorous explanation of the processes and methods involved in the creation of a novel framework with the ability to consistently classify continuous values representing the sea height in given RGB colour satellite regions.

By using multiple convolutional neural networks we automated steps that previously had manual involvement. The first network was trained to distinguish the difference between cloud contamination and land in a satellite image to a 90% level of accuracy. We created a method to train these images through a continuous convolutional neural network model which learned to an average of 0.17-meter difference between actual sea height and predicted sea height.

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