Estimation of Abundance and Distribution of Salt Marsh Plants from Images Using Deep Learning

Jayant Parashar[1] Suchendra M. Bhandarkar[1,2] Jacob Simon[3] Brian M. Hopkinson[3] Steven C. Pennings[4]

[1]Institute of Artificial Intelligence, [2]Dept. of Computer Science, [3]Dept. of Marine Sciences, University of Georgia, Athens, Georgia, USA

[4]Dept. of Biology & Biochemistry, University of Houston, Houston, Texas, USA

{jayant.parashar, suchi, jacob.simon25, bmhopkin}@uga.edu scpenning@central.uh.edu

Introduction

A limiting step in ecological research is the time required to identify and enumerate species of interest. New advances in computer vision and machine learning, most notably deep convolutional neural networks (CNNs), make it possible to accurately identify and localize the species of interest in images. We assess the ability of various convolutional neural network (CNN) architectures to automatically identify plants and invertebrates in salt marsh images.

Dataset

A section of salt marsh (≈ 3200 m^2) on Sapelo Island, GA, USA spanning an elevation and plant community gradient was imaged annually for ≈ 10 years. Each year, ≈ 12,000 images were collected in rows of approximately constant elevation from a distance of ≈ 1 m ensuring adequate image resolution. Our goal is to identify the six plant species in the resulting salt marsh images shown in **Fig. 1**.

Fig. 1. Example images of marsh plant species (from left to right and top to bottom): *Sarcocornia, Spartina, Limonium, Borrichia, Batis* and *Juncus*.

Abundance Estimation of Plant Species

Presence/Absence Determination

In **presence/absence determination**, we partition an image into $5 \times 3 = 15$ patches and perform multi-label/multi-class classification on each image patch. We note the presence/absence of each plant species within the image patch.

Percent Cover Computation

In **percent cover computation**, we sample a random point in the image and perform single-label/multi-class classification within a local window (512 × 512 pixels) centered at the point. Percent cover is computed for each plant species by considering several (≈ 100) such samples.

Semantic Segmentation

In **semantic segmentation**, we perform pixel-level classification to estimate species abundance at the finest spatial resolution.

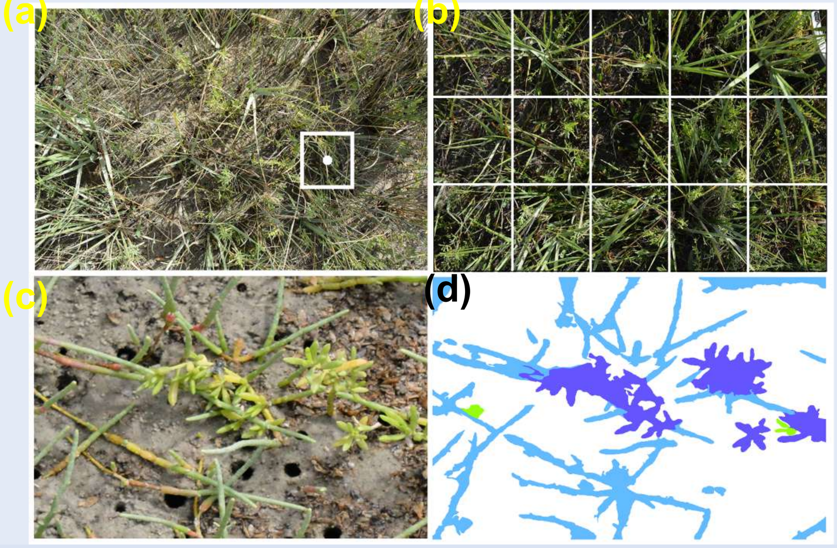


Fig. 2. Abundance estimation (a) percent cover computation, (b) presence/absence determination, (c) semantic segmentation & (d) corresponding segmentation masks

Evaluation Metrics

Precision, **recall** and ***f-1* scores** are used as evaluation metrics to compare various deep learning models in terms of overall (macro) performance and (micro) performance on specific classes. The macro- and micro-averaged metrics are computed for presence/absence determination. For percent cover computation, macro- and micro-averaged metrics are identical. For semantic segmentation, the **mean Intersection-over-Union** (**mIoU**) metric is used for evaluation and comparison.

Image Classification with CNNs

We compared various CNNs: **ResNet, ResNext, Dual Path Network (DPN), Residual Attention Network** and **DenseNet**. **ResNet** showed the best **overall** performance. **ResNext** and **DPN** showed better **precision** and **recall** performance by a small margin.

Results

Presence/Absence Determination

TABLE I
PRESENCE/ABSENCE MICRO-AVERAGED RESULTS

CNN type	*Micro precision*	*Micro recall*	*Micro f-1 score*
ResNet101	0.918	0.932	0.925
DenseNet121	0.912	0.930	0.921
DPN92	0.906	**0.938**	0.922
ResNext101	**0.928**	0.931	**0.930**
Inception	0.910	0.923	0.916
RAN	0.924	0.889	0.906
PyramidNet101	0.911	0.923	0.917

Approximately 17,000 salt marsh image sections (from ≈ 1150 images) were manually labeled for presence/absence of the six plant species. We achieved the best **overall** results with **ResNext101** whereas **DPN92** performed best in terms of **recall**.

Percent Cover Computation

TABLE III
RESULTS OF PERCENT COVER COMPUTATION

CNN type	*precision*	*recall*	*f-1 score*	*Accuracy*
ResNet101	0.742	0.700	0.720	0.833
DenseNet121	0.717	0.668	0.692	0.846
DPN92	0.743	0.732	0.737	0.843
ResNext101	**0.767**	0.736	**0.751**	**0.857**
Inception	0.738	0.672	0.703	0.833
RAN	0.713	0.618	0.662	0.851
PyramidNet101	0.751	**0.743**	0.748	0.844

Approximately 7,500 randomly sampled points were manually labeled in ≈ 250 salt marsh images. Best results were achieved with **ResNext101** in terms of **precision** and ***f-1* score**. **PyramidNet101** performed best in terms of **recall**.

Semantic Segmentation

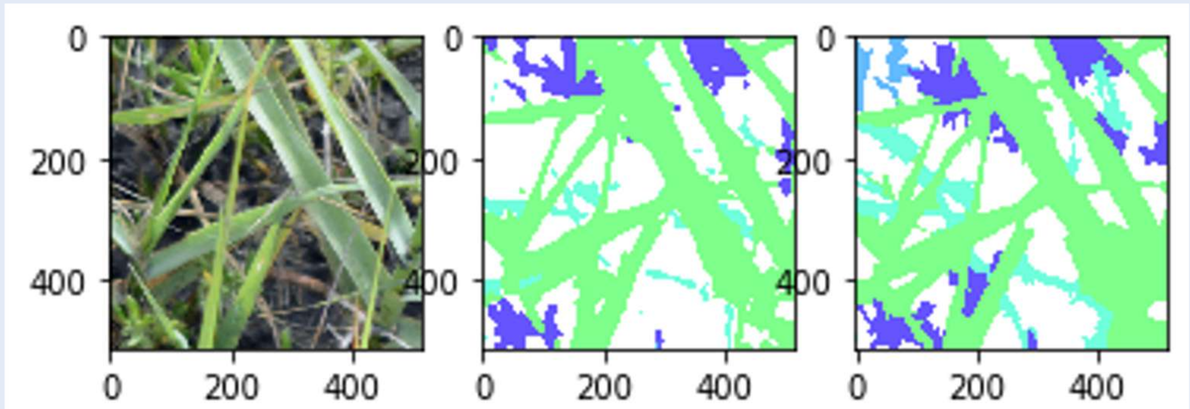


Fig 3: Semantic segmentation results for **DeepLab-V3**, showing from right to left: original image, output mask and target mask.

The best **mIoU measure** of 0.54 was achieved using the **ResNet** backbone for **DeepLab-V3** on the test data set with an **overall pixel-level accuracy** of 85%, and **macro-averaged precision** and **macro-averaged recall** scores of 0.570 and 0.607 respectively.

Comparison of Estimation Approaches

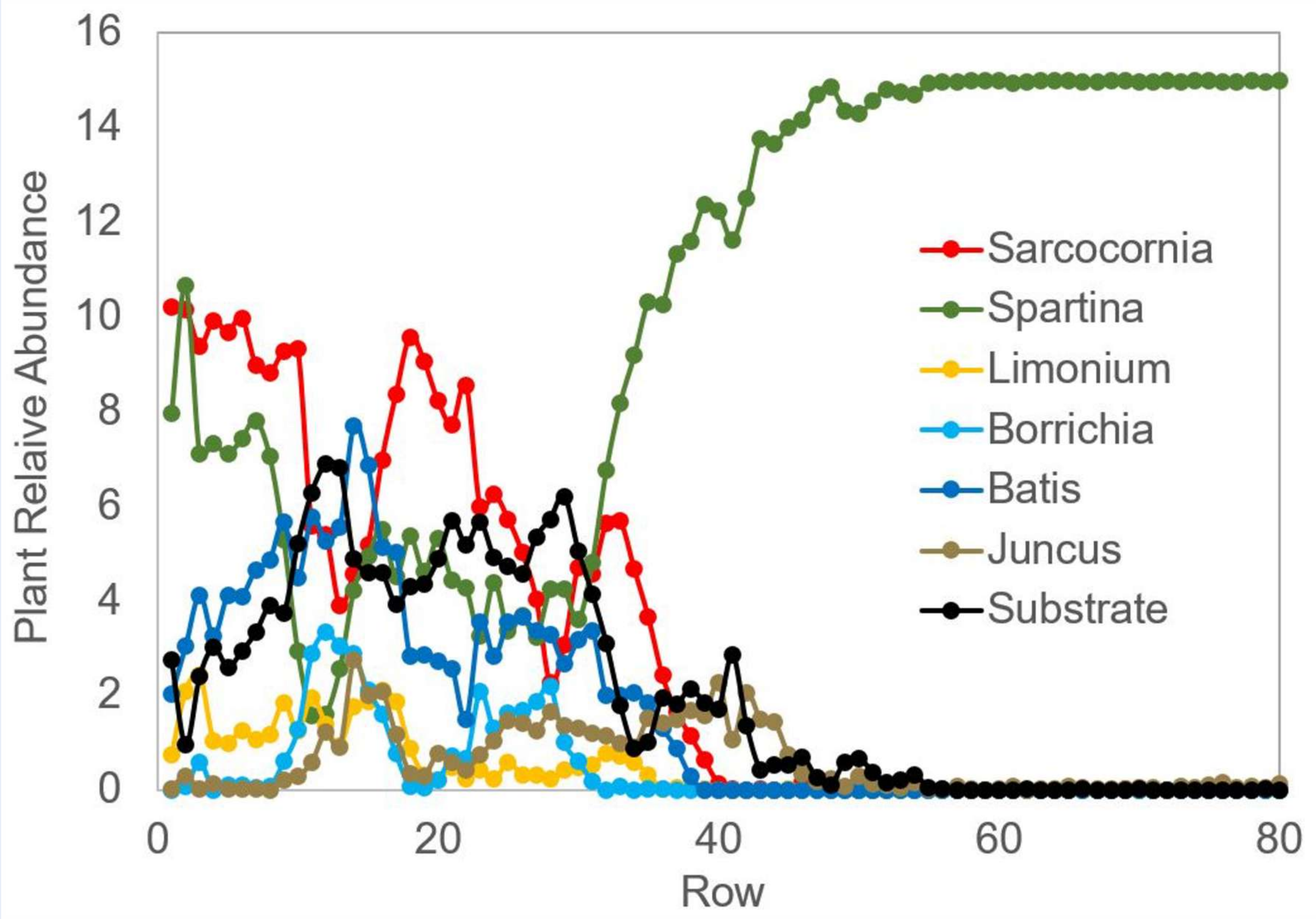
TABLE IV
COMPARISON OF RESULTS FROM DIFFERENT APPROACHES

Approach	*Model*	*Accuracy*	*f-1 score*	*Resolution*
Presence/Absence	*ResNext*	0.929	0.853	e-7
Percent Cover	*ResNext*	0.857	0.770	e-3
Segmentation	*DeepLab-V3*	0.849	0.587	1

A clear trade-off was observed between the **performance** (in terms of **precision** and **recall**) and **spatial resolution of estimation** with higher-resolution approaches exhibiting lower performance (Table IV). The **accuracy** (**micro-averaged *f-1 score***) and the **macro-averaged *f-1 score*** decrease from the presence/absence computation approach to the semantic segmentation approach whereas the **spatial estimation resolution** (estimations per pixel) increases.

Application of Abundance Estimation

We employed the **ResNext101** classifier designed for presence/absence computation on the image data set from the salt marsh on Sapelo Island, Georgia, USA. The results show a diverse plant community in the high-elevation marsh regions (row numbers < 25) transitioning to *Spartina* dominance in the low-elevation marsh regions (row numbers > 35) which is consistent with the expected distribution based on Biological Ecology. This illustrates the potential of presence/absence computation using CNN-based image analysis to rapidly assess plant community structure across environmental (elevation) gradients in a salt marsh.



Conclusions

We observed that **multi-path CNN architectures** such as **ResNext** and **DPN** outperform other CNN architectures in the context of analysis of salt marsh images. We compared three abundance estimation approaches and observed a tradeoff between the spatial resolution and accuracy of estimation.

Acknowledgements

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