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An attention-based U-Net for detecting deforestation within satellite sensor imagery☆

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ABSTRACT

In this paper, we implement and analyse an Attention U-Net deep network for semantic segmentation using Sentinel-2 satellite sensor imagery, for the purpose of detecting deforestation within two forest biomes in South America, the Amazon Rainforest and the Atlantic Forest. The performance of Attention U-Net is compared with U-Net, Residual U-Net, ResNet50-SegNet and FCN32-VGG16 across three different datasets (three-band Amazon, four-band Amazon and Atlantic Forest). Results indicate that Attention U-Net provides the best deforestation masks when tested on each dataset, achieving average pixel-wise F1-scores of 0.9550, 0.9769 and 0.9461 for each dataset, respectively. Mask reproductions from each classifier were also analysed, showing that compared to the ground reference Attention U-Net could detect non-forest polygons more accurately than U-Net and overall it provides the most accurate segmentation of forest/deforest compared with benchmark approaches despite its reduced complexity and training time, thus being the first application of an Attention U-Net to an important deforestation segmentation task. This paper concludes with a brief discussion on the ability of the attention mechanism to offset the reduced complexity of Attention U-Net, as well as ideas for further research into optimising the architecture and applying attention mechanisms into other architectures for deforestation detection. Our code is available at https://github.com/davej23/attention-mechanism-unet.

1. Introduction

The Amazon Rainforest represents around 40% of the remaining tropical forests on Earth (Hubbell et al., 2008), and provides refuge for 10% of the world's species (WWF, 2020). Therefore, the enormous carbon sequestering capability of the Amazon Rainforest is pivotal to the regulation of the continental, and global climate, since it is estimated to store 76 billion tonnes of carbon in the form of 390 billion trees (Müller, 2020). However, the region has seen large-scale deforestation for agriculture, raw materials, and for land to build housing due to rapid development of South America (Garcia-Ayllon, 2016).

This destruction poses an existential threat to the Amazon Rainforest and threatens to further worsen the effects of global warming. It is estimated that the Amazon's ability to act as a carbon sink will disappear in 2035 (Hubau et al., 2020), and is already showing signs of being close to this (Harris et al., 2021), thus resulting in extreme weather such as drought and forest fires locally and globally.

In 2020, an average of 2309.5 hectares of forest per day was destroyed (MapBiomas, 2020); roughly equating to an area the size of Ottawa, the capital city of Canada every month (Statistics Canada, 2011). As a result, it has become a global priority to minimise the rate of deforestation of the Amazon by designating protected areas, campaigning against companies which produce products in illegally-cleared areas of the forest, as well as by regular monitoring (Tollefson, 2015). The latter has long been a problem as on-the-ground monitoring is infeasible due to the sheer surface area that the Amazon Rainforest covers (Gong et al., 1994). This paper looks to further the effort towards remotely-sensed deforestation detection/monitoring within the Amazon region, but also for use in other forest biomes, through the use of artificial intelligence (AI) in the form of an Attention U-Net deep neural network (Oktay et al., 2018).

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1.1. Architecture fundamentals

Attention U-Net is based upon the U-Net architecture (Ronneberger et al., 2015), which itself is a specific type of fully convolutional network (FCN); a family of neural networks characterised by an encoder-decoder, or contraction and expansion, structure. These are designed for semantic segmentation, also known as pixel-wise classification.

U-Net builds upon the standard FCN architecture by introducing skip connections, meaning that blocks of layers within the contraction phase can pass their output directly to blocks within the expansion phase, which greatly improves the ability to extract high-level features from images. Previously, U-Net has been applied to deforestation segmentation of the Amazon Rainforest using Sentinel-2 satellite imagery with high success (Bragagnolo et al., 2021), and the aim of this paper is to explore the incorporation of an attention mechanism into U-Net to improve upon U-Net.

An attention mechanism aims to replicate the human ability to direct focus, or to concentrate on, specific stimuli. In the domain of neural networks, this involves learning which parts of the input to focus attention on. Attention mechanisms are prominently used within the field of natural language processing (NLP), where they focus on sections of an input corpus, which is useful within tasks such as sentiment analysis (Galassi et al., 2020).

Attention U-Net is created by adding an attention gate to the skip connection within U-Net. Rather than concatenating each upscaled layer in the expansion phase with the appropriate contraction-phase layer, the upscaled layer is concatenated with the output from the attention mechanism, a function of the pre-upscaled layer and the aforementioned contraction-phase layer.

1.2. Previous work

Machine learning-based forest cover change monitoring of the Amazon has been ongoing for almost a decade (Souza et al., 2013), with deep learning (DL) methods being the current state-of-the-art. This has been demonstrated within comparisons of cutting-edge methods such as U-Net, ResUNet (Diakogiannis et al., 2020) and SharpMask (Pinheiro et al., 2016), using Landsat imagery of the Amazon Rainforest, versus less sophisticated methods such as the multi-layer perceptron (MLP) and random forests (de Bem et al., 2020).

Previous segmentation work using U-Net, and involving Sentinel-2 satellite data, has also been carried out, such as detecting change within Ukrainian forests (Isaienkov et al., 2021), as well as mapping irrigation systems (Graf, 2020). Desertification detection within Algeria, using Landsat ETM+ satellite data, with a variational autoencoder (VAE) (Verstraete, 1986) is another example of the wide variety of contexts and approaches that have been used with semantic segmentation. Importantly, previous applications of Attention U-Net have only been within medical contexts, such as brain tumour segmentation (Islam et al., 2021), liver computerised tomography (CT) scan segmentation (Li et al., 2020) and gland segmentation (Zhao et al., 2020). As a result, we believe that this paper represents the first, or one of the first, successful applications of Attention U-Net to a land cover segmentation problem.

It is clear that much work has been undertaken within the realm of land cover segmentation, with recent work showcasing the superiority of U-Net over other state-of-the-art methods, however there are very few which look to test model generalisability or to evaluate performance over multiple locations and instead evaluate over a single data source/location (Lee et al., 2020; Irvin et al., 2020).

Within this paper, we will test Attention U-Net extensively, testing on two different biomes as well as testing its generalisability and transferability. Previous work in this area has not looked to show that a model performs well over multiple scenarios, nor has an attention-based network, the state-of-the-art in deep learning, been applied to land cover segmentation. Therefore, this paper represents the first time such work has been done. The advantage of Attention U-Net, as configured in this paper, is its much-reduced complexity compared to U-Net and other state-of-the-art models. Previous applications of Attention U-Net have shown that it outperforms U-Net and if the same were to be for land cover segmentation, Attention U-Net represents a state-of-the-art in terms of efficiency and performance for land cover segmentation. It is important to recognise that deforestation land cover segmentation is a hugely important application due to the threat posed by climate change, and a model with increased performance and efficiency, which also performs at that level over multiple scenarios, is extremely useful for researchers monitoring deforestation or measuring other land cover from satellite imagery.

2. Methodology

2.1. Datasets

To evaluate Attention U-Net for deforestation segmentation, we used three datasets produced from images in the satellite imagery database SentinelHub (Sinergise, 2014). The number of images within these datasets, as well as forest and non-forest class balance, can be seen in Fig. 1. The first dataset, referred to as the 3-band or RGB dataset, is a collection of RGB-converted images and deforestation masks, where 0s and 1s represent non-forest and forest areas respectively, of the Amazon Rainforest (Bragagnolo et al., 2019). In order to have more unseen data to evaluate our models, we took five images from the training data and added them to the testing dataset.

The other datasets, referred to as the 4-band datasets, are both composed of 4-band RGB + near-infrared imagery, one containing images from the Amazon Rainforest and the other from the Atlantic Forest (Mata Atlantica) (Bragagnolo et al., 2021). Fig. 1 shows the location of these biomes, as well as example images which highlight the fact that the images are highly concentrated within two geographically distinct regions. For training, we randomly selected 250 training images due to memory limitations.

Each image is of shape $(512, 512, N)$, where N refers to the number of bands. Each deforestation mask is of shape $(512, 512, 1)$. In order to produce the images and masks found within each dataset, the author of the dataset split a large satellite image into sub-images and produced masks using a modified version of the k-means classification algorithm with the GRASS-GIS 7.6.1 software suite (GRASS Development Team, 2020). Images were repeatedly re-classified until the corresponding masks had 'a satisfactory rating'.

2.1.1. Difference between U-Net and attention U-Net

The architecture of U-Net is similar to that of Attention U-Net, shown in Fig. 3, except the number of filters used within each convolutional layer, in each respective block, are 64, 128, 256, and 512, with 1024 filters used in the bottleneck layers, and there are no attention mechanisms. We chose to use 16,32,64, and 128 filters, with 256 filters in the bottleneck layers for Attention U-Net through experimentation. When keeping the number of filters the same, Attention U-Net has more parameters and a greater training time than U-Net, but with fewer filters

Table 1
Number of images within each dataset, as well as the forest (F) and non-forest (NF) class balance within each dataset. Numbers in brackets indicate when the number of images used in experimentation differs to the original total.

Dataset	Number of Images & F-NF Class Balance		
	Training	Testing	Validation
3-band (RGB) Amazon	30 (25)	15 (20)	N/A
	51.2% - 48.8%	52.1% - 47.9%	N/A
4-band Amazon	499 (250)	20	100
	50.0% - 50.0%	49.8% - 50.2%	47.8% - 52.2%
4-band Atlantic Forest	485 (250)	20	100
	33.3% - 66.7%	31.5% - 68.5%	33.8% - 66.2%

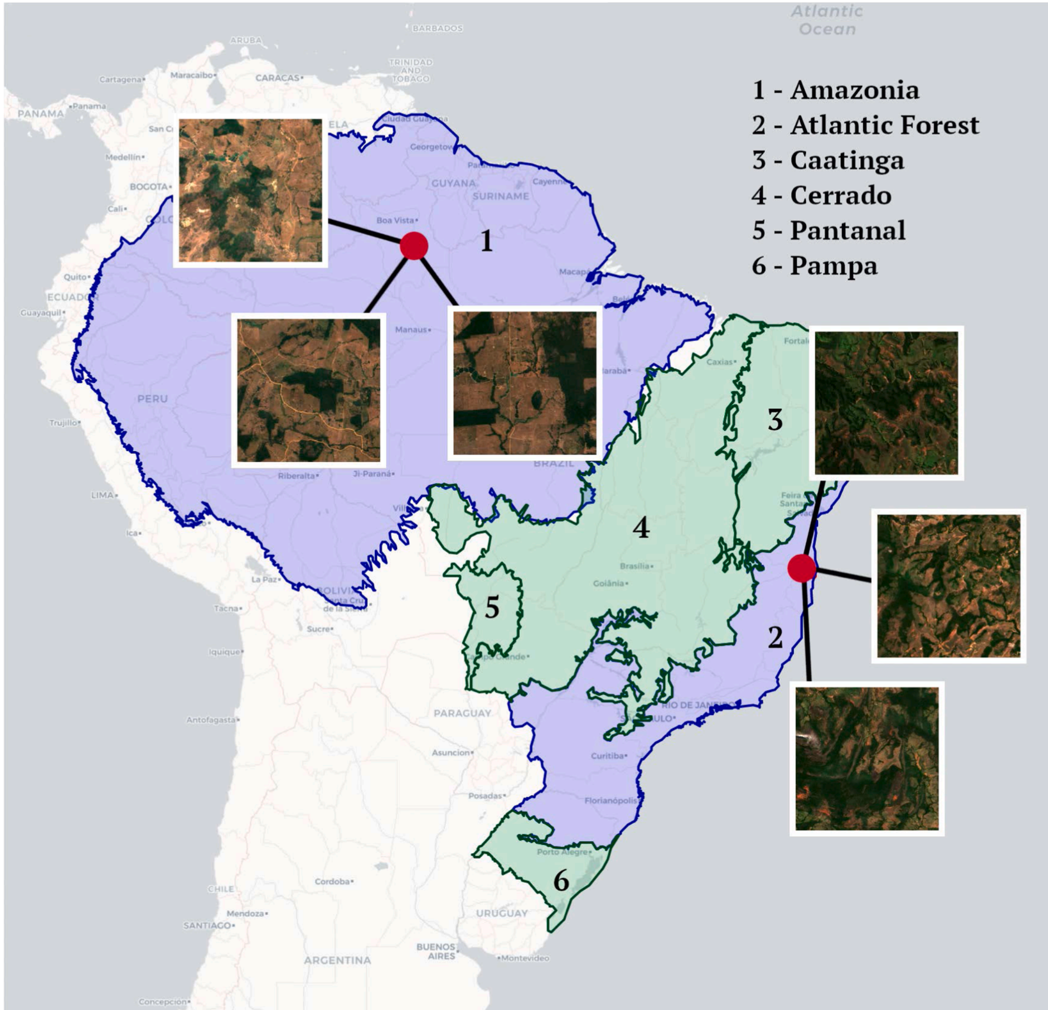


Fig. 1. Map of the Amazon Rainforest and Atlantic Forest biomes within South America, including images from the 4-band datasets.

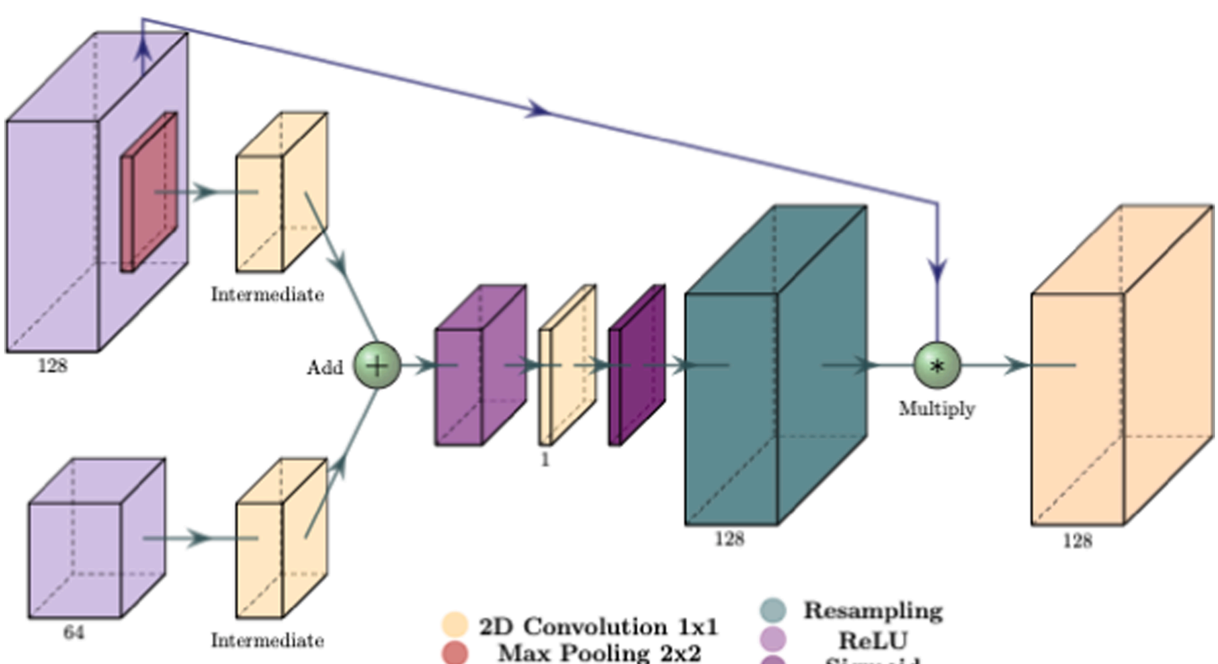


Fig. 2. A network architecture diagram for the Attention Mechanism. The AG marker signifies the location of the attention gate, or attention mechanism.

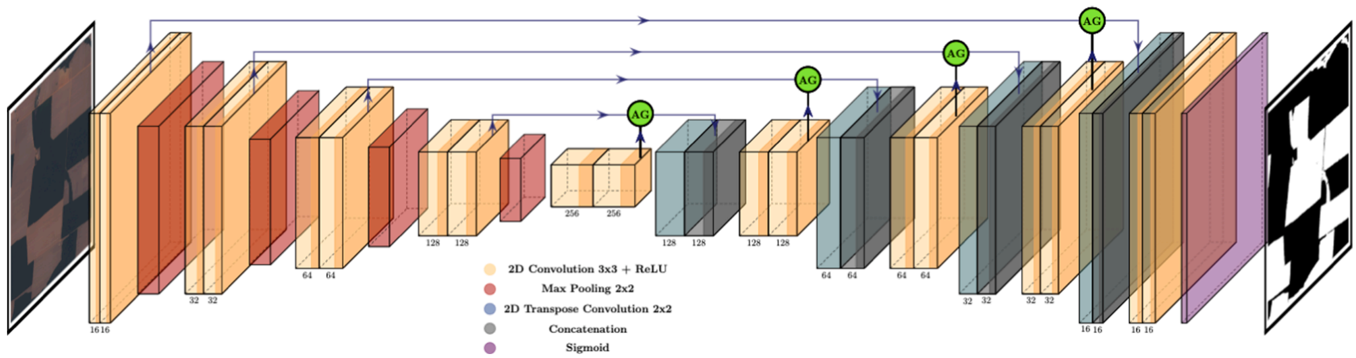


Fig. 3. A network architecture diagram for Attention U-Net.

the architecture becomes much less complex in turn causing reduced training time. The reason for this is that the attention mechanism, seen in Fig. 2, adds complexity in the form of additional parameters.

In order to evaluate the performance of Attention U-Net, four other models were also tested: U-Net, Residual U-Net, ResNet50 (He et al., 2015) with a SegNet backbone (Badrinarayanan et al., 2016), and FCN32 with a VGG16 backbone (Simonyan and Zisserman, 2015). Each of the models were trained from scratch, including the backbone architecture, in order to provide a fair comparison.

2.1.2. *Training and testing procedure*

The number of epochs and the learning rate used for each network can be found in Table 2. These values were found to be the values which gave maximal validation accuracy through experimentation. Models were trained using different learning rates and epochs until the highest validation accuracy was obtained. Once the optimal hyperparameters were found, models were not re-trained due to usage limits within the Google Colab environment. However, our results cover multiple datasets and each show Attention U-Net to be the stronger performer, therefore reducing the likelihood of the results being down to weight initialisation alone. Also, data augmentation was used on the RGB dataset, including rotation, reflection, zooming and shearing, in order to facilitate the need for a greater amount of training data. Finally, each image was normalised, such that each pixel channel value was in the interval [0,1]. The Adam optimiser (Kingma and Ba, 2017) was used as it provided the greatest peak validation accuracy compared to the stochastic gradient descent (SGD) optimiser. The Binary Crossentropy (BCE) loss function was used as it has been shown to work well within binary semantic segmentation tasks (Jadon, 2020).

After training, each of the models were evaluated on the validation data from the dataset they were trained on, and the models trained on the 4-band datasets were tested on the test dataset also. Each 4-band model was also evaluated on the data from the opposite location, for instance the models trained on the 4-band Amazon data were also tested on the Atlantic Forest data, and vice versa. This gives us the ability to test how transferable each model is to imagery from a different location, which could show whether our model could be used successfully for deforestation segmentation within other regions globally. The evaluation process of a model involves generating mask reproductions for each unseen image by passing an image I into it, obtaining a $512 \times 512 \times 1$ output with values being in the range $[0,1]$. These values are rounded to the nearest integer to create a binary mask. The performance of a model is then evaluated by computing the pixel-wise differences between these masks and the original ground truth masks.

Table 2
Number of Training Epochs and Learning Rate Used for Training Each Classifier on RGB and 4-band Datasets; Values Chosen Through Trial and Improvement.

Classifier	Learning Rate	Epochs	
		RGB	4-band
Attention U-Net	0.0005	50	60
U-Net	0.0001	30	20
ResNet50-SegNet	0.0001	40	20
FCN32-VGG16	0.0001	50	50
Residual U-Net	0.0001	40	20

2.1.3. *Quantifying results*

To quantify our results, the weighted Precision, Recall, F1-score and Jaccard Index, also known as the Intersection over Union (IoU) score, were used. The IoU score was selected as it is describes the similarity of the predicted deforestation polygons to the ground truth, which is a better measure within image segmentation compared to pixel accuracy which only measures the number of accurate pixel predictions. Weighted metrics were used as they account for class imbalance between forest and non-forest pixels (Tague-Sutcliffe, 1992). For reference, the positive class refers to the forest pixels.

Another essential piece of the analysis of a model is determining its computational efficiency; a factor which determines whether it is viable for real-world use. If the training time is too high, it may be more suitable to opt for a less performant model with lower training time. Furthermore, models with large parameter spaces are more likely to overfit and have worse generalisability than less complex models (Ying, 2019). Therefore, to evaluate the efficiency of each model in this paper we compare the number of learnable parameters and the total training time on each dataset.

To carry out our experimentation, we used the Google Colaboratory Python environment (Google, 2017) with an NVIDIA Tesla P100 16 GB GPU and 12 GB of RAM. Models were written with the Keras (Chollet et al., 2015) Application Programming Interface (API) of the TensorFlow machine learning framework (Abadi et al., 2015).

3. Experimental results

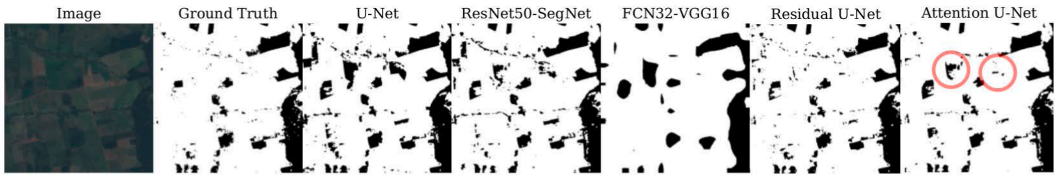
3.1. *RGB dataset*

When testing the models on the RGB validation data, Attention U-Net achieved the highest results overall, as can be seen in Table 5. This is evidenced in Fig. 4a where the mask prediction from Attention U-Net is markedly more accurate than those produced by the other classifiers. There is a reduced tendency to incorrectly classify forest as non-forest, false-positives, in contrast to U-Net, which appears to often exaggerate the non-forest polygons. The exception to this is the upper red circle within the upper Attention U-Net reconstructed mask, where the other classifiers fail to identify the extent of the forested polygon being highlighted.

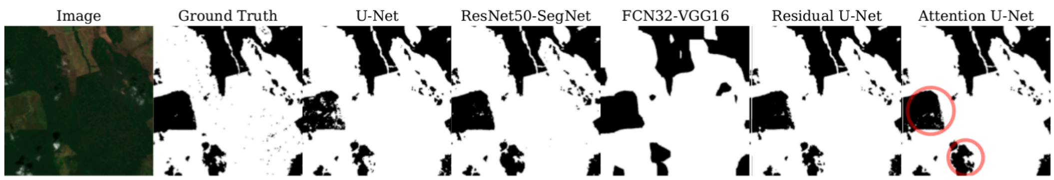
3.2. *4-band Datasets*

3.2.1. *Amazon dataset*

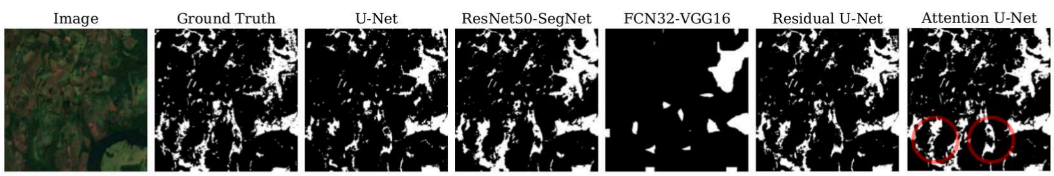
A similar result is seen with the validation and test metrics for the 4-



(a) Image from the RGB Amazon dataset.



(b) Image from the 4-band Amazon dataset.



(c) Image from the 4-band Atlantic Forest dataset.

Fig. 4. Comparison of ground truth deforestation masks versus classifier-generated mask predictions. Deforested areas appear in black, and forested areas in white. Notable differences are highlighted with red circles.

band Amazon data. Table 3 shows that Attention U-Net outperforms each of the other classifiers, with a 0.5% improvement in F1-score over the standard U-Net. We can see this within Fig. 4b where Attention U-Net produces deforestation polygons with greater detail than U-Net and gives less false-positives than ResNet50-SegNet.

3.2.2. *Atlantic forest dataset*

Following on from this, Attention U-Net once again outperforms other models on the Atlantic Forest data. In particular, Fig. 4 shows that the F1-score produced by Attention U-Net is significantly greater than for the other models. This difference can be witnessed within Fig. 4c where Attention U-Net is again able to identify more complex polygons when compared to U-Net. Although ResNet50-SegNet can also accurately identify the same polygons, it also produces more false-positives than Attention U-Net.

3.3. *Testing on non-local imagery*

When testing the Amazon-trained models on the Atlantic Forest data, in Table 6, we see that Attention U-Net is the most performant overall, except for the recall score in which it is bested by U-Net, however more importantly it has a higher F1-score and IoU score meaning that the reproduced mask is more similar to the ground truth and has a greater precision and recall overall. When we look at the results from the opposite scenario, the difference in performance between Attention U-Net and the other models is much greater suggesting that Attention U-Net provides greater transferability to data from a different location than the other methods.

3.4. *Computational efficiency*

Fig. 7 shows that Attention U-Net is the most efficient model, containing both the fewest number of parameters, as well as the lowest training time for each of the datasets; it is also vastly more efficient, training between 20% to 56% faster than other models. The training time of both '4-band' models was identical, due to being trained over the same number of epochs with the same learning rate.

3.5. *Attention U-Net versus U-Net*

Finally, we compare the ground truth masks to the predictions made by Attention U-Net and U-Net. Fig. 5 shows that Attention U-Net

Table 3
Quantitative Evaluation of the Performance of Four Classifiers at Classifying Forest and Non-Forest Areas Within the 4-band Amazon Test and Validation Satellite Imagery. Bold Text Identifies the Best Result.

Classifier	Dataset							
	Validation				Test			
	IoU	Precision	Recall	F1-score	IoU	Precision	Recall	F1-score
Attention U-Net	**0.9581**	**0.9790**	**0.9779**	**0.9785**	**0.9516**	**0.9758**	**0.9748**	**0.9753**
U-Net	0.9530	0.9766	0.9752	0.9759	0.9473	0.9738	0.9724	0.9731
Residual U-Net	0.9432	0.9723	0.9696	0.9720	0.9429	0.9715	0.9703	0.9709
ResNet50-SegNet	0.9467	0.9733	0.9717	0.9725	0.9416	0.9707	0.9694	0.9701
FCN32-VGG16	0.8592	0.9210	0.9214	0.9212	0.8557	0.9212	0.9205	0.9208

Table 4
Quantitative Evaluation of the Performance of Four Classifiers at Classifying Forest and Non-Forest Areas Within the 4-band Atlantic Forest Test and Validation Satellite Imagery. Bold Text Identifies the Best Result.

Classifier	Dataset							
	Validation				Test			
	IoU	Precision	Recall	F1-score	IoU	Precision	Recall	F1-score
Attention U-Net	**0.9120**	**0.9563**	**0.9520**	**0.9541**	**0.9199**	**0.9591**	**0.9571**	**0.9581**
U-Net	0.8818	0.9387	0.9346	0.9366	0.8883	0.9424	0.9373	0.9399
Residual U-Net	0.9102	0.9544	0.9514	0.9512	0.9073	0.9542	0.9493	0.9517
ResNet50-SegNet	0.9043	0.9514	0.9480	0.9497	0.9026	0.9510	0.9466	0.9488
FCN32-VGG16	0.7182	0.8319	0.8290	0.8304	0.6902	0.8186	0.8077	0.8131

Table 5
Quantitative Evaluation of the Performance of Four Classifiers at Classifying Forested/Deforested Areas Within the RGB Amazon Validation Set Satellite Imagery. Bold Text Identifies the Best Result.

Classifier	IoU	Precision	Recall	F1-score
Attention U-Net	0.9028	**0.9574**	**0.9526**	**0.9550**
U-Net	0.8888	0.9571	0.9473	0.9522
Residual U-Net	**0.9127**	0.9539	0.9505	0.9493
ResNet50-SegNet	0.9025	0.9519	0.9470	0.9495
FCN32-VGG16	0.8198	0.8988	0.8978	0.8983

correctly identifies a greater percentage of forest pixels compared to U-Net on both the RGB and Atlantic Forest datasets, by 2.47% and 3.06% respectively and produces 2.47% and 3.16% fewer false-positives, respectively. On the 4-band Amazon dataset, Attention U-Net produces fewer misclassifications as well as a greater proportion of correct predictions overall compared to U-Net; this is highlighted by the fact that only 2.21% of pixels are mis-classified. When taking into account the correctly identified pixels within each dataset, Attention U-Net identifies 1.03%, 0.274% and 1.73% more pixels correctly on the respective datasets. When using a model to determine deforested regions in satellite imagery in order to estimate total deforested area, false-positives are more desirable than false-negatives as deforested area being underestimated can potentially caused new deforestation within an area to go undetected. However, in this case, as Attention U-Net more accurately identifies a greater number of pixels than U-Net the greater number of false-negatives is not an issue.

4. Discussion

4.1. General comments

Throughout our analysis, Attention U-Net outperforms the other models on forest/deforest segmentation. Despite the Residual U-Net providing better results in some cases, Attention U-Net consistently provides the best results. The improvement of Attention U-Net upon U-Net is likely due to the attention mechanism being able to distinguish high levels of detail in complex polygons, resulting in fewer errors within mask predictions. It was also shown within our experimentation that the 4-band Attention U-Net models are transferable to images from a different region, and this could be further confirmed by testing on a similar dataset from a different forest. We also found that Attention U-Net is more efficient than U-Net, where the training time was up to 30% lower yet had noticeably improved performance. In regards to the datasets themselves, we can see in Fig. 5 that the Atlantic Forest dataset has a large class imbalance in favour of non-forest pixels, which accounted for two-thirds of the total number of pixels. This is likely the reason why the Atlantic Forest models performed very well when evaluated on Amazon data.

4.2. Limitations

We conjecture that the performance of classifiers is limited by the quality of the ground truth masks, as they were produced using an imperfect classification method. It was noted in the dataset author’s paper (Bragagnolo et al., 2021) that some model mask predictions identify deforested polygons which were not picked up within ground truth masks; an example can be seen in Fig. 6. As a result, it could be useful for future work to update the ground truth masks by adding in the polygons found by our Attention U-Net model and further increasing the quality of ground truth masks.

4.3. Future work

To build upon the work from this paper, other loss functions such as Jaccard loss (Bertels et al., 2019), Dice loss (Sudre et al., 2017), or

Table 7
Comparison of the Computational Efficiency of Four Classifiers, in Terms of the Number of Parameters and Training Time Per Step/Image. Bold Text Identifies the Best Result.

Classifier	Parameters ($\times 10^6$)	Training time (s)	
		RGB	4-band
Attention U-Net	**2.01**	**365**	**465**
U-Net	31.03	366	650
Residual U-Net	31.3	744	975
ResNet50-SegNet	72.27	1092	1475
FCN32-VGG16	134.3	650	2300

Table 6
Quantitative Evaluation of the Performance of Four Classifiers at Classifying Forest and Non-Forest Areas Within Imagery from the Dataset from the Other Location. Bold Text Identifies the Best Result.

Classifier	Training Data Location - Testing Data Location							
	Amazon - Atlantic Forest				Atlantic Forest - Amazon			
	IoU	Precision	Recall	F1-score	IoU	Precision	Recall	F1-score
Attention U-Net	**0.8143**	**0.9222**	0.8829	**0.9021**	**0.8722**	**0.9445**	**0.9266**	**0.9355**
U-Net	0.8134	0.9169	**0.8847**	0.9005	0.8254	0.9323	0.8915	0.9115
Residual U-Net	0.7707	0.9164	0.8508	0.8824	0.8709	0.9440	0.9256	0.9347
ResNet50-SegNet	0.7921	0.9156	0.8670	0.8906	0.8453	0.9355	0.9088	0.9220
FCN32-VGG16	0.6797	0.8246	0.7930	0.8085	0.7913	0.8985	0.8750	0.8866

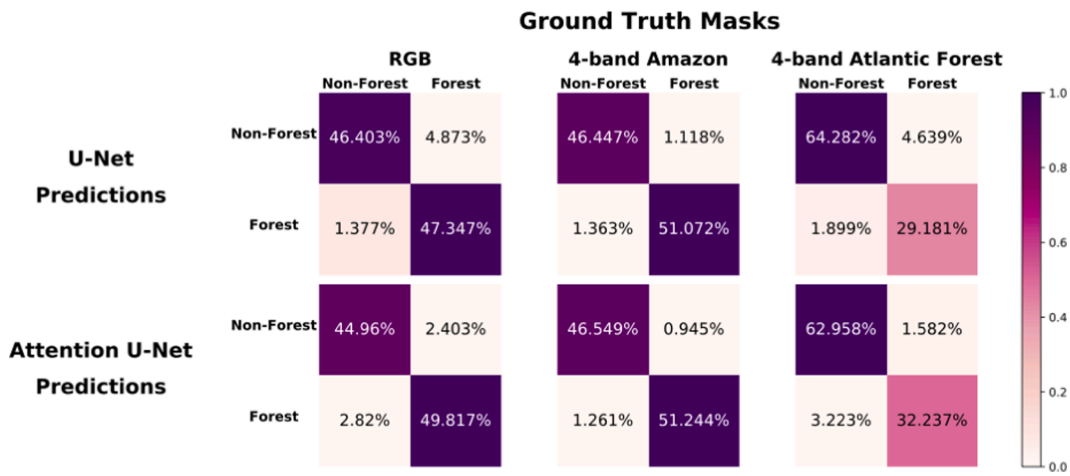


Fig. 5. Confusion matrix comparing U-Net and Attention U-Net mask predictions versus ground truth masks within each dataset.

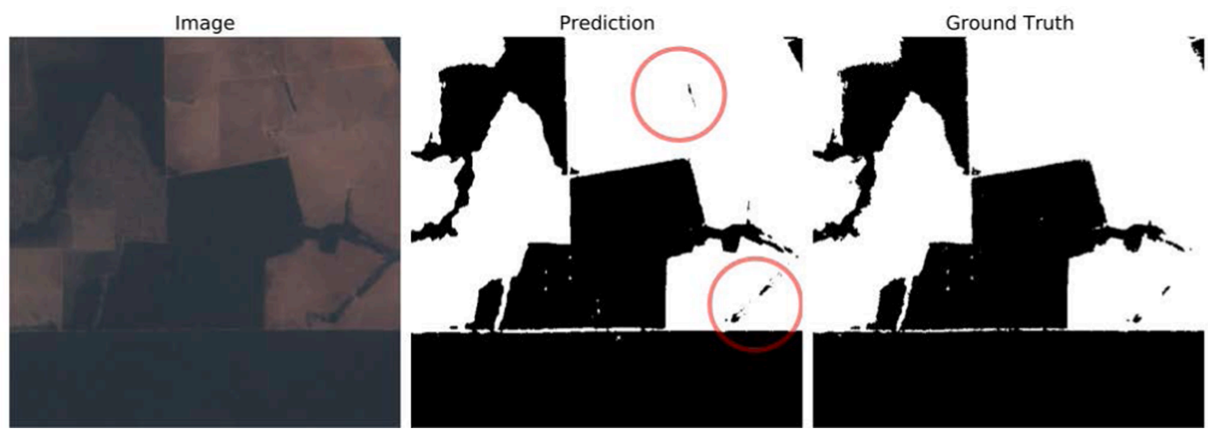


Fig. 6. An example of a ground truth mask not being as detailed as Attention U-Net predicted mask. Red circles highlight polygons which have been correctly identified by Attention U-Net but do not exist within the ground truth mask.

derivatives such as DiceTopK and DiceFocal, could be tested as they have been successfully used within other segmentation tasks (Ma et al., 2021). Also, the addition of regularisation layers such as Dropout and Batch Normalisation could reduce overfitting and validation loss. These were not tested in our experimentation, but have been shown to provide improvements to deep learning models in multiple scenarios.

Since the addition of the attention mechanism allows Attention U-Net to perform to such a degree despite having very few parameters, we believe that others may have success implementing attention mechanisms into less complex versions of other models to a similar effect. One such possibility is the use of a Residual Attention U-Net which would contain more parameters than Attention U-Net, and perhaps longer training time, but may improve upon the Residual U-Net.

Finally, we suggest that transfer learning could be used with either of the 4-band Attention U-Net models by training on both 4-band training datasets. This could allow for greater transferability to images from a wider set of locations. It was shown in Section 3.3 that the models trained on a single location were transferable, so it is sensible to suggest that transfer learning would further improve this and allow for successful applicability to forest imagery from around the world.

5. Conclusion

In this paper, we have carried out a quantitative analysis of the performance of Attention U-Net at the detecting deforestation in South American tropical rainforest imagery. We found that the addition of an attention mechanism to a less complex version of U-Net provides greater performance than the standard U-Net architecture, as well as several other state-of-the-art methods. The attention mechanism enables the network to retain high levels of spatial information despite containing layers of much lower dimensionality than U-Net. Due to the successful application of an attention mechanism to a deep neural network for this task, we can recommend the use of an Attention U-Net for other land cover segmentation tasks in the field.

CRediT authorship contribution statement

David John: Data curation, Formal analysis, Investigation, Methodology, Software, Visualisation, Writing – original draft, Writing – review & editing. **Ce Zhang:** Conceptualisation, Writing – review & editing, Supervision, Project Administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Network architecture diagrams were produced using PlotNeuralNet (IIqbal, 2018). The Amazon basin shapefile is from Harvard WorldMap

(Villegas, 2021) and the South American biome shapefiles are from TerraBrasilis (Assis et al., 2019). Dataset augmentation code was modified from (Bragagnolu, 2021), and U-Net code was inspired by (Xuhao, 2018). ResNet50-SegNet code was used from (Bhatnagar et al., 2020) and code inspiration was used from (Dwivedi, 2019). The code for our FCN32-VGG16 model was modified from (Gupta et al., 2021).

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