HealTech - A System for Predicting Patient Hospitalization Risk and Wound Progression in Old Patients

Subba Reddy Oota[1,2], Vijay Rowtula[1,2], Shahid Mohammed[1], Jeffrey Galitz[1], Minghsun Liu[1], Manish Gupta[2]

[1]Woundtech Innovative Healthcare Solutions, [2]IIIT-Hyderabad, India

Woundtech

INTERNATIONAL INSTITUTE OF INFORMATION TECHNOLOGY

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Why automate prediction of hospitalization risk?

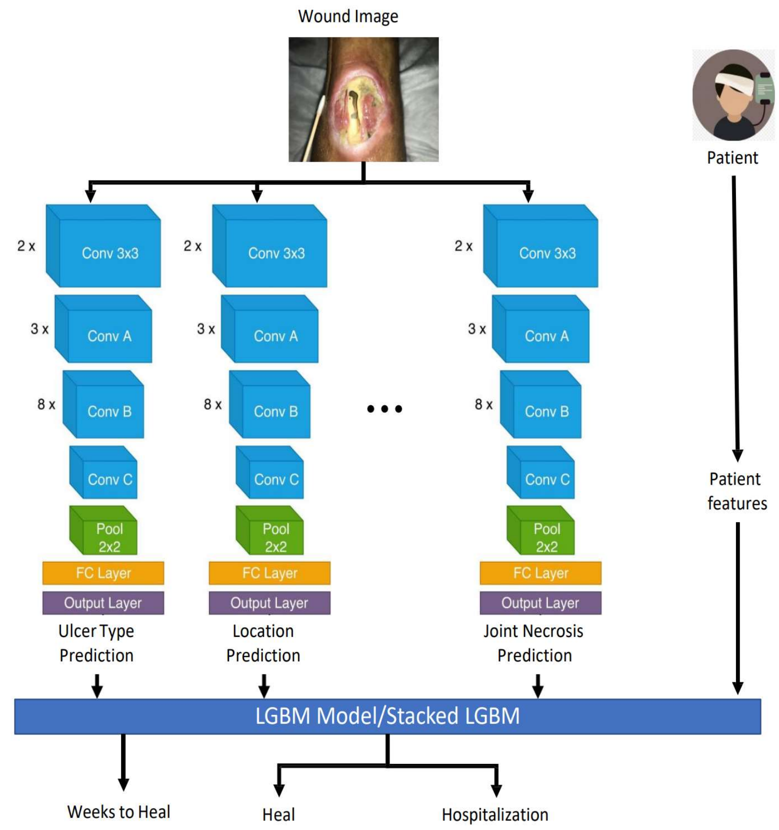
- The total Medicare spending estimates for all wound types (in the US) ranged from $28.1 to $96.8 billion.
- How bad is my wound? How fast will the wound heal? Do I need to get hospitalized? Questions like these are critical for wound assessment, but challenging to answer.
- Unnecessary hospitalization leads to discomfort for the patient, costs, and possible hospital-acquired infections.
- Delay in hospitalization may lead to increased treatment costs, less effective treatment, infections, and in general, worsening of the wound.
- Challenges for the manual diagnosis by clinicians include
  - Frequent assessments of a patient
  - Data entry of wound attributes in the database
  - Applying the right diagnosis
  - Inter-observer discordance.
- Such a system can help in early detection of the complexities in the wound, which might affect the healing process and also reduce the time spent by a clinician to diagnose the wound.

Problem Definition and challenges

- Build a model to predict the patient’s risk of hospitalization.
- For wounds that show a higher likelihood of healing without hospitalization, predict the number of weeks to heal.
- HealTech depends on wound images and patient attributes like age, BMI, etc.
- Challenges
  - Wound progression and hospitalization risk can depend on multiple factors like wound/ulcer type, wound location, wound size, etc.
  - Combining multiple wound image related factors with patient demography parameters, variations across images in terms of lighting conditions, skin color variations, etc.
- Related Work
  - Wound image analysis
  - Deep learning for medical imaging

HealTech

- Two-stage CNN method.
- First stage: predicts 14 factors from wound images for wound characterization.
- Second stage: Evolutionary algorithm-based stacked Light Gradient Boosted Machines (LGBM), which uses the wound factors predicted from first stage, as well as a list of five patient features.
- Experiment with a large dataset of 125711 images.



Model architecture with two stages of wound assessment. The first stage predicts features from wound images. The second stage uses wound image features along with patient features to predict hospitalization risk and weeks to heal.

Stage 1: Wound Feature Prediction

- 125711 images obtained from 11632 patients. 4 years (Jun 2015–Mar 2019) of patients' wound care data.
- The average age of patients is 73.63 years and the average BMI is 29.66.
- We use ImageNet pretrained 71-layer deep Xception architecture.
- Multi-task learning (MTL): Joint learning of highly correlated variables.
  - We learn a total of 9 Xception CNN models.
- Baseline method: color histogram, canny edge detector features, Hough transform features, and Histogram of Gradients (HOG) features to train an LGBM classifier.
- 5-fold cross-validation precision and recall values

Wound attribute	Baseline (similar to [5])		Single Task CNN		Single Multi-Task CNN		Multi-Task CNN	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
Wound/Ulcer Type	0.46	0.48	**0.80**	**0.81**	0.64	0.70	0.66	0.80
Wound Location	0.49	0.48	**0.87**	**0.87**	0.66	0.58	0.66	0.65
Wound Stage	0.58	0.54	0.63	0.65	0.50	0.55	**0.78**	**0.71**
Wound Margin	0.46	0.46	0.54	0.58	0.29	0.35	**0.60**	**0.63**
Joint Necrosis Exposed	0.55	0.55	0.79	0.83	0.67	0.71	**0.77**	**0.84**
Ligament Necrosis Exposed	0.71	0.61	0.77	0.70	0.67	0.69	**0.74**	**0.81**
Adipose Necrosis Exposed	0.64	0.64	0.69	0.83	0.66	0.69	**0.71**	**0.83**
Muscle Necrosis Exposed	0.66	0.64	0.69	0.83	0.66	0.69	**0.72**	**0.83**
Exudate	0.60	0.60	0.65	0.68	0.59	0.61	**0.71**	**0.73**
Red Granulation	0.44	0.44	0.65	0.68	0.44	0.61	**0.66**	**0.68**
Bone Necrosis Exposed	0.67	0.74	0.76	0.74	0.69	0.72	**0.74**	**0.81**
Adherent Yellow Slough	0.42	0.44	0.62	0.64	0.51	0.54	**0.65**	**0.67**

Stage 1 Results

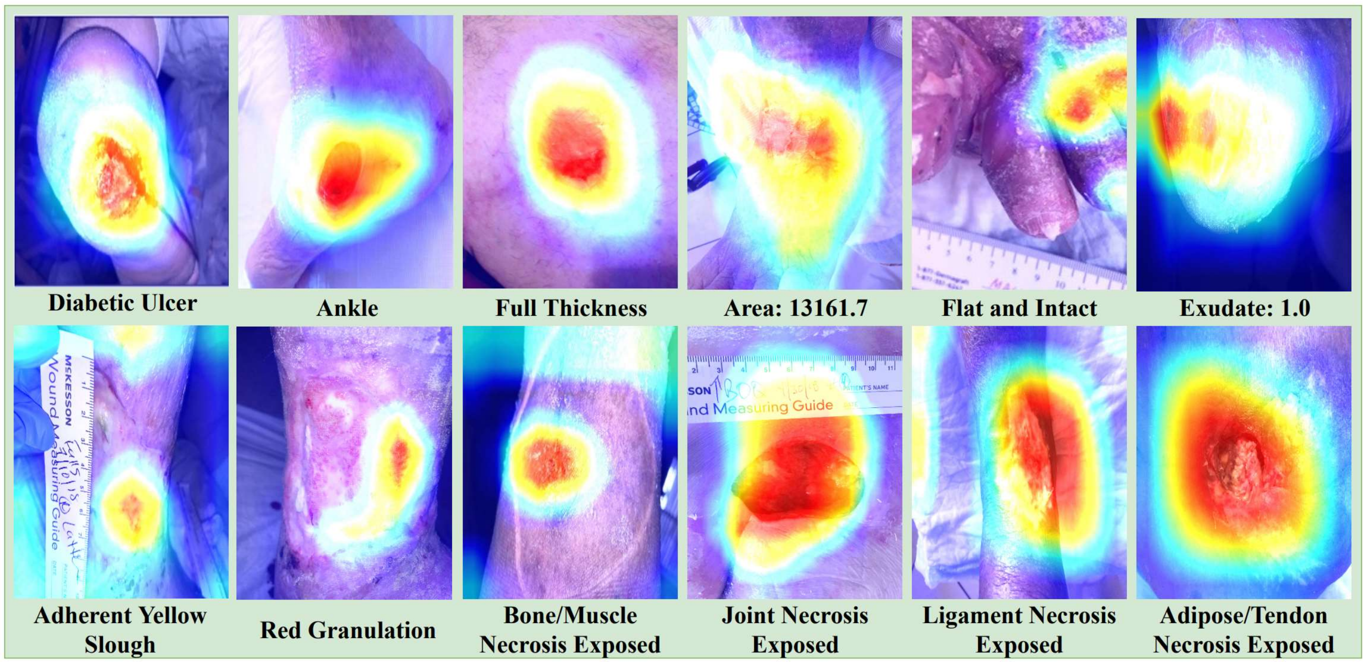


Figure 4. GradMaps of different wound variables predicted by Xception models trained by respective wound variables. We can observe that the model accurately predicted the location of the wound, despite occlusion and other limitations.

Stage 2: Heal/Hospitalization Classification and Weeks to Heal Prediction

- The 14 predictions from the first stage are combined with 5 patient features (age, BMI (body mass index), ethnicity, pulse rate, location), which cannot be predicted using wound images.
- Data imbalance: Of a total of 20376 samples, 18932 examples are of heal category, and 1444 examples belong to the hospitalization class. Use SMOTE.
- Oracle Method: We used the ground truth values for the 14 image features and the 5 patient features.
- (Genetic Algorithms Tuned) GAT-Stacked LGBM

		Baseline				Oracle				Xception CNN (HealTech)			
Sampling Method→		Over		Under		Over		Under		Over		Under	
Feature set↓	Class↓	P	R	P	R	P	R	P	R	P	R	P	R
All	Heal	0.98	0.99	0.99	0.93	0.98	0.99	0.99	0.94	**0.99**	**0.99**	1	0.94
All	Hospitalization	0.86	0.78	0.49	0.86	0.89	0.79	0.52	0.91	**0.92**	**0.83**	0.55	0.95
Image	Heal	0.97	0.98	0.98	0.78	0.98	0.99	0.99	0.79	**0.98**	**0.99**	0.99	0.8
Image	Hospitalization	0.77	0.65	0.23	0.84	0.78	0.74	0.24	0.86	**0.78**	**0.76**	0.24	0.85

Stage 2 Results: Heal/Hospitalization accuracy comparison for GAT Stacked LGBM method using different sampling methods with Baseline/Oracle/Xception-CNN (HealTech).

	Baseline			Oracle			Xception CNN (HealTech)		
Feature set↓	LR	LGBM	GS-LGBM	LR	LGBM	GS-LGBM	LR	LGBM	GS-LGBM
All	4.4	4.1	4.0	4.0	3.4	**3.1**	4.0	3.6	3.3
Image	4.4	4.3	4.1	4.2	3.8	**3.3**	4.3	4.0	3.4

Stage 2 Results: Weeks to Heal prediction comparison for LGBM (HealTech) method and the baseline Linear Regression on MAE. LR=Linear Regression. GS-LGBM=GAT Stacked LGBM

Conclusion

- Proposed two interesting wound assessment tasks: hospitalization risk prediction and weeks to heal prediction.
- HealTech operates in two stages
  - Wound image is analyzed by Xception CNN models to predict 14 critical wound attributes.
  - These attributes are leveraged to perform the two wound assessment predictions.
- We are the first to perform extensive experiments on a large dataset for wound analysis.
- HealTech leads to good accuracy values, and therefore can be practically deployed.