A Unified Framework for Automatic Wound Segmentation and Analysis with Deep Convolutional Neural Networks

Changhan Wang , Xinchen Yan, Max Smith, Kanika Kochhar, Marcie Rubin, Stephen M. Warren, James Wrobel and Honglak Lee

Background

- According to the report published in 2009, chronic wounds affect **6.5 million patients** in the United States.
- An estimated excess of **US$25 billion** is spent annually on treatment of chronic wounds.
- The burden is growing due to **increasing healthcare costs**, **an aging population** and **a sharp rise in diabetes and obesity** worldwide.

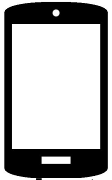



Background

- Care is given in patient’s homes, clinics, acute care hospitals, rehabilitation facilitie[s] and extended care facilities.
- However, accurate diagnosis and timely treatment will highly rely on **expertise and experience**.

Motivations

- Automate the process of wound surface area measurement & wound infection detection with lower cost


- Predict the wound healing date


Proposed Solution

- Automatic process of wound surface estimation, infection detection & condition analysis

	Silhouette Star	Manual Judgement	Our proposed solution
Auxiliary device	high-resolution camera	scalpels	digital camera
Machine Learning	no	no	yes
Accuracy	gold-standard	rough estimation	finer estimation
Time	medical admission	time-consuming	photograph: one-click process: a few secs
Cost	high	low	low

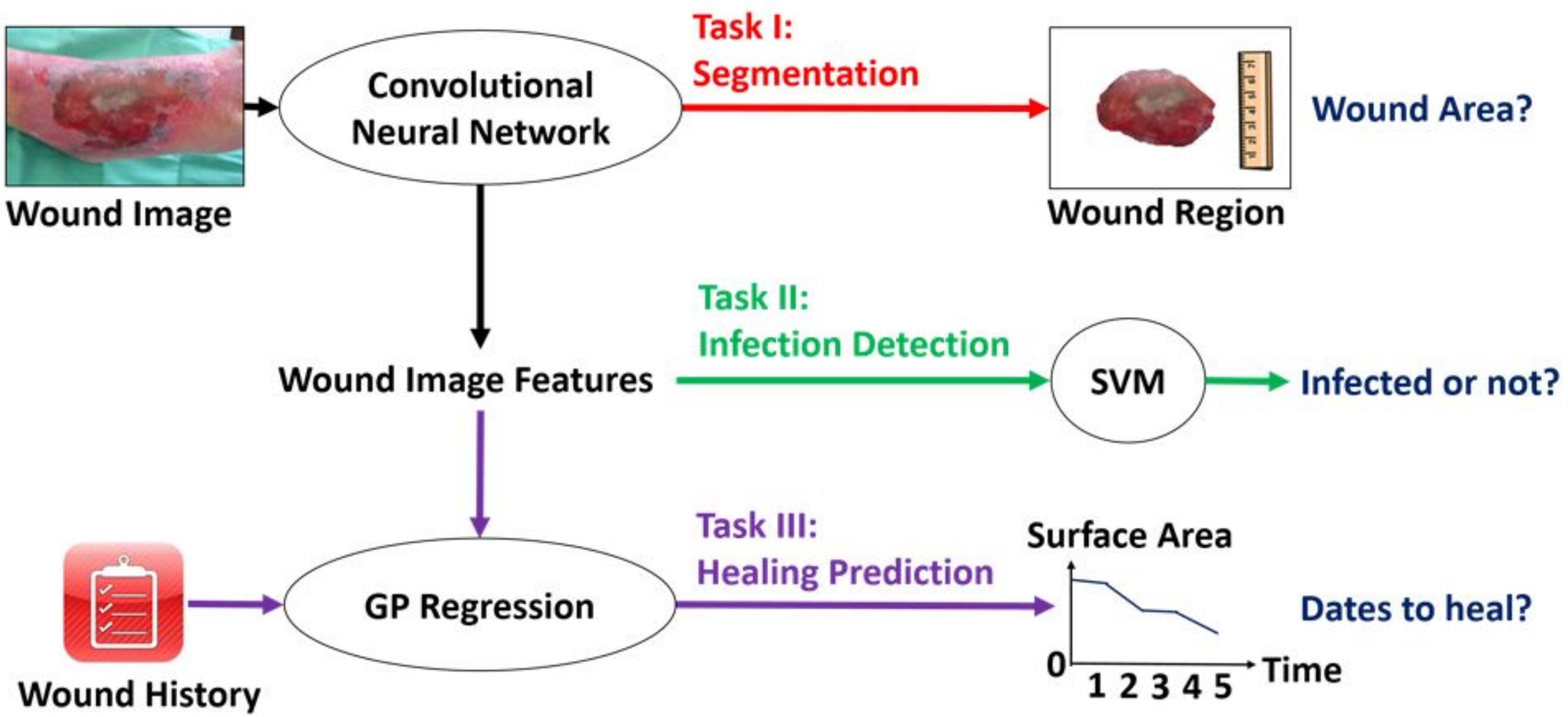
Related work

- Wound segmentation/area estimation: hand-crafted features [Kolesnik et al. 2005][Kolesnik et al. 2006][Veredas et al. 2010]

- Healing progress prediction: short-term predictions based on simple color histogram features [Gurtner et al. 2008][Loizou et al. 2012]

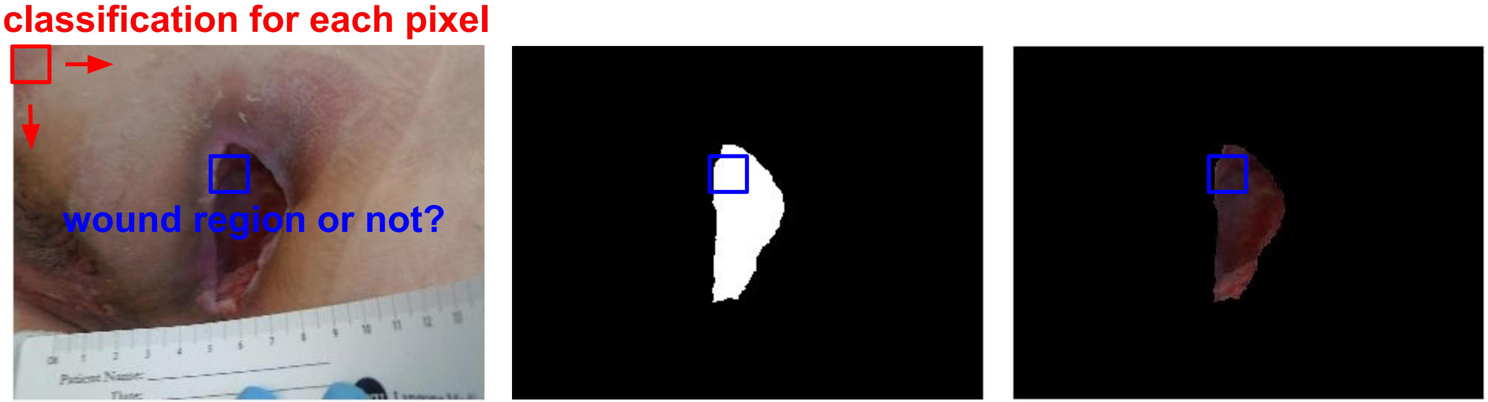
- Dataset for evaluation
  - lack diversity in wound types
  - limited number of subjects/wound images
  - Images have to be manually preprocessed

Our system: a **unified** framework



Task I: wound segmentation

- Foreground/background segmentation: binary classification for each pixel in the scene

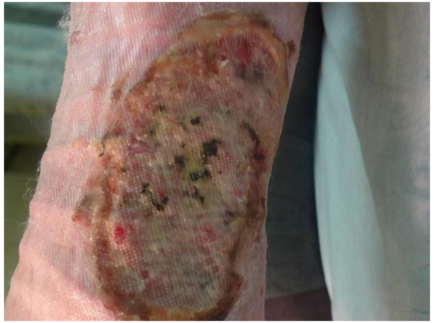


Wound Image Wound Mask Overlay

Task II: infection detection

- Infection detection as a binary classification problem

Wound Image

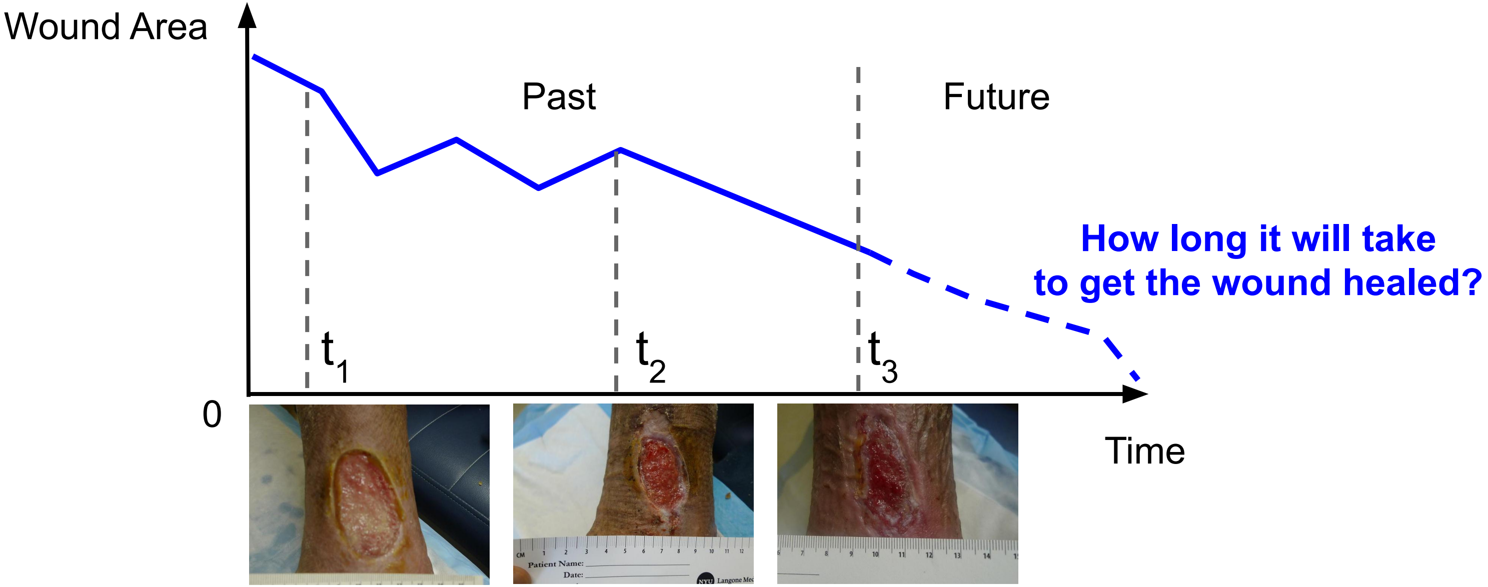


Infected or not?

Infected | **Infected** | **Not infected**

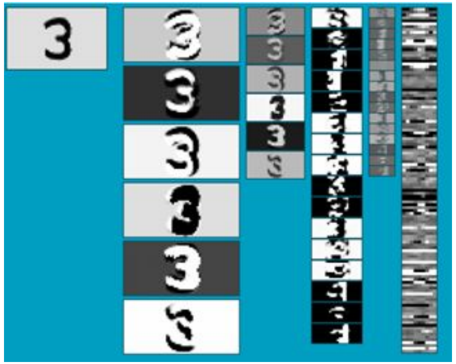
Task III: healing progress prediction

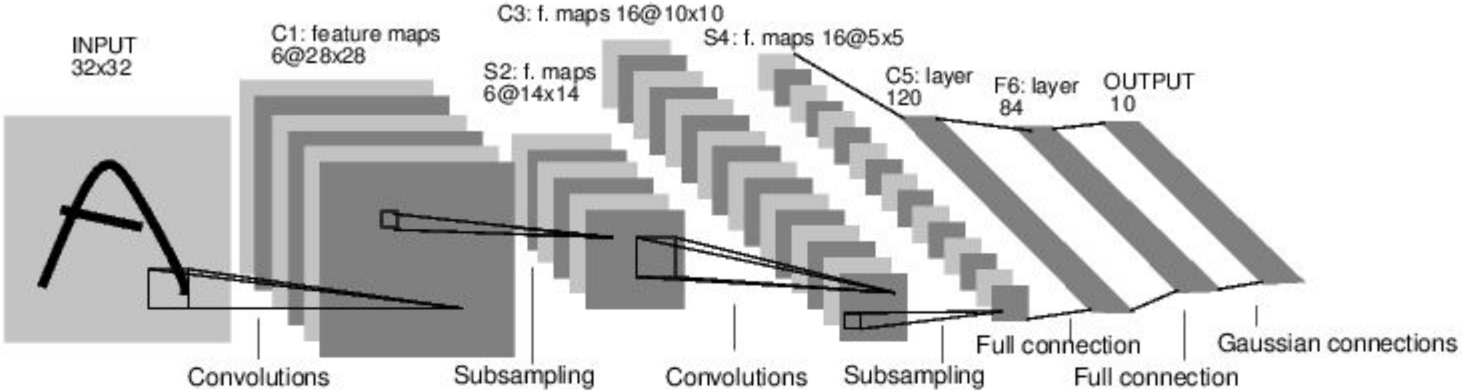
- Predicting the trend and date of healing



Convolutional Neural Networks

- LeCun et al. 1989
- Neural network with specialized connectivity structure

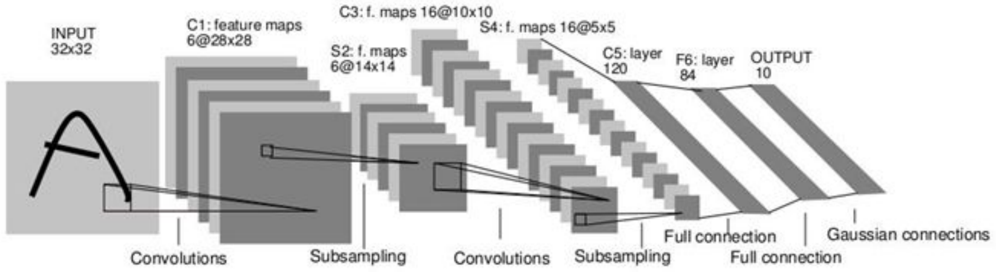




Convolutional Neural Networks

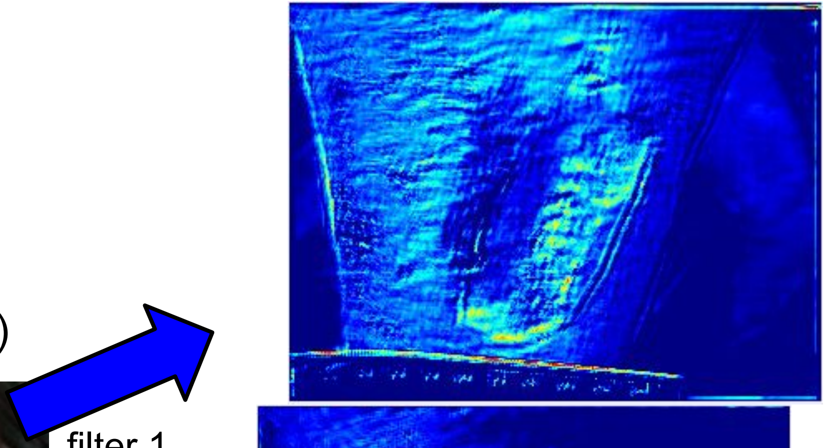
- Feed-forward:
    - Convolve input
    - Non-linearity (rectified linear)
    - Pooling (local max)
- Supervised
- Train convolutional filters by back-propagating classification error

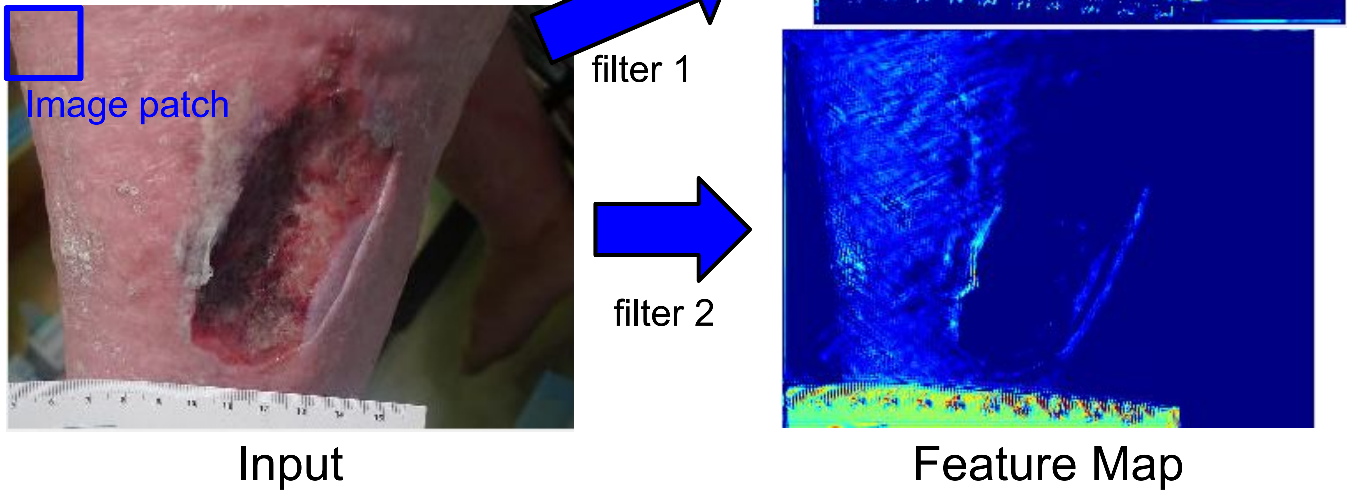
LeCun et al. 1998



Filtering

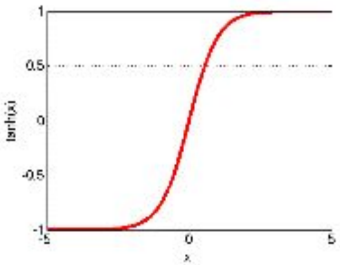
- Convolutional
  - Dependencies are local
  - Translation equivariance
  - Tied filter weights (few params)
  - Stride 1, 2, … (faster, less mem)

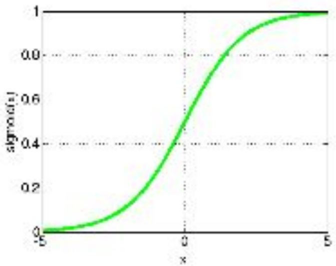


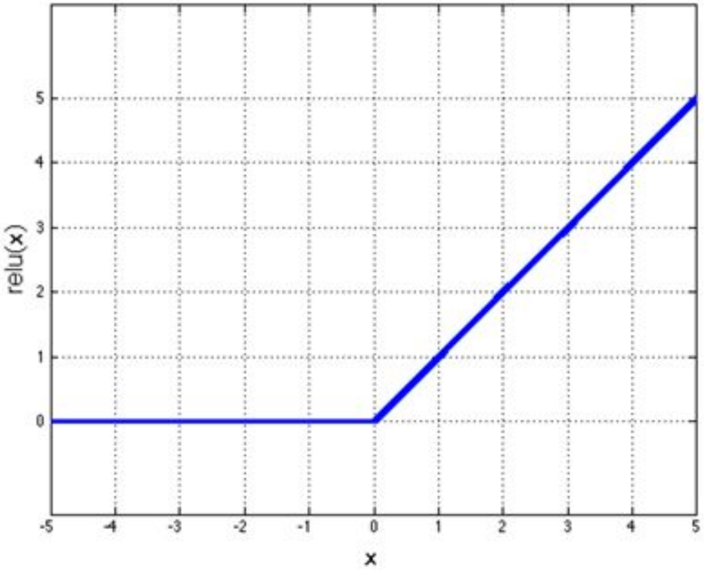


Non-Linearity

- Non-linearity
- Per-element (independent)
- Tanh
- Sigmoid: 1/(1+exp(-x))
- Rectified linear
  - Simplifies backprop
  - Makes learning faster
  - Avoids saturation issues

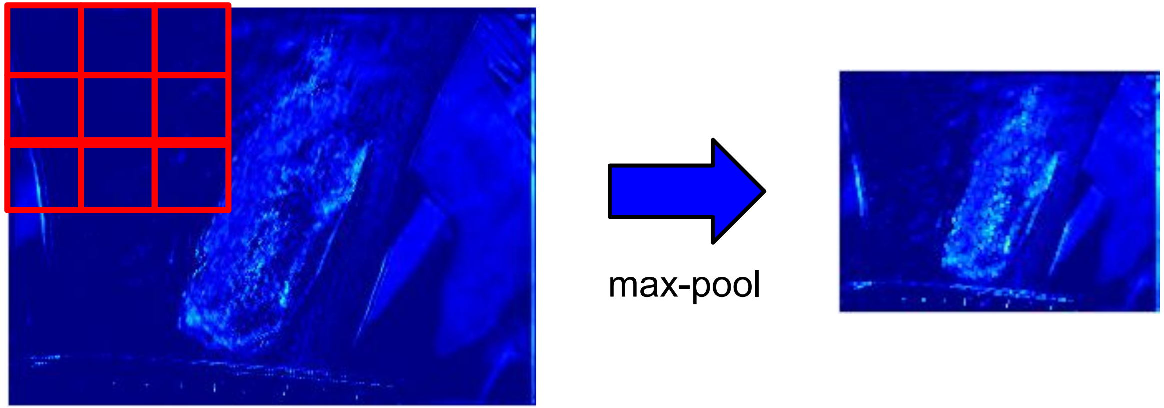




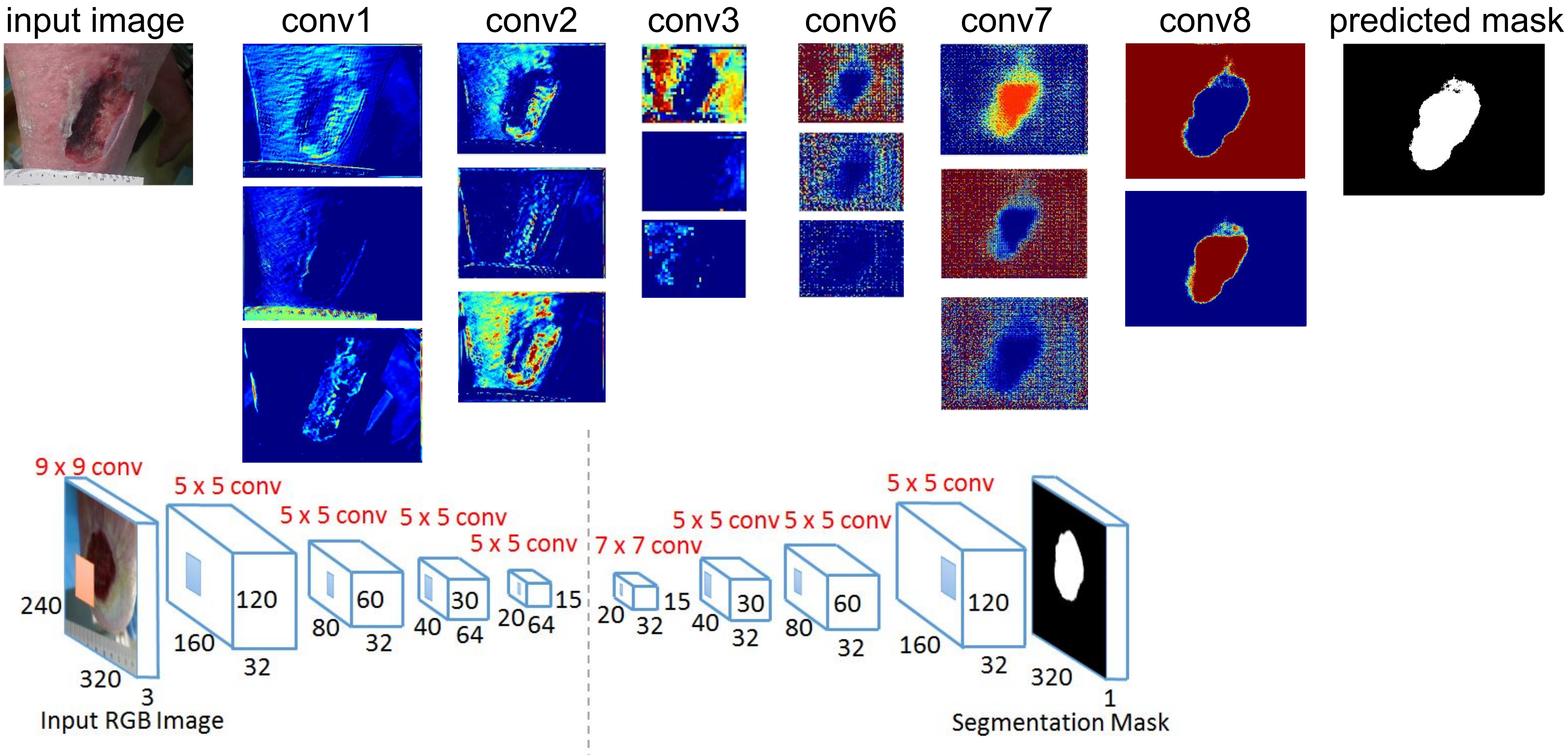


Pooling

- Spatial Pooling
  - Non-overlapping / overlapping regions
  - Sum or max
  - Boureau et al. ICML'10 for theoretical analysis



Convolutional Neural Networks



Contributions

- Learning & evaluations on a large-scale dataset
  - Large number of patients and wound images
  - Weekly wound images that enables temporal analysis
  - Various wound types that ensures generalization
  - Annotated by wound experts for supervised learning

diabetic wound

venous wound

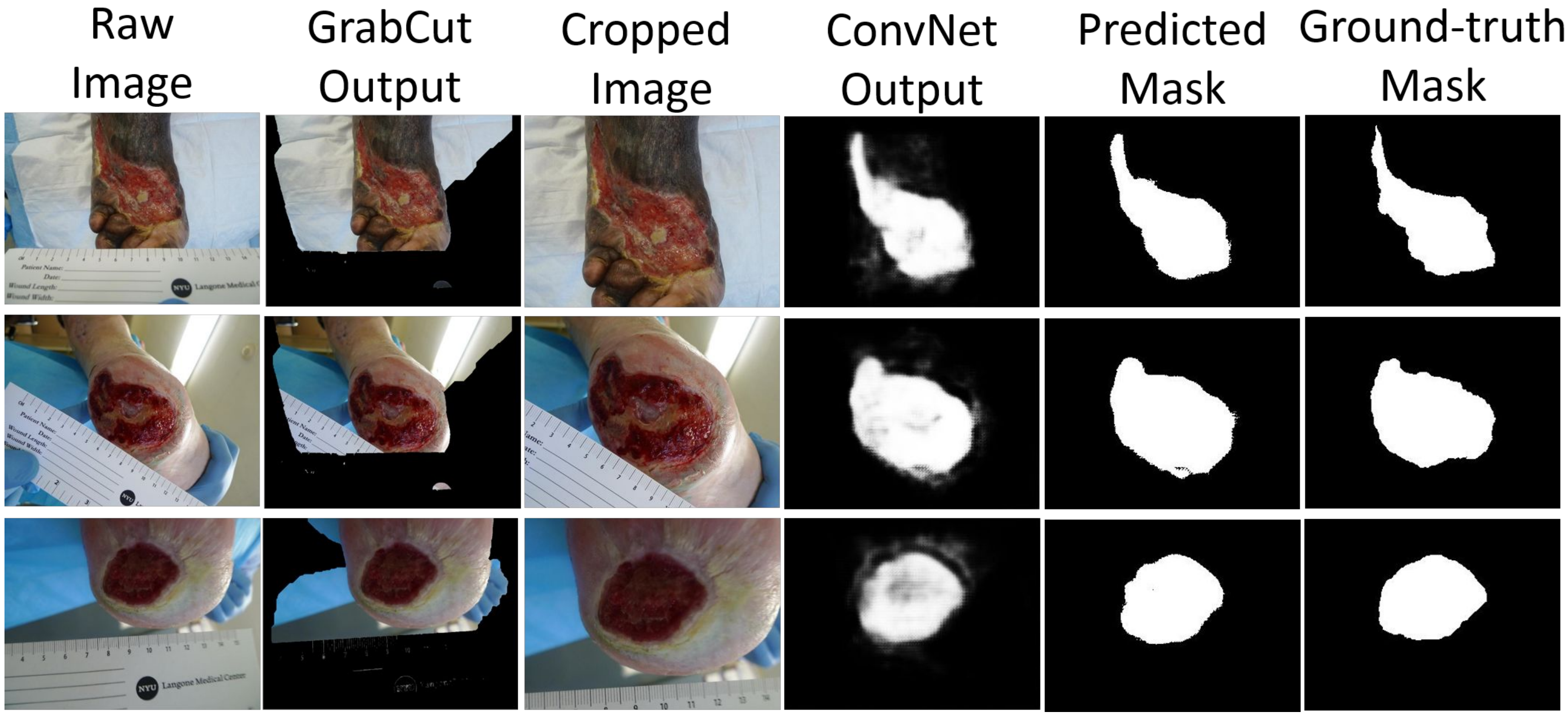
arterial wound

pressure ulcer wound

Contributions

- Learning & evaluations on a large-scale dataset
- Automatic system for wound region segmentation in wound images
- Accurate wound surface area estimation based on the segments
- Infection detection based on learned visual wound features
- First attempt to automate long-term predictions of wound healing rates and healing dates

Results: Segmentation



Crop images by Grabcut

Mark background areas with strokes. Automated by sampling strokes in marginal areas.

Grabcut: segment the wound area and the background (indicated by the strokes)

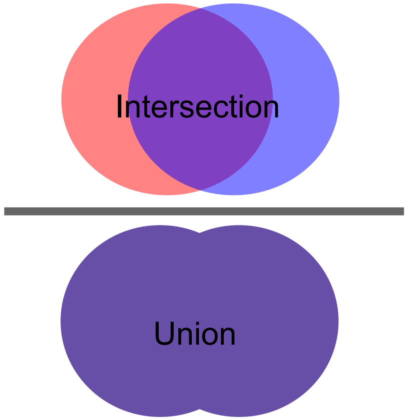
Locate a bounding box by the center of the wound area

Crop the image to the bounding box

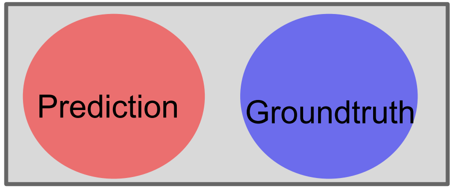
Results: Segmentation

	Pixel Accuracy	Mean IoU
SVM (RGB)	77.60%	26.40%
ConvNet	95.00%	47.30%

IoU=

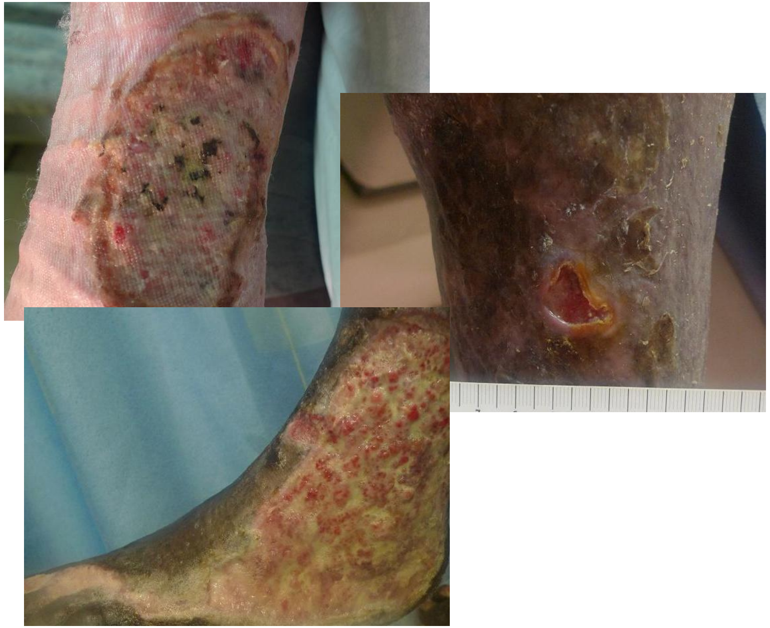


- Intersection over union (IoU)
- Larger IoU suggests better overlap between the prediction and groundtruth (hence better prediction)



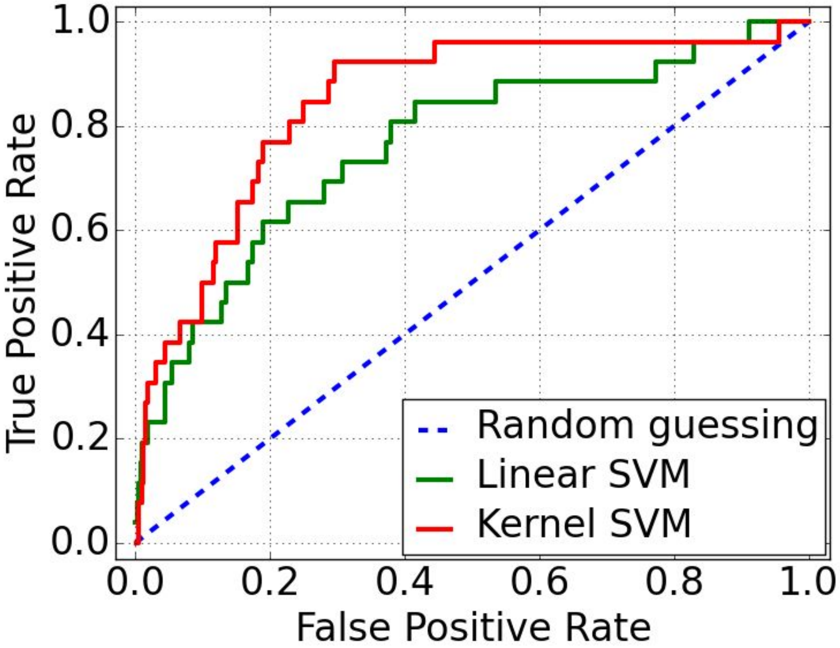
Results: Infection Detection

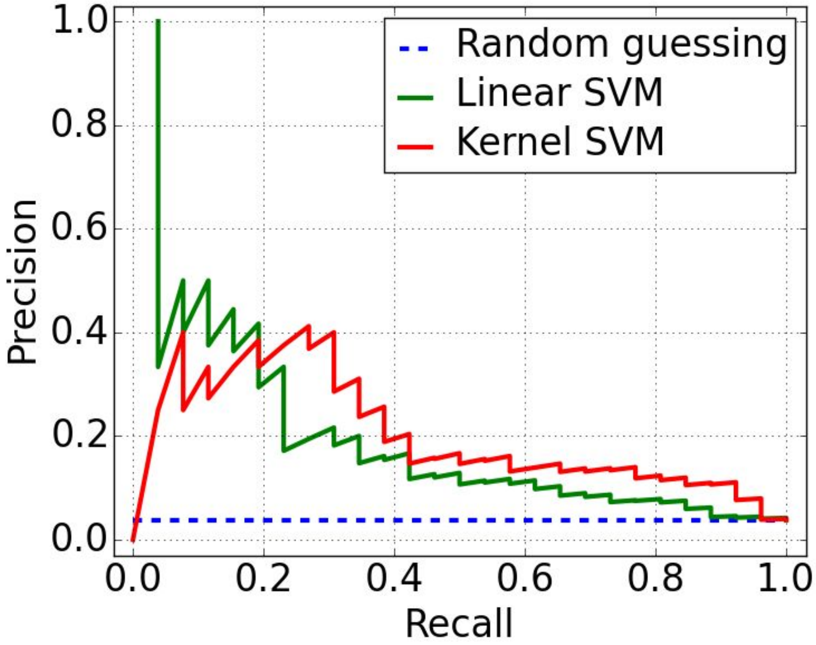
Infection



Non-infection

Results: Infection Detection

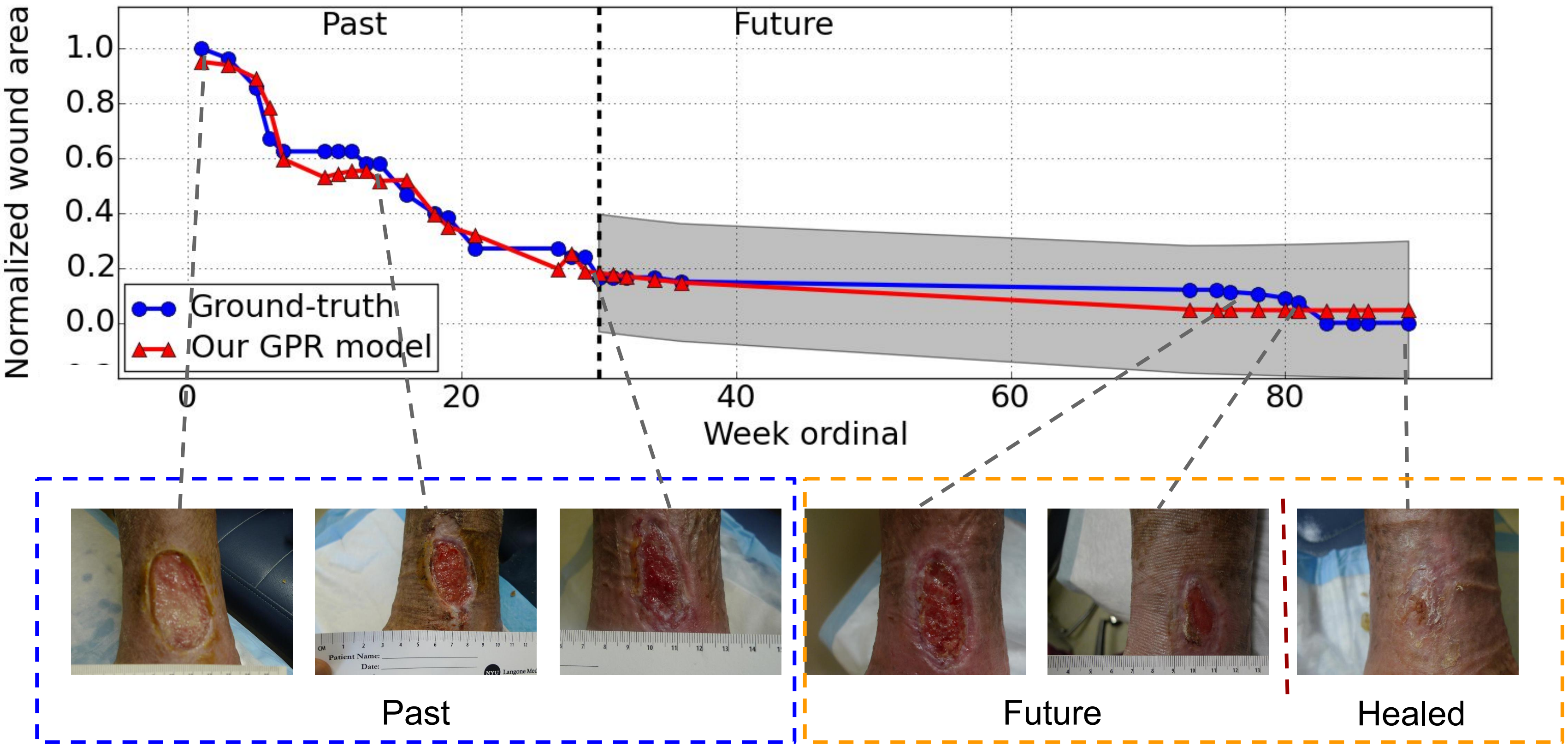




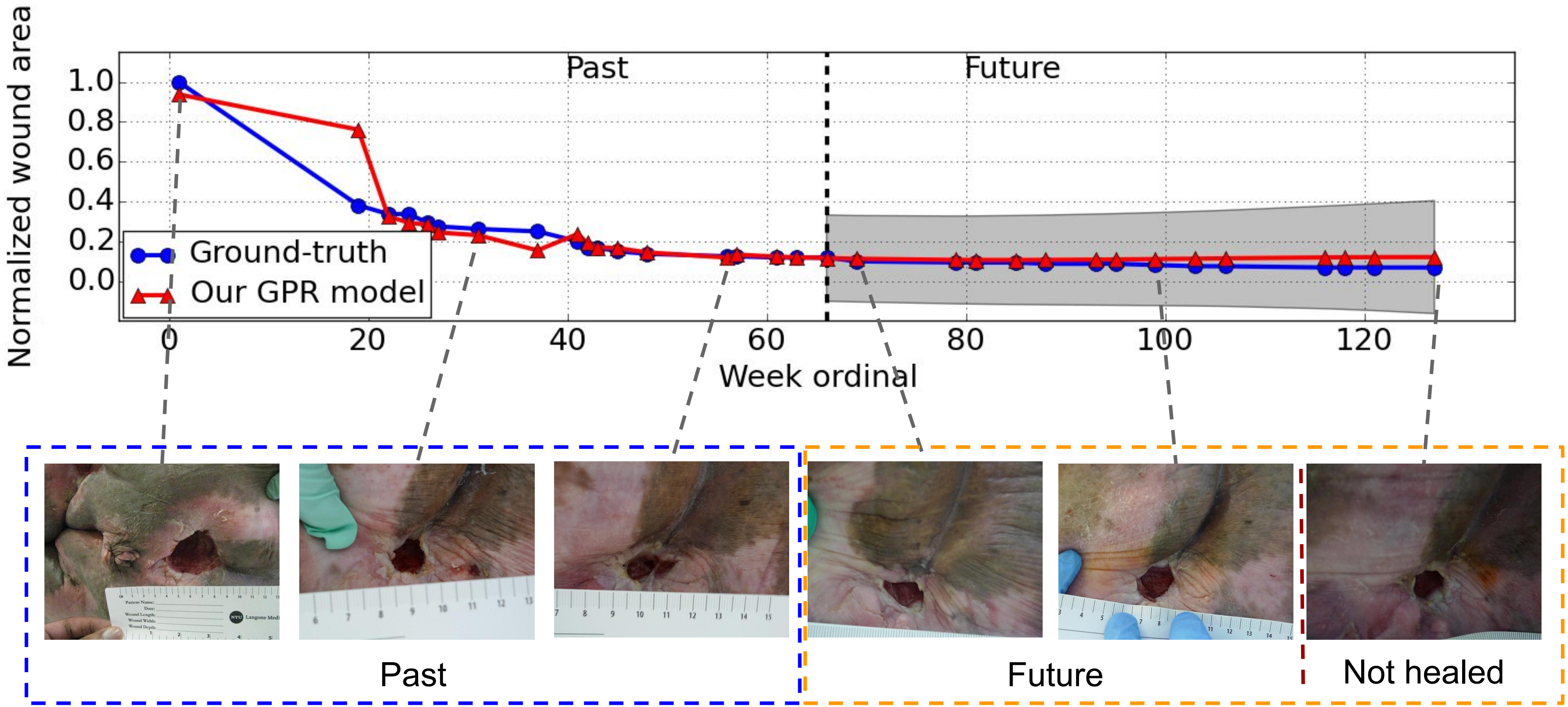
Results: Infection Detection

	p	Accuracy	Recall	Precision	F-1 Score	AUC
Random guessing	10%	86.90%	10%	3.83%	0.055	50%
	50%	50%	50%	3.83%	0.071	
	100%	3.83%	100%	3.83%	0.074	
CNN features + Linear SVM		95.30%	23.10%	33.30%	0.273	76.30%
CNN features + Kernel SVM		95.60%	30.80%	40.00%	0.348	84.70%

Results: Healing Progress Prediction



Results: Healing Progress Prediction



Results: Healing Progress Prediction

- It is well known that wound surface area changes at 4 weeks are highly predictive of subsequent wound closure.
- Construct Gaussian process regression model to capture healing dynamics

Results: Healing Progress Prediction

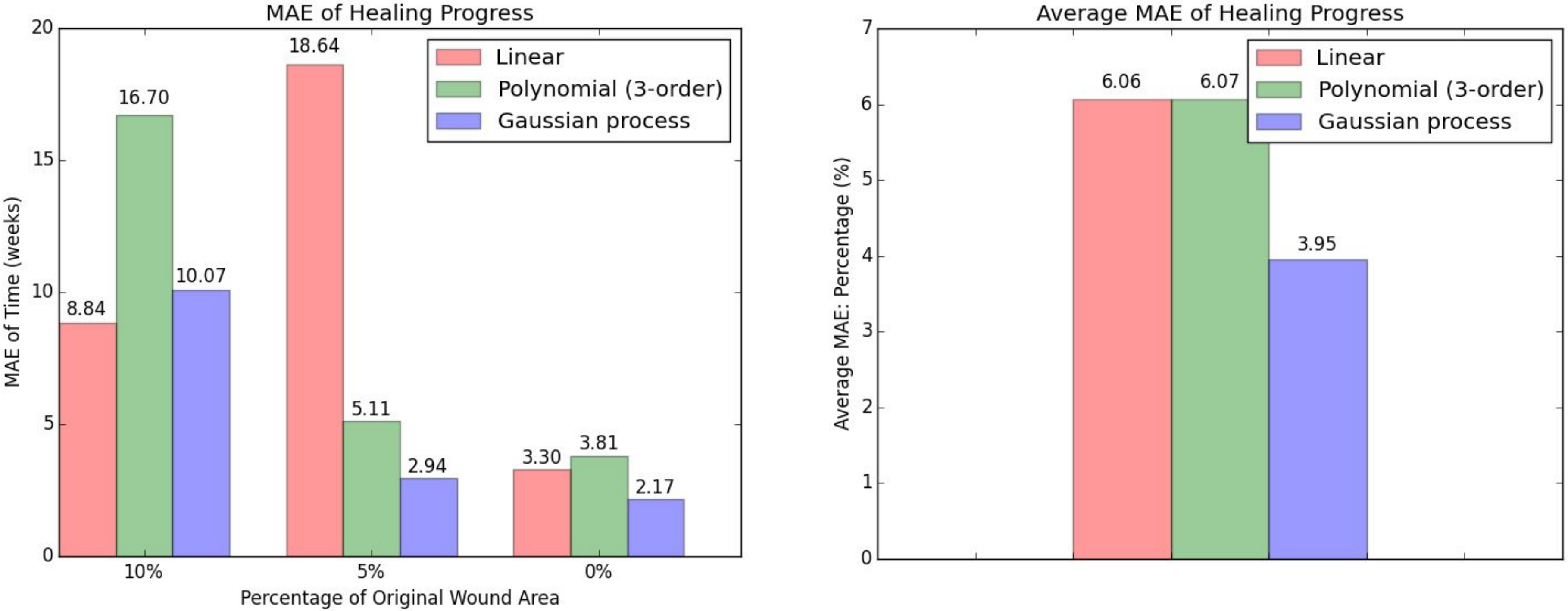
- We analyzed the time (weeks) it took until the wound size became 10%, 5%, and 0% of the original wound area.
- Measured using mean absolute error (MAE); namely, the average of the absolute errors:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |f_i - y_i| = \frac{1}{n}\sum_{i=1}^{n} |e_i|\,.$$

- We also report the average MAE across all time frames

Results: Healing Progress Prediction

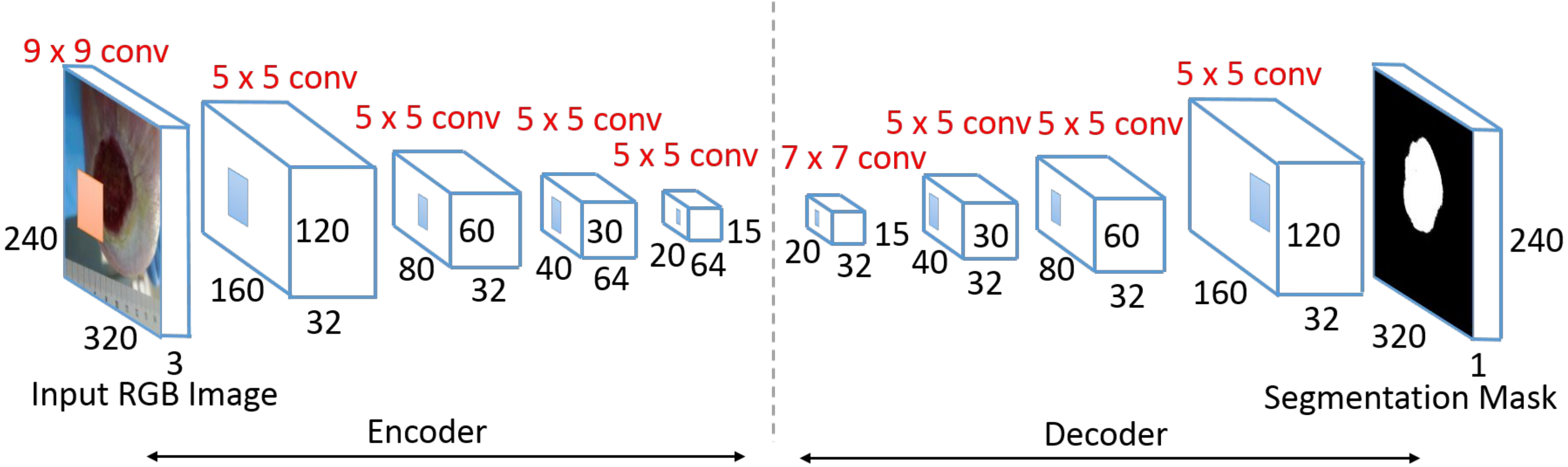
	MAE_{time} (10%)	MAE_{time} (5%)	MAE_{time} (0%)	Avg. MAE_{area}
CNN feature + Linear regression	8.84	18.64	3.3	6.06%
CNN feature + Polynomial regression	16.7	5.11	3.81	6.07%
CNN feature + GP regression	10.07	2.94	2.17	3.95%


MAE of Healing Progress
MAE of Time (weeks)
Percentage of Original Wound Area
10%
5%
0%
8.84
16.70
10.07
18.64
5.11
2.94
3.30
3.81
2.17
Linear
Polynomial (3-order)
Gaussian process
Average MAE of Healing Progress
Average MAE: Percentage (%)
6.06
6.07
3.95

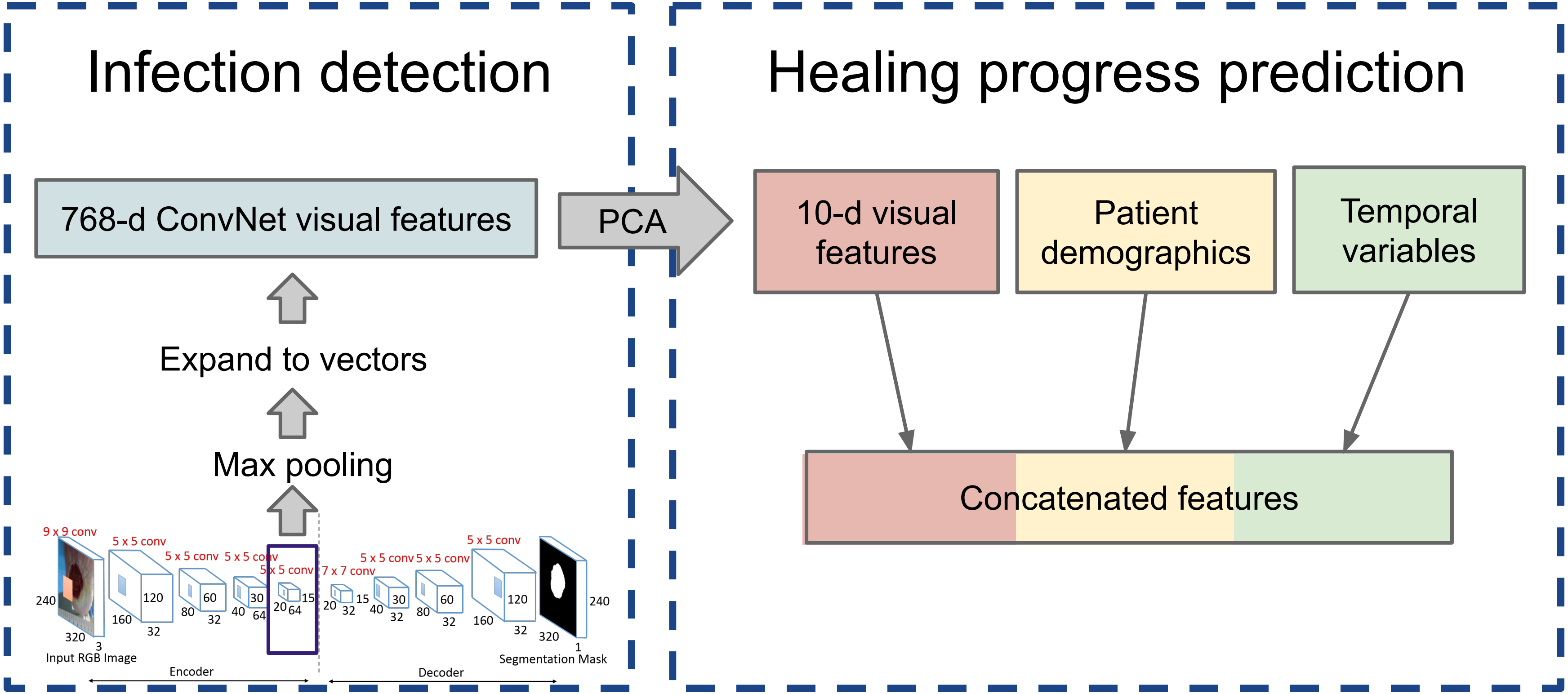
Methods

- ConvNets for wound segmentation
- Gaussian Process Regression for healing progress prediction

Our ConvNet Model



Features for Wound Analysis



Gaussian Process Regression

- Bayesian linear regression
- Anisotropic Gaussian kernel

Value Add

What our work adds to the general community

- save money
- better diagnostic
- etc.

Reference

[1] Kolesnik, Marina, and Ales Fexa. "Multi-dimensional color histograms for segmentation of wounds in images." *Image Analysis and Recognition* (2005): 1014-1022.

[2] Kolesnik, Marina, and Aleš Fexa. "How robust is the SVM wound segmentation?." *Signal Processing Symposium, 2006. NORSIG 2006. Proceedings of the 7th Nordic*. IEEE, 2006.

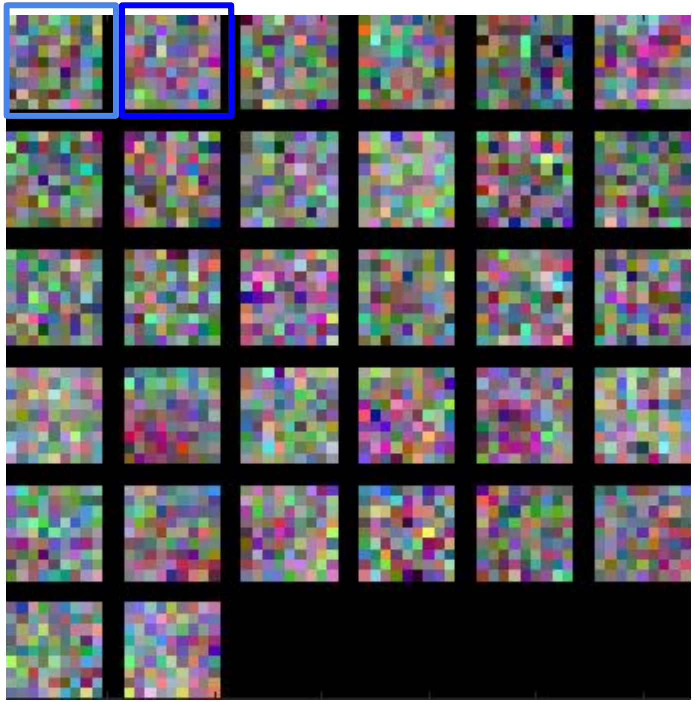
[3] Veredas, Francisco, Héctor Mesa, and Laura Morente. "Binary tissue classification on wound images with neural networks and bayesian classifiers." *Medical Imaging, IEEE Transactions on*29.2 (2010): 410-427.

[4] Gurtner, Geoffrey C., et al. "Wound repair and regeneration." *Nature* 453.7193 (2008): 314-321.

[5] Loizou, Christos P., et al. "Evaluation of wound healing process based on texture analysis."Bioinformatics & Bioengineering (BIBE), 2012 IEEE 12th International Conference on. IEEE, 2012.

Q & A

filter visualization by projection



filter visualization by finding the patches (in particular image) that maximize the activation

filter visualization by finding the patches (in entire training set) that maximize the activation