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WSNet: Towards An Effective Method for Wound Image Segmentation

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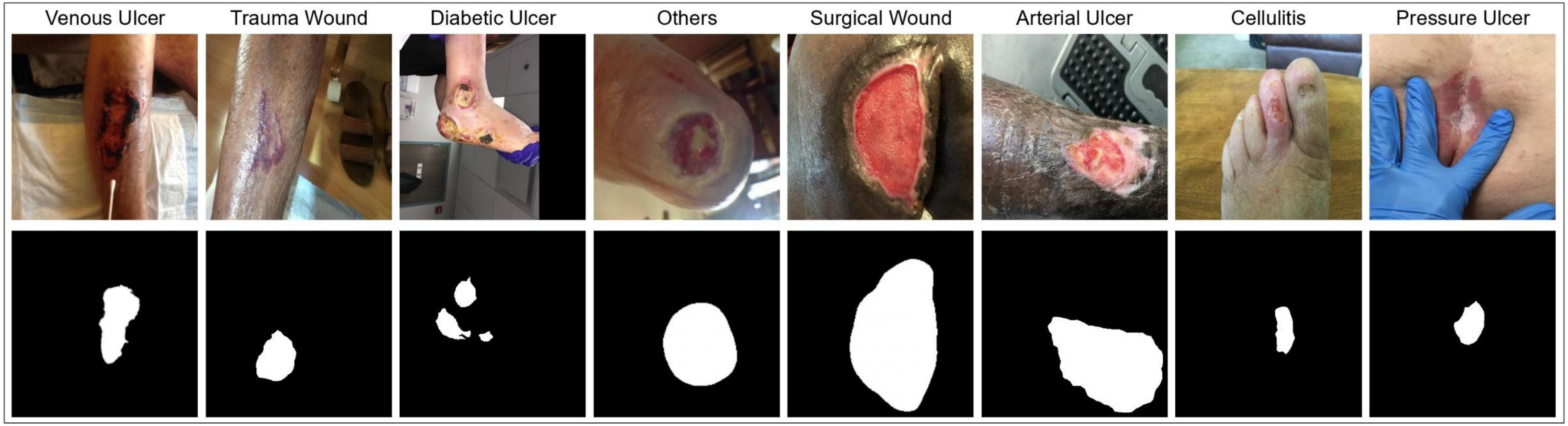
Motivation

- Automated segmentation of wound regions from patient images.
  - Can aid clinicians in measuring and managing chronic wounds and monitoring the wound healing trajectory.
- Existing methods are limited to segmenting a smaller subset of ulcers, such as foot ulcers, with no special processing for wound images.
- We build segmentation models for eight different types of wound images.
- Impact of using segmentation for improving the accuracy of downstream tasks
  - E.g. wound area and volume prediction.

Challenges

- Wound image analysis is a challenging due to lack of availability of extensive data.
  - AZH dataset has 1 wound type (foot ulcer) and 1K images
  - Medetec has 1 wound type (foot ulcer) and 600 images
- Annotation is also challenging due to the shortage of well-trained wound care clinicians.
- Complexity - the heterogeneous appearance of wound area across images of similar wound types.

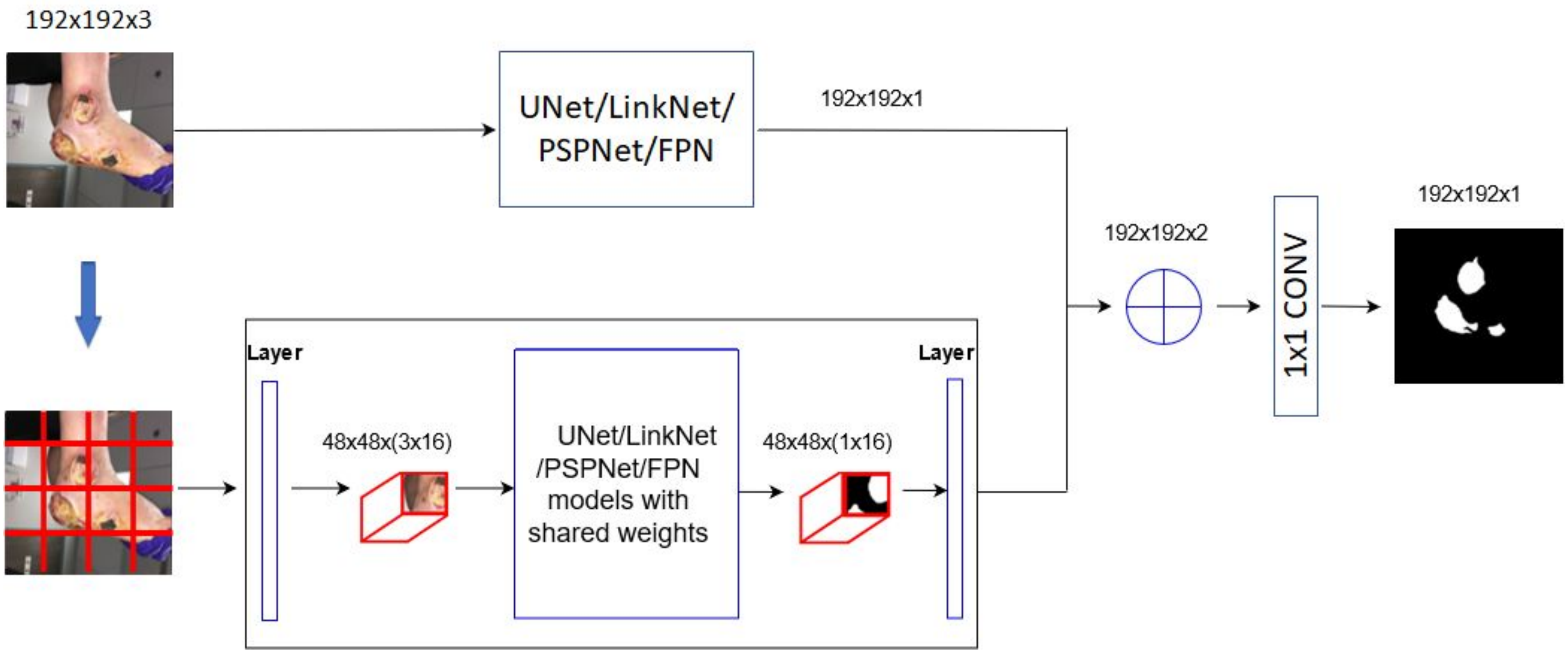
Different wound types from our WOUNDSEG dataset



Contributions

- WOUNDSEG - a large and diverse dataset of segmented wound images.
  - 8 wound types (diabetic, pressure, trauma, venous, surgical, arterial, cellulitis, and others)
  - 2686 images
- A novel image segmentation framework, WSNET, which leverages
  - wound domain adaptive pre-training on a large unlabeled wound image collection.
  - a global-local architecture that utilizes full image and its patches to learn fine-grained details of heterogeneous wounds.
- On WOUNDSEG, we achieve a decent Dice score of 0.847.
- On existing AZH Woundcare and Medetec datasets, we establish a new state-of-the-art.

Model Architecture



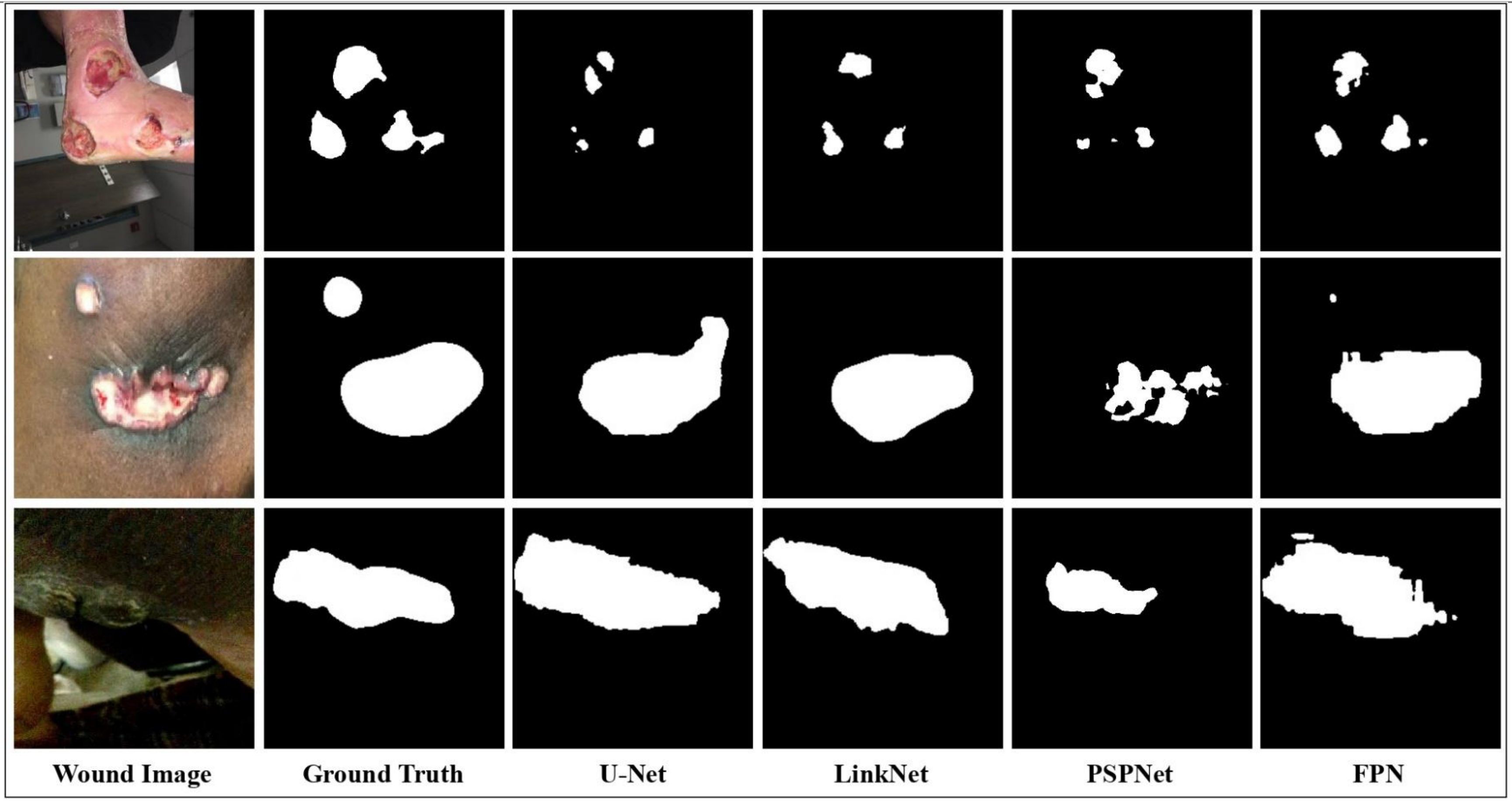
WSNET Methodology

- **Wound Segmentation Models** - We experiment with the following four popular segmentation architectures, and with 17 backbones to explore the accuracy versus model size trade-off .
- **Wound-Domain Adaptive Pre-training (WDAP)** - we create pre-trained models specifically on the wound image dataset instead of using Imagenet pre-trained weights.
- **Fine-tuning** – Pre-trained models are fine-tuned on labeled image segmentation data.
- **Data augmentation** – we chose horizontal flip, random rotation, optical distortion, grid distortion, blur, random brightness contrast, and transpose to perform the data augmentation.
- **Global-Local Architecture** - for effective segmentation, it is essential to obtain (global) signals from the entire image and (local) signals from individual patches extracted to capture the intricate details in wound images.

Performance results of image segmentation models on WOUNDSEG dataset.

		U-Net		LinkNet		PSPNet		FPN	
		IoU	Dice	IoU	Dice	IoU	Dice	IoU	Dice
(A) Models with ImageNet pretraining	DenseNet121	0.617	0.761	0.617	0.762	0.585	0.736	0.623	0.766
	DenseNet169	0.613	0.758	0.624	0.768	0.596	0.745	0.614	0.760
	MobileNet	0.593	0.742	0.571	0.724	0.561	0.717	0.594	0.743
(B) Models with wound domain adaptive pretraining (WDAP)	DenseNet121	0.648	0.783	0.657	0.800	0.625	0.765	0.652	0.793
	DenseNet169	0.647	0.781	0.651	0.788	0.636	0.773	0.637	0.773
	MobileNet	0.615	0.760	0.611	0.755	0.563	0.718	0.616	0.758
(C) Models with WDAP and data augmentation	DenseNet121	0.680	0.818	0.687	0.820	0.653	0.797	0.680	0.817
	DenseNet169	0.672	0.810	0.675	0.812	0.656	0.801	0.664	0.807
	MobileNet	0.636	0.778	0.647	0.780	0.598	0.744	0.634	0.775
(D) Local (patch-based) models with WDAP	DenseNet121	0.527	0.689	0.537	0.698	0.520	0.682	0.532	0.694
	DenseNet169	0.534	0.696	0.530	0.691	0.519	0.681	0.533	0.696
	MobileNet	0.512	0.673	0.514	0.677	0.493	0.660	0.510	0.670
(E) Global-local models with ImageNet pretraining and data augmentation	DenseNet121	0.648	0.784	0.649	0.786	0.621	0.763	0.651	0.792
	DenseNet169	0.649	0.787	0.650	0.790	0.624	0.767	0.648	0.785
	MobileNet	0.620	0.761	0.621	0.763	0.565	0.722	0.618	0.760
(F) WSNET-FF: Global-local models with WDAP and data augmentation	DenseNet121	0.685	0.823	0.706	0.840	0.663	0.805	0.700	0.834
	DenseNet169	0.684	0.821	0.694	0.830	0.675	0.815	0.680	0.818
	MobileNet	0.650	0.790	0.651	0.792	0.590	0.740	0.651	0.792
(G) WSNET: Global-local models with WDAP, data augmentation, end-to-end fine-tuning	DenseNet121	0.695	0.831	**0.713**	**0.847**	0.683	0.820	**0.707**	**0.840**
	DenseNet169	**0.701**	**0.834**	0.707	0.841	**0.686**	**0.823**	0.697	0.832
	MobileNet	0.661	0.800	0.662	0.800	0.601	0.748	0.661	0.798

WSNET Predictions using the four global-local architectures.



Dice-score comparison on the WoundSeg Dataset

Models	Methods	Wound Type							
		Diabetic	Pressure	Surgical	Venous	Trauma	Arterial	Cellulitis	Other
U-Net	DN121	0.744	0.792	0.786	0.761	0.749	0.747	0.745	0.825
	DN169	0.742	0.789	0.771	0.761	0.757	0.752	0.752	0.826
	MN	0.719	0.749	0.745	0.755	0.737	**0.768**	0.736	0.786
LinkNet	DN121	0.733	0.774	0.767	0.748	0.748	0.745	0.761	0.815
	DN169	**0.763**	**0.803**	**0.800**	**0.774**	**0.769**	0.760	**0.794**	0.811
	MN	0.719	0.744	0.740	0.738	0.720	0.729	0.734	0.772
PSPNet	DN121	0.630	0.662	0.654	0.674	0.640	0.643	0.662	0.642
	DN169	0.616	0.640	0.643	0.660	0.633	0.621	0.627	0.653
	MN	0.580	0.591	0.587	0.584	0.594	0.590	0.572	0.613
FPN	DN121	0.747	0.779	0.768	0.764	0.760	0.742	0.783	0.806
	DN169	0.747	0.794	0.796	0.770	**0.769**	0.756	0.787	**0.839**
	MN	0.722	0.771	0.760	0.770	0.753	0.751	0.782	0.803

Wound Area and Volume Prediction Results

Method	Area MAE	Volume MAE
HealTech	1.14	1.28
WSNET with U-Net	0.66	0.78
WSNET with LinkNet	0.65	0.78
WSNET with PSPNet	0.71	0.82
WSNET with FPN	0.66	0.78

Conclusions

- We contribute a diverse dataset, WOUNDSEG, of 2686 images across eight wound types for the wound image segmentation task.
- We experimented extensively with four CNN model architectures and 17 backbones.
- We propose a novel WSNET framework that consists of wound-domain adaptive pretraining, data augmentation, global-local architecture, and end-to-end fine-tuning.
- The proposed methods outperform baselines on existing benchmark datasets, show beneficial results on the WOUNDSEG dataset, and even establish a new state-of-the-art on wound area and volume prediction tasks.

Thanks!