

Joint Plant-Spraypoint Detector with ConvNeXt Modules and HistMatch Normalization

Supplementary Material

Authors:

Ford, J.

Sadgrove, E.

Paul, D.

Figure S1: Lottes' model: **(a)** A dense block containing a total of three convolutional layers. Each layer adds four filters to the feature map ($L=3$, $G=4$). **(b)** Macro structure showing the input image (green), the encoder (blue), the decoders (red) and the output feature maps (purple). Arrows display the flow of information through the model. Image resolutions presented are those given in the original paper.

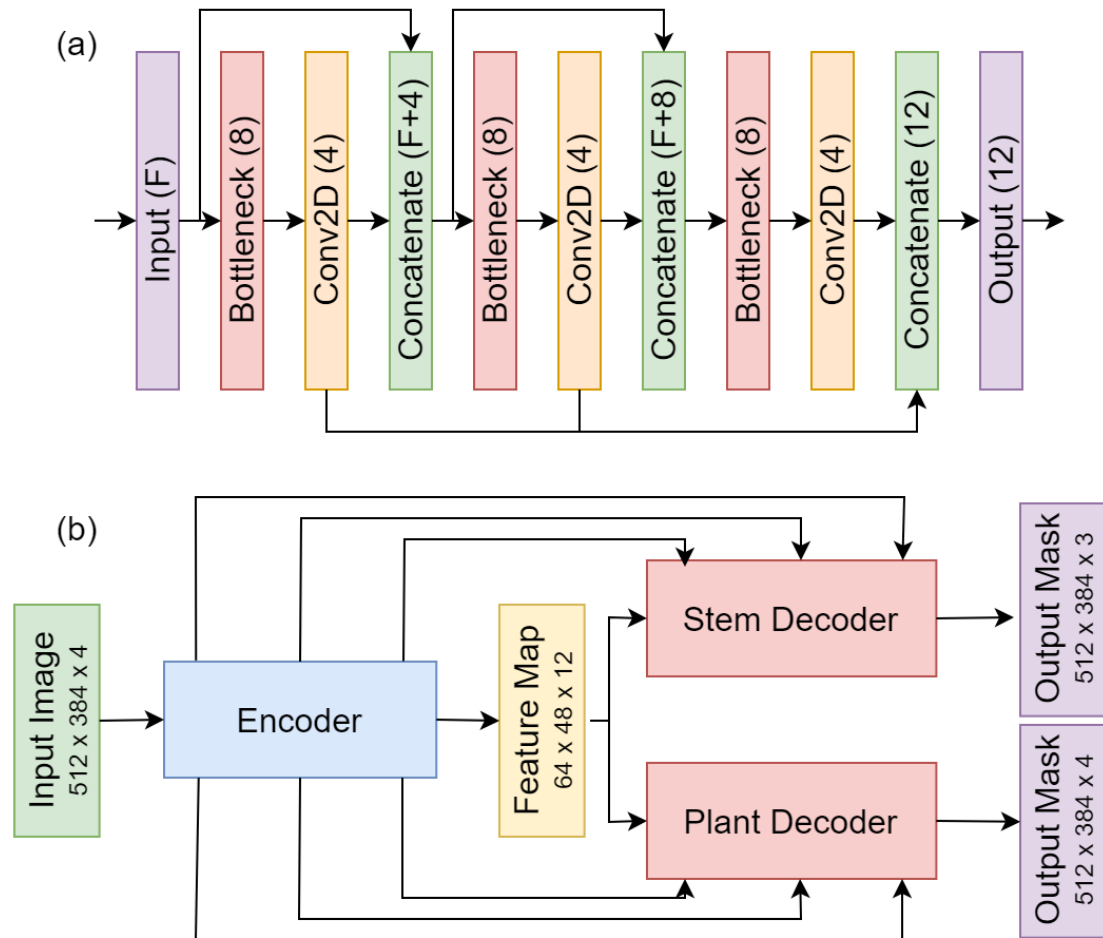


Figure S2: Zhang's model: **(a)** An IRM which employs two point-wise convolutions (orange), with a depth-wise convolution (red) in between. In the IRM, normalization occurs after each convolution, and activation occurs after the first point-wise convolution and the depth-wise convolution. **(b)** Macro structure showing the input image (green), the backbone (blue), the decoders (red) and the output feature maps (purple). Loss layers are shown in yellow, and include losses for deep supervision (small rectangles), as well as for the final outputs of the model (large rectangles). Arrows display the flow of information through the model. In particular, the cross-task feature fusion is given with a dashed line, and the bidirectional feature map exchanges are given with a dotted line. Image resolutions presented are those given in the original paper.

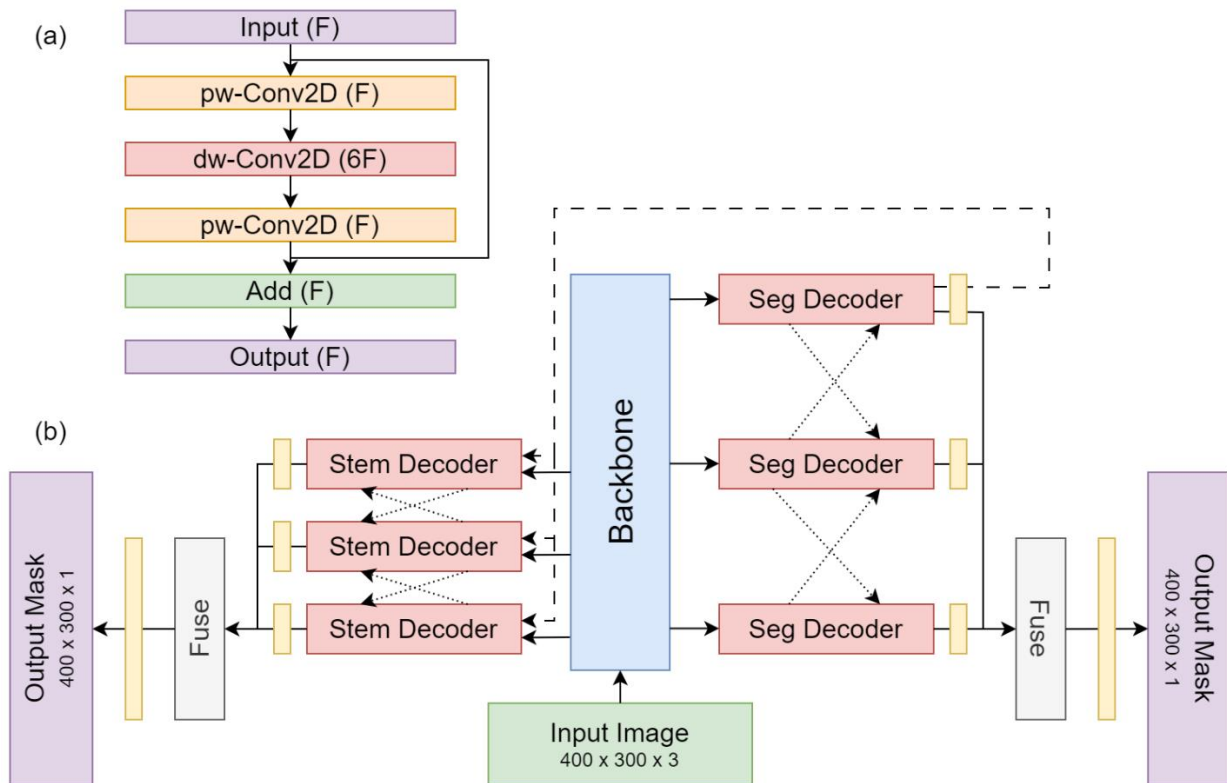


Figure S3: Ours-4s model: The 4s version of our model, which has one additional decoder for each tasks, which is situated at the 8x downsampling level for the spraypoint (or stem) task, and 4x downsampling level for the segmentation task. Components show are input image (green), patchify stem (orange), backbone (blue), decoders (red) and the output feature maps (purple). Loss layers are shown in yellow, and include losses for deep supervision (small rectangles), as well as for the final outputs of the model (large rectangles). Arrows display the flow of information through the model. In particular, the cross-task feature fusion is given with a dashed line, and the bidirectional feature map exchanges are given with a dotted line.

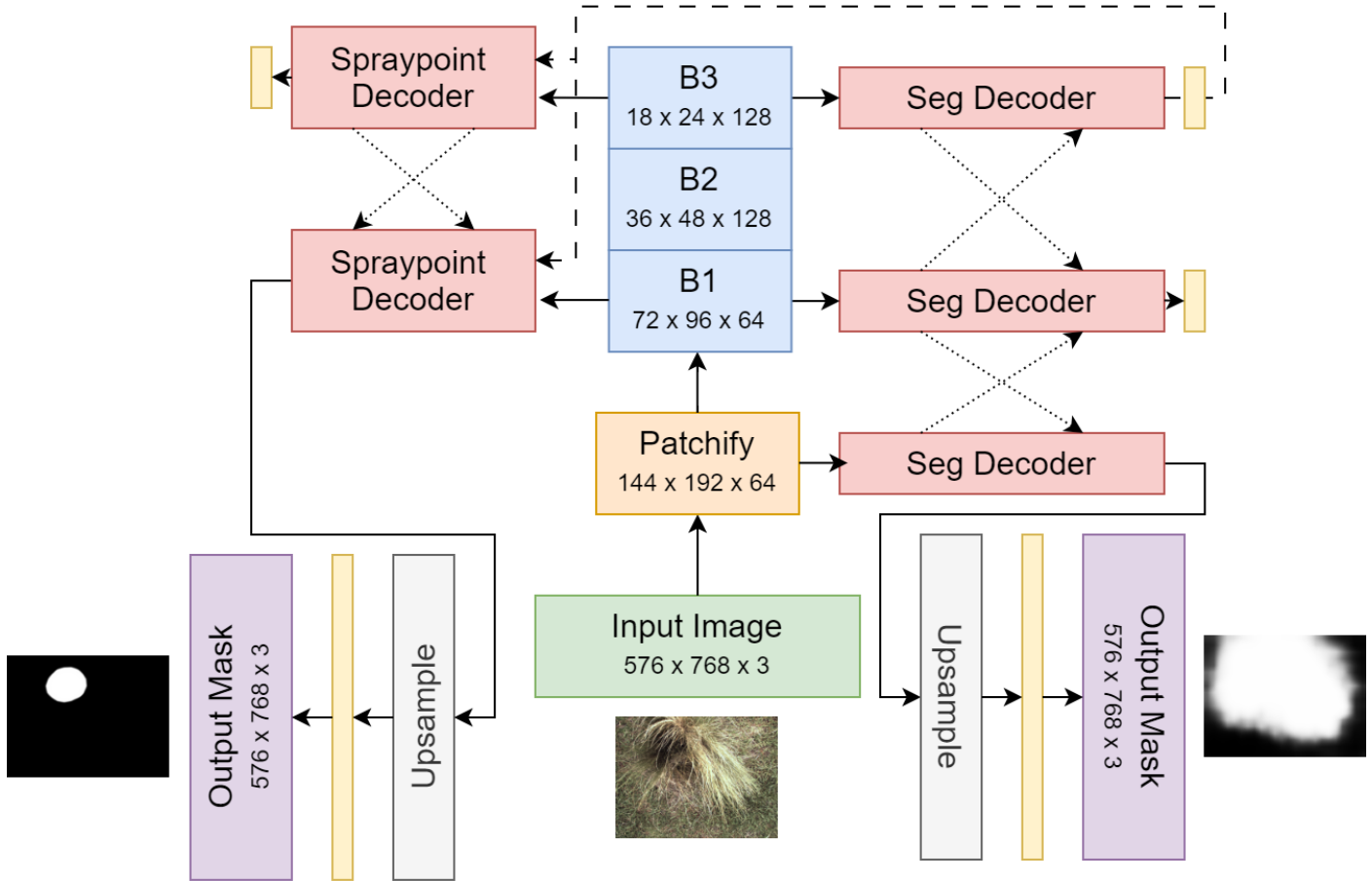


Figure S4: Normalized confusion matrices for the plant segmentation task for all models, for experiments 1, 2 and 3.

		Lottes		Zhang		Ours		
Experiment 1	Actual	Neg	Predicted		Actual	Neg	Predicted	
			Neg	Pos			Neg	Pos
	Pos	33.4	66.6	97.6	2.4	97.8	2.2	
Experiment 2	Actual	Neg	Predicted		Actual	Neg	Predicted	
			Neg	Pos			Neg	Pos
	Pos	9.0	91.0	33.7	66.3	96.2	3.8	
Experiment 3	Actual	Neg	Predicted		Actual	Neg	Predicted	
			Neg	Pos			Neg	Pos
	Pos	84.3	15.7	91.8	8.2	93.6	6.4	
Experiment 1	Actual	Pos	Predicted		Actual	Pos	Predicted	
			Neg	Pos			Neg	Pos
	Pos	34.2	65.8	5.0	95.0	6.4	93.6	

Table S1: Experiment 1a metrics:

Task	Model	Normalization	mIoU									
			mean	std								
Plant	Lottes	Image	default	0.874	0.014							
		Norm	std norm	0.843	0.030							
			hist match	0.871	0.010							
			Batch	default	0.838	0.012						
		Norm	std norm	0.624	0.041							
			hist match	0.583	0.045							
	Zhang		Image	default	0.911	0.002						
		Norm	std norm	0.913	0.001							
			hist match	0.911	0.002							
			Batch	default	0.909	0.001						
		Norm		std norm	0.867	0.005						
				hist match	0.862	0.008						
	Ours4		Image	default	0.920	0.001						
		Norm	std norm	0.918	0.002							
			hist match	0.920	0.001							
			Batch	default	0.913	0.003						
		Norm		std norm	0.886	0.004	Precision		Recall		F1	
				hist match	0.879	0.002	mean	std	mean	std	mean	std
Lottes	Image		default	0.646	0.021	0.550	0.109	0.629	0.062	0.585	0.091	
	Norm	std norm	0.656	0.007	0.682	0.060	0.631	0.028	0.653	0.028		
		hist match	0.695	0.002	0.760	0.010	0.697	0.016	0.727	0.012		
		Batch	default	0.603	0.013	0.452	0.047	0.437	0.062	0.441	0.038	
	Norm		std norm	0.570	0.017	0.529	0.121	0.319	0.078	0.384	0.070	
			hist match	0.543	0.017	0.457	0.101	0.181	0.046	0.252	0.051	
Spray		Zhang	Image	default	0.800	0.005	0.851	0.015	0.900	0.022	0.875	0.014
	Norm		std norm	0.792	0.008	0.819	0.020	0.880	0.021	0.848	0.017	
			hist match	0.792	0.007	0.825	0.026	0.890	0.012	0.856	0.016	
			Batch	default	0.797	0.006	0.837	0.015	0.902	0.016	0.868	0.011
	Norm			std norm	0.787	0.003	0.833	0.039	0.846	0.025	0.838	0.009
				hist match	0.778	0.007	0.862	0.020	0.834	0.029	0.847	0.022
		Ours4	Image	default	0.830	0.003	0.879	0.020	0.905	0.016	0.892	0.015
	Norm		std norm	0.822	0.006	0.870	0.009	0.895	0.020	0.882	0.012	
			hist match	0.822	0.002	0.878	0.012	0.903	0.018	0.891	0.009	
			Batch	default	0.823	0.004	0.863	0.037	0.900	0.024	0.881	0.026
	Norm			std norm	0.812	0.005	0.871	0.017	0.854	0.020	0.862	0.017
				hist match	0.815	0.006	0.884	0.038	0.892	0.012	0.887	0.021

Table S2: Experiment 2a metrics:

Task	Model	Normalization	mIoU									
			mean	std								
Plant	Lottes	Image	default	0.376	0.077							
		Norm	std norm	0.534	0.054							
			hist match	0.703	0.052							
		Batch	default	0.409	0.058							
			Norm	std norm	0.402	0.037						
				hist match	0.438	0.083						
	Zhang	Image	default	0.643	0.085							
		Norm	std norm	0.810	0.016							
			hist match	0.821	0.054							
		Batch	default	0.654	0.150							
			Norm	std norm	0.787	0.051						
				hist match	0.813	0.025						
	Ours4	Image	default	0.821	0.008							
		Norm	std norm	0.826	0.039							
			hist match	0.854	0.006							
		Batch	default	0.820	0.016							
			Norm	std norm	0.831	0.008	Precision		Recall		F1	
				hist match	0.841	0.005	mean	std	mean	std	mean	std
Spray	Lottes	Image	default	0.307	0.096	0.037	0.014	0.114	0.051	0.056	0.022	
		Norm	std norm	0.577	0.010	0.325	0.059	0.454	0.028	0.376	0.041	
			hist match	0.633	0.021	0.634	0.052	0.572	0.040	0.599	0.019	
		Batch	default	0.429	0.085	0.064	0.041	0.154	0.034	0.086	0.039	
			Norm	std norm	0.522	0.011	0.296	0.070	0.182	0.062	0.214	0.050
				hist match	0.528	0.016	0.274	0.078	0.192	0.069	0.214	0.063
	Zhang	Image	default	0.690	0.026	0.717	0.101	0.595	0.051	0.646	0.058	
		Norm	std norm	0.685	0.019	0.452	0.093	0.754	0.023	0.559	0.063	
			hist match	0.734	0.010	0.735	0.043	0.732	0.039	0.733	0.037	
		Batch	default	0.667	0.047	0.524	0.274	0.629	0.110	0.505	0.140	
			Norm	std norm	0.702	0.010	0.652	0.077	0.675	0.014	0.660	0.034
				hist match	0.700	0.011	0.832	0.063	0.672	0.027	0.741	0.024
	Ours4	Image	default	0.747	0.005	0.882	0.045	0.637	0.017	0.740	0.025	
		Norm	std norm	0.739	0.037	0.650	0.120	0.769	0.029	0.700	0.081	
			hist match	0.776	0.008	0.843	0.023	0.772	0.034	0.806	0.028	
		Batch	default	0.752	0.006	0.946	0.008	0.676	0.021	0.788	0.015	
			Norm	std norm	0.783	0.004	0.871	0.019	0.758	0.020	0.810	0.014
				hist match	0.776	0.002	0.822	0.016	0.777	0.017	0.799	0.010

HistMatch Normalization in Python (numpy):

```
import numpy as np
from math import erf

# CDF for N(0,1)
def phi(x):
    return (1.0 + erf(x / 2.0**0.5))/2.0

# The number of points for which to calculate phi
N = 301

# [-3,3] will capture 99.7% of a standard normal distribution
yval = np.linspace(-3,3,N,endpoint=True)
ncdf = np.tile(np.array(list(map(phi,yval))).reshape(1,-1), (256,1))

# perform HistMatch normalization on an image.
def hist_match_norm(I):
    # Assume greyscale. Pixel values from 0 to 255
    # Normalize each channel separately for colour image

    # Cumulative histogram (normalized)
    h1 = np.sum(I.reshape(-1,1) <= range(256),0)
    h1 = h1/h1[-1]

    # Calculate midpoints
    h1 = (np.pad(h1,(1,0))[:-1] + h1)/2

    # Reshape for comparison
    h1 = h1.reshape(-1,1)

    # Find closest match between h1 and ncdf
    A = np.abs(h1-ncdf)
    f = yval[np.argmin(A,axis=1)]

    # apply function to I and return
    return f[I]

if __name__ == "__main__":
    # Display normalization graphs of test image (red channel)
    import PIL
    import matplotlib.pyplot as plt
    from matplotlib import gridspec

    I = np.array(PIL.Image.open("test.png"))
    I = I[:, :, 0]

    J = (I - np.mean(I))/np.std(I)

    K = hist_match_norm(I)

    def snpdf(x):
        return (1 / np.sqrt(2*np.pi)) * np.exp(-0.5*x**2)

    x = np.linspace(-3,3,101,endpoint=True)
    p = snpdf(x)
```



```
fig = plt.figure(figsize=(6,8))
gs = gridspec.GridSpec(3,1,height_ratios=[4,1,1])

ax = [plt.subplot(g) for g in gs]

ax[0].imshow(I,cmap='gray')
ax[0].set_title('Image')
ax[0].set_axis_off()

ax[1].hist(J.flatten(),bins=50,density=True,alpha=0.6)
ax[1].plot(x,p,'k',linewidth=2)
ax[1].set_title('Naive')

ax[2].hist(K.flatten(),bins=50,density=True,alpha=0.6)
ax[2].plot(x,p,'k',linewidth=2)
ax[2].set_title('HistMatch')

plt.tight_layout()
plt.show()
```