Sea ice Concentration Estimation Using Machine Learning

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Abstract

The current state of affairs in sea ice concentration estimations are aimed at producing numerical models calibrated in the Northern hemisphere. These models utilise the behaviour and features present in sea ice regions and produce somewhat biased predictions. Remote-sensing instrumentation such as passive microwaves and synthetic aperture radar has the capabilities to provide a useful set of data that can be implemented with a Machine Learning approach. Deep Learning is a subset of Machine Learning and coupled with the remote-sensed data, it stands to deliver a promising solution to the problem presented. An engineering investigation will take place that employs the use of the scientific method with relevant research substantiating the results. Google Colab is used for all coding aspects of the investigation and provides the platform for which the results are produced. The code and some of the models and data sets are uploaded to a GitHub repository and available for viewing purposes.

GitHub Repository:
`https://github.com/MuneebBray/UCT-SIC`

1 Introduction

1.1 Background to the study

This investigation furthers the research conducted during the EEE4022S final year project pertaining to sea ice concentration **(SIC)** estimation using machine learning. The techniques implemented in that investigation provided SIC prediction models with lower accuracies than what was required, but resulted in a suitable performance to conclude the research performed.

The problem that this paper and the previous research [1] aimed to address, is the lack of SIC data present in the Southern Hemisphere. With the passive microwave **(PMW)** instrumentation unable to perform as well down South as it does compared to the North, an alternative method for SIC acquisition was needed to be developed. Synthetic aperture radar **(SAR)** instrumentation has the capability to penetrate the high water vapour atmosphere present in Southern regions and poses the uses of high resolution images to be implemented in a SIC estimation model.

1.2 Existing Research

From the results obtained in the previous investigation the following findings were made. SIC estimation models trained with more images provided the best performance. This was observed through assessment of all the various Neural Network **(NN)** architectures in the model training process. One change from previous research that this investigation made, was to implement the seasonal melting and freezing cycles of the Southern hemisphere. This resulted in more "useful images" obtained during the melting period than the freezing period and gave the SIC estimation models more data to learn from. Another finding was that models using skip connections like UNet and the newer LinkNet performed the best when compared to dense-layer-based architectures such as DenseNet.

1.3 What is lacking in the research?

The research conducted previously, although thorough, was not able to cover all aspects of the challenge presented. the models provided predictions trained on images based on two single sources of data. This elected choice of single sources of data does not take into account any skewing of the data except the uncertainty layer that is present in the SIC labels. The investigation fails to produce and analyse models trained with high resolution images with an image dimension of 256 x 256, but instead with 128 x 128 images. This provided each NN with less information and prevented an analysis of a complete model prediction.

1.4 Objectives of this study

The tasks that this paper aims to complete, involves incorporating some of what is lacking in previous research, and to improve model performance by optimising the training process of each NN model. This is to be conducted by fine-tuning the curation & pre-processing of the data fed into the NN's, while simultaneously training each SIC estimation model.

1.5 Plan of development

The plan presented below provides a detailed sequence of events which elaborates each step of investigation.

Stage 1: This stage introduces the problem to be researched throughout the investigation and outlines what will be included and excluded. A project objective is defined and the purpose of the study is presented.

Stage 2: This stage details the process of data source selection and acquisition. The entirety of the data pre-processing is explained and the data is prepared for use in the next stage of the investigation.

Stage 3: Here, the Neural Networks are defined, created and the Python libraries specified. Each Neural Network choice is then adapted to produce SIC estimations.

Stage 4: The results stage analyses all the performances and predictions of each model while explaining specific decisions made in the experimental process.

Stage 5: This stage summarises what was achieved in this investigation and draws conclusions based on the evidence found pertaining to any initial theories.

2 Data Processing

The acquisition and pre-processing of the data follows the same method as the previous investigation [1]. For the purpose of this investigation, only the data acquired during the melting period in the Southern hemisphere will be acquired due the evidence of more "useful" images available in this specific periods.

Two data sources have to be selected, one source providing the input satellite images for the Neural Network model to train and the other source providing the output SIC images.

Firstly, the selection of the input image source needs to be selected. **Copernicus Open Access HUB** [3] provides the suitable satellite images sourced from the various SENTINEL missions.

The second source is required to provide SIC images for the Southern hemisphere. The **OSI-401-b** [4] product presents a promising tool for this investigation due to the inclusion of an uncertainty layer in each SIC label. This uncertainty layer can be incorporated into a loss function and implemented in a SIC estimation model. This product provides PMW sourced SIC images with superior spatio-temporal resolution compared to similar data sources.

This data was then **pre-processed** to be fed into each NN by resampling each image to the same image dimension and by matching every pixel pair of each SAR satellite image and PMW SIC image using the *OData* footprint provided by CMEMS.

In order to prevent the Neural Network models from learning unimportant data, a selection process was developed that curated all the images within each data set. It is important for the Neural Network model to pass through images containing useful data. This means that images used as inputs to the model should contain variation in SIC. An image that displays 100% or 0% SIC presents no room for improvement in SIC estimation models. Therefore, a selection process is needed to filter out the unimportant images.

A **data curation** algorithm was created that disregards all SAR images along with its corresponding OSI-401-b labels producing a variance below the specified minimum threshold of either 0.05 or 0.03.

2.1 Summary of the Data Sets

A summary of all the data sets obtained in the data acquisition process is presented in Table 1. A dedicated focus based on the information regarding the melting seasonal cycles in the Southern hemisphere was implemented with the goal in determining if this additional information improved the results of SIC estimations using Machine Learning.

Data Set	**Period of Acquisition**	**Image Dimension**	**Min Variance**	**Total Images**	**Curated Images**	**% of Total Images**
South_Melting_Old	01/04/2020 - 30/09/2020 (6 Months)	128	0.05	5293	1867	35.27 %
South_Melting_New_1	01/12/2018 - 30/05/2019 (6 Months)	256	0.05	6547	2482	37.91 %
South_Melting_New_2	01/01/2020 - 30/06/2020 (6 Months)	128	0.03	5293	2172	41.03 %

Table 1: Table representing a summary of the data sets used to train the models

Three data sets were acquired with distinct changes in specific variables. These changes in the variables were chosen with the potential to produce improvements on the previously trained SIC models. The South_Melting_Old data set was used in the previous investigation [1] and provided the opportunity to assess the new models against the previous models. South_Melting_New_1 data set has the same features as the first data set except the image dimension. Increasing the image dimension presents more information to the NN's with the intention of improving accuracy. South_Melting_New_2 is also the same as the first data set, but the variance threshold is reduced to allow more images to pass through in the data curation process.

The inclusion of these specific data sets poses a trial and error process that is able to fine-tune the various parameters of the data source in question and in turn provide insight into the performances of the machine learning process in relation to these changes.

3 Neural Network Architectures

When looking at newer or alternative architectures it is apparent that it would need to be adapted for the specific application of SIC estimation. Based on the information presented in previous research, models that implemented a simple downsample-upsample architecture performed the best and provided higher accuracy.

Two different NN's were implemented during the conduction of this investigation. The first being a LinkNet network architecture and the second network to be implemented is a UNet NN.

3.1 LinkNet

LinkNet is an advanced supervised NN based on a simple encoder-decoder architecture which is represented in Fig. 1 below. It is commonly implemented for use in pixel-wise semantic segmentation algorithms due to its ability to process high resolution images. The reason it is chosen over other neural networks is because of its efficiency and timeliness while utilising all the parameters within the network. The number of parameters is considerably less compared to similar network architectures like UNet, with the number of parameters approximately close to 120 million [2]. This amount of parameters is significantly larger than the LinkNet architecture, which has an approximate number of 11 million parameters [5]. This parameter reduction, close to a factor of 10, speeds up the training process of the model compared to other similar network architectures implemented in the past.

Another benefit of LinkNet is the use of *skip connections*. Skip connections help traverse information in deep neural networks. Gradient information can be lost as we pass through many layers, this is called vanishing gradient. Advantages of skip connection are they pass feature information to lower layers so using it to classify minute details becomes easier. As MaxPooling is performed some amount of spatial information is lost. Skip connections can help increasing the classification accuracy because the final layer feature will have more information.

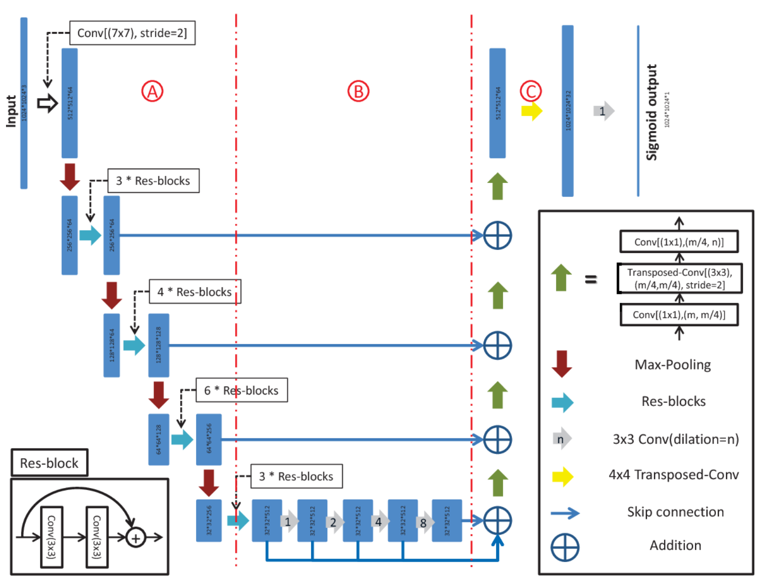

Figure 1: A diagram illustrating the connections within the LinkNet architecture. Source: Adapted from [6].

3.1.1 Implementing LinkNet for SIC Estimations

The LinkNet architecture in its original form cannot immediately be implemented for SIC estimations since it was originally intended for image segmentation. Therefore, the inner architecture needs to be adapted while still maintaining the core features of the original architecture.

An implementation of the LinkNet architecture found on GitHub using the *Keras* library [7]. This code was used for the bulk of the model definition during the neural network implementation.

By acquiring the code from the GitHub repository it was then ready to be adapted to produce SIC estimations. The single adaptation in the original architecture was to change the padding of each convolutional and MaxPooling layer from "valid" to "same" where applicable. This change in the padding parameter for each function ensured that the output image dimension would be identical to the input image dimension.

3.2 UNet

The U-Net architecture was introduced in 2015 and has been successful in many image segmentation tasks. Since segmentation in this context is little more than pixel-wise classification, this architecture can be easily modified for concentration mapping, which is essentially pixel-wise regression. By simply modifying the final output layer in Figure 2, all of the advantages of this network structure are retained, and very little design work is required.

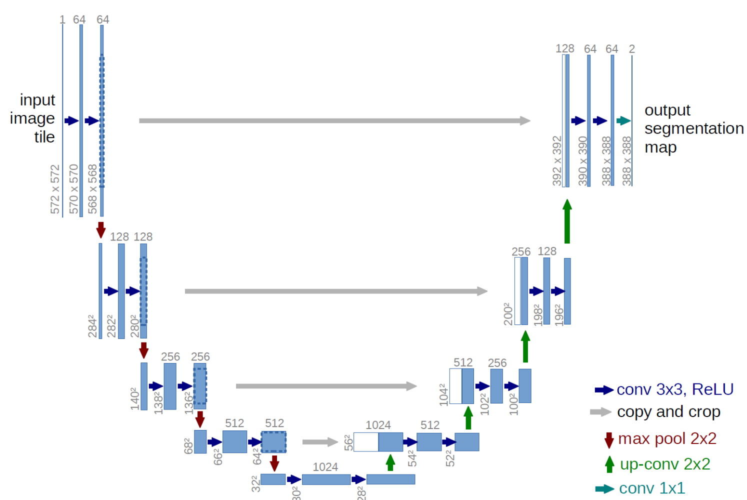

Figure 2: A diagram illustrating the connections within the UNet architecture.

3.2.1 Implementing UNet for SIC Estimations

A Keras implementation of the U-Net architecture found on GitHub was used for the bulk of the model definition [8]. Some simple changes were made to the convolutional padding parameters (padding = "same") so that the output dimension was the same as the input dimension. The segmentation output layer was then replaced with a single filter convolutional layer followed by a Sigmoid activation function.

4 Results

The models obtained throughout the training process were all created with the objective of producing SIC estimations in the Southern hemisphere. Various models where trained containing specific features that produced beneficial results regarding the investigation.

The models are named with the following convention so that each model is easily distinguishable from one another highlighting its important features: **ModelName_DataSet_TrainRegion_TestRegion_SeasonalCycle**

An analysis of the LinkNet and UNet model losses is presented in Table 2 below, and serves as a numerical performance metric for which the success of this investigation can be determined.

Model	Train Loss	Test Loss
LinkNet_1_S_S_M	0.0962	0.1291
UNet_1_S_S_M	0.0528	0.0742
LinkNet_2_S_S_M	0.0637	0.1199
LinkNet_3_S_S_M	0.0854	0.1212

Table 2: A summary of the Uncertainty Weighted Mean Absolute Error (UWMAE) of each model during the training and testing phase. The *DataSet* numbering followed the following order: 1 - South_Melting_Old, 2 - South_Melting_New_1, 3 - South_Melting_New_2.

As stated in the objective of this investigation, an improvement of the previous models was intended, specifically with pixel-wise accuracy in mind. Previously, the best model accuracy that a model produced with a satisfactory visual performance, was 87.09%. So any improvement on this accuracy would result in a success.

The first model in Table 2 is from the previous investigation [1] and acts as a comparison for the newly trained SIC estimation models. The LinkNet_2_S_S_M model performed the best, with a 0.92% increase in accuracy due to the inclusion of 615 more images (256x256). The LinkNet_3_S_S_M model had a 0.79% improvement on the first model's accuracy with the use of 305 more images (128x128).

4.1 Comparing Model Predictions

For the melting period in the Southern hemisphere, the following models were chosen to be analysed against a specific criteria. One of the inherent requirements of the models is that the predicted SIC estimations have to visually resemble the ground truth image. This pertains to image dimensionality, colour, distinguishing small land masses and presenting a SIC estimation relevant to the concentration key paired with each SIC.

The LinkNet_1_S_S_M model below produces accurate SIC estimations with an even distribution of the colour representing the SIC's. The colour is not overly bright and shows no signs of overfitting. Although the edges are hazy in some areas and the inability to recognise intermediary concentrations (orange-red), the model still provides an effective model to be implemented in the Southern hemisphere.

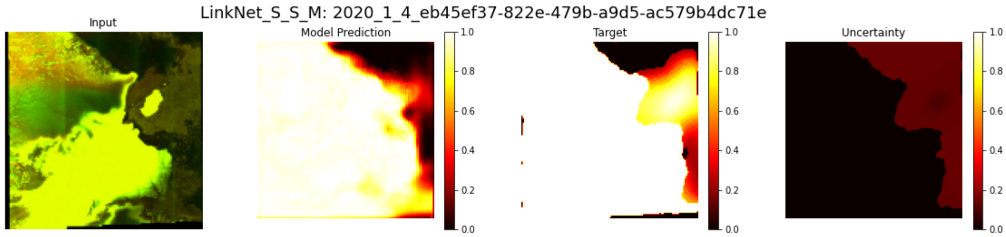

Figure 3: A LinkNet model trained and tested on Southern hemisphere data during its melting period (South_Melting_Old). The figure contains 4 images, the input to the model, the prediction produces by the model, the ground truth image for which the prediction is compared to and the uncertainty label obtained from the OSI-410-b product.

The UNet_1_S_S_M model below produces accurate SIC estimations with an even smoother overall distribution of the colour compared to the prediction above using the same data set. The colour is not overly bright and highlights the key areas of focus. The edges are hazy in some areas but cleaner than the LinkNet model and has the ability to recognise intermediary concentrations (orange-red). This model is effective in terms of visual and pixel-wise accuracy in the Southern hemisphere.

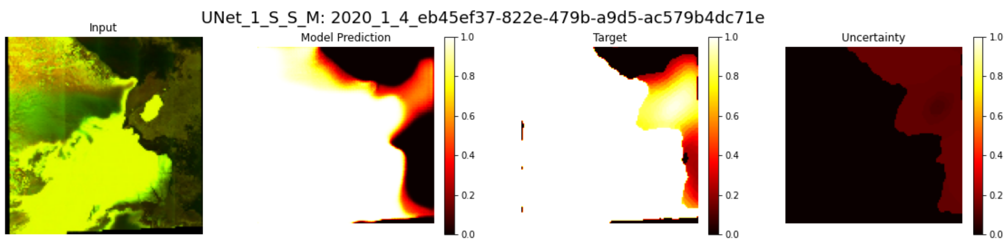

Figure 4: A UNet model trained and tested on Southern hemisphere data during its melting period (South_Melting_Old). The figure contains 4 images, the input to the model, the prediction produces by the model, the ground truth image for which the prediction is compared to and the uncertainty label obtained from the OSI-410-b product.

The LinkNet_3_S_S_M model below is very much similar to the LinkNet_1_S_S_M but superior in every aspect of the aforementioned criteria. It produces accurate SIC estimations with an even distribution of the colour as well as edge detection. Although the edges are still hazy in some areas, the model still provides an improved model to be implemented in the Southern hemisphere.

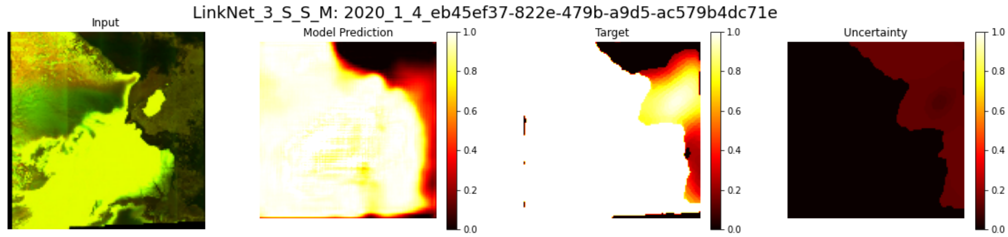

Figure 5: A LinkNet model trained and tested on Southern hemisphere data during its melting period (South_Melting_New_3). The figure contains 4 images, the input to the model, the prediction produces by the model, the ground truth image for which the prediction is compared to and the uncertainty label obtained from the OSI-410-b product.

The LinkNet_2_S_S_M model below is noticeably superior to all the model presented in terms of visual accuracy. It produces the most accurate SIC estimations with an even distribution of the colour almost identical to the ground truth image with exceptional edge detection. A noticeable difference in improvement is the ability to predict the cave-in of the sea ice in the top half of the image, that non of the previous models were able to predict. Therefore, this model provides the most improved model to be implemented in the Southern hemisphere in terms of visual and pixel-wise accuracy.

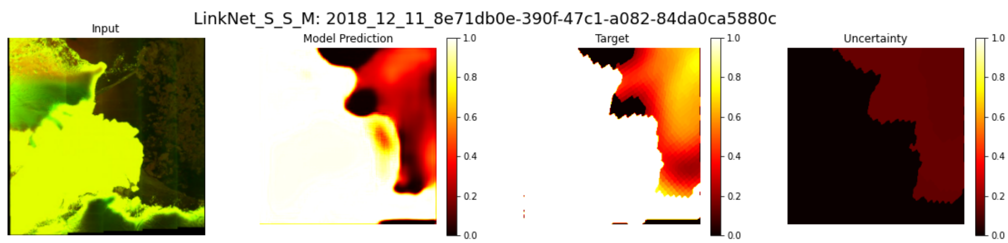

Figure 6: A LinkNet model trained and tested on Southern hemisphere data during its melting period (South_Melting_New_2). The figure contains 4 images, the input to the model, the prediction produces by the model, the ground truth image for which the prediction is compared to and the uncertainty label obtained from the OSI-410-b product.

5 Conclusions

This investigation aimed to develop a SIC estimation model with high performance in the Southern hemisphere region containing the Antarctic Circle. The LinkNet Neural Network architecture as well as a UNet architecture was chosen to be implemented.

The loss for each model was defined by the uncertainty weighted mean absolute error (UW MAE). An important observation made in the previous study [1] indicated that models trained on the Southern hemisphere during its melting period, produces the best results in terms of accuracy and visual assessment. As mentioned before, this is likely due to more images available in the melting period than compared to the freezing period.

Three different data sets were used to train each model. The model that performed the best, implemented data with the higher resolution images (256x265). This is could also be due to there being more images, but its ability to recognise key features of the image such as sea ice edges and to predict close to identical colour estimations to the ground truth SIC, proves that the inclusion of more pixels (information) benefits the training process of any new SIC estimation models.

As a final note, it is important to mention the excellent efficacy of models trained using Neural Network architectures like LinkNet and UNet. Both these models intended for image segmentation were easily adapted for SIC estimations and achieved its purpose with high performance. The training time for the UNet models were significantly larger than the LinkNet models, which prevented the training of models with larger data sets, a reduction of the epoch number temporarily solved this issue an allowed the UNet models to be analysed accordingly for this investigation.

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