Using Artificial Intelligence (AI) to Model Healing Prediction - A Preliminary Study

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INTRODUCTION

Accurate wound healing prediction can help guide treatment decisions through early identification of patients presenting non-healing risk. Prior efforts include the development of a Wound Healing Index for diabetic foot ulcers [1].

Such prediction and risk stratification systems demonstrate some efficacy, but they exclude vital wound information associated with the visual details.

Using data set from a chronic wound data repository, we apply the latest advances in deep learning to develop a healing prediction model that simultaneously integrates information from wound images.

With 13,007 images used for training the AI model, this is the biggest dataset used to train a hybrid architecture to date.

METHOD

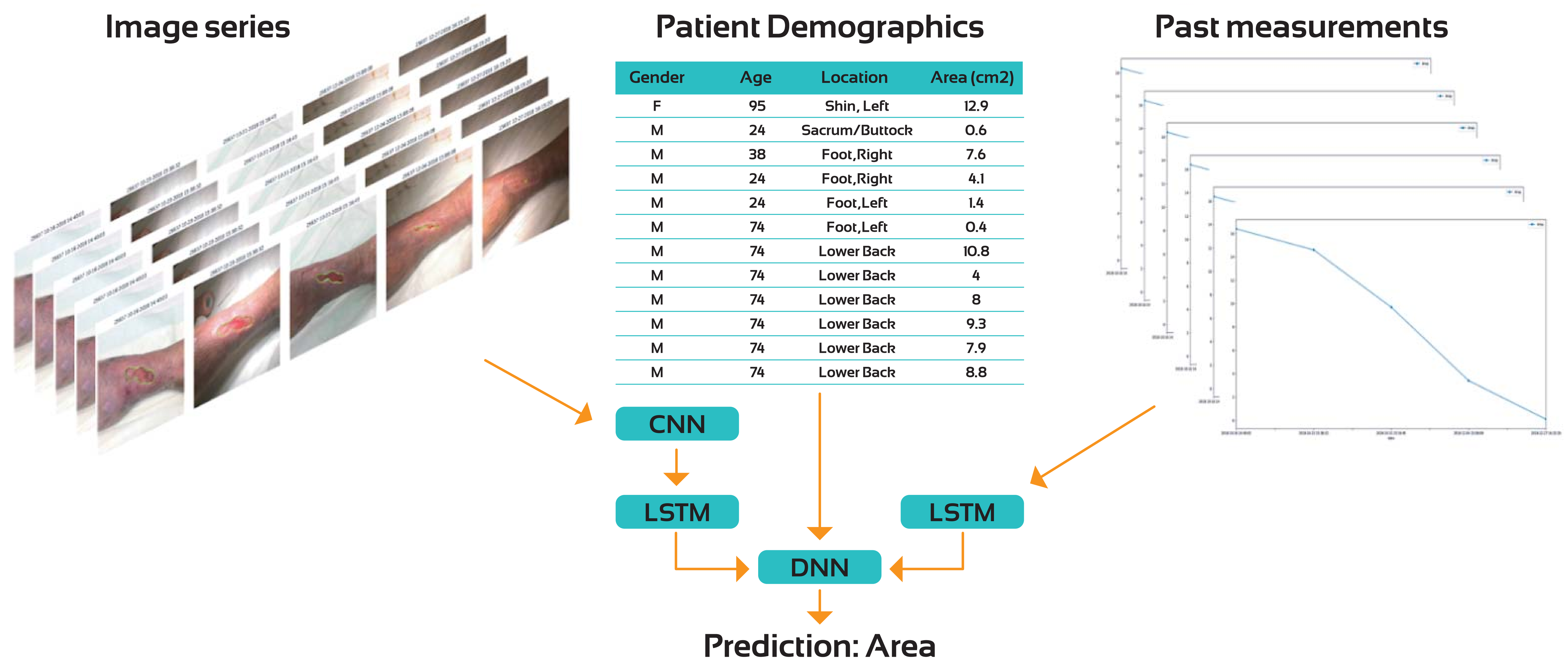
The proposed deep learning framework combines wound images, patient demographics, as well as historical healing rates to develop a healing prediction model utilizing Long Short-Term Memory (LSTM) network [2].

An open source Python deep learning library [3] was employed to develop the machine-learning framework. The model, a combination of Convolutional Neural Network (CNN) and Deep Neural Network, was trained using the Adam [4] optimizer. The model output is the predicted wound dimension (area).

Data Source: Subset of an internal, anonymized, chronic wound data repository. Inclusion criteria:
- US Only
- Wounds with >= 5 measurements
- > 5 weeks duration
- Initial area: >= 1 cm^2 and <= 100 cm^2
- Number of Images: 13,007
- Train/Validation split: 12,507 vs. 500

SETUP

Keras [3], an open source Python deep learning library was used to develop a machine learning framework in the Python programming Language. The model, a combination of DCN DNN and LSTM, was trained utilizing early stopping with learning rate adaptation on plateaus, 1000 epochs long with batch size 32 using the Adam [2] optimizer and categorical cross entropy as the loss function.



Gender	Age	Location	Area (cm2)
F	95	Shin, Left	12.9
M	24	Sacrum/Buttock	0.6
M	38	Foot, Right	7.6
M	24	Foot, Right	4.1
M	24	Foot, Left	1.4
M	74	Foot, Left	0.4
M	74	Lower Back	10.8
M	74	Lower Back	4
M	74	Lower Back	8
M	74	Lower Back	9.3
M	74	Lower Back	7.9
M	74	Lower Back	8.8

Figure 1: Machine learning architecture. The hybrid model accepts images, patient demographics, and past measurements as input and predicts healing outcome.

RESULTS

- We tested the proposed model on an input data source comprised of 4 weeks of longitudinal data from the chronic wound data repository.
- The predicted and actual healing outcomes are compared using mean absolute percentage error (MAPE) as an error metric. Lower MAPE signifies better model accuracy and performance.
- Two deep learning models were evaluated, one incorporating visible-light imagery, and one without.
  - Without image data: MAPE = ~34%, see Figure 2.
  - Incorporating image data: MAPE = ~16%, see Figure 3.

Figure 2: Model Results without incorporating image data. MAPE plateaus at ~34%.

Left: Prediction accuracy (measured in MAPE) vs. training iterations (Epochs).
Right: Predicted value vs. Ground Truth value.

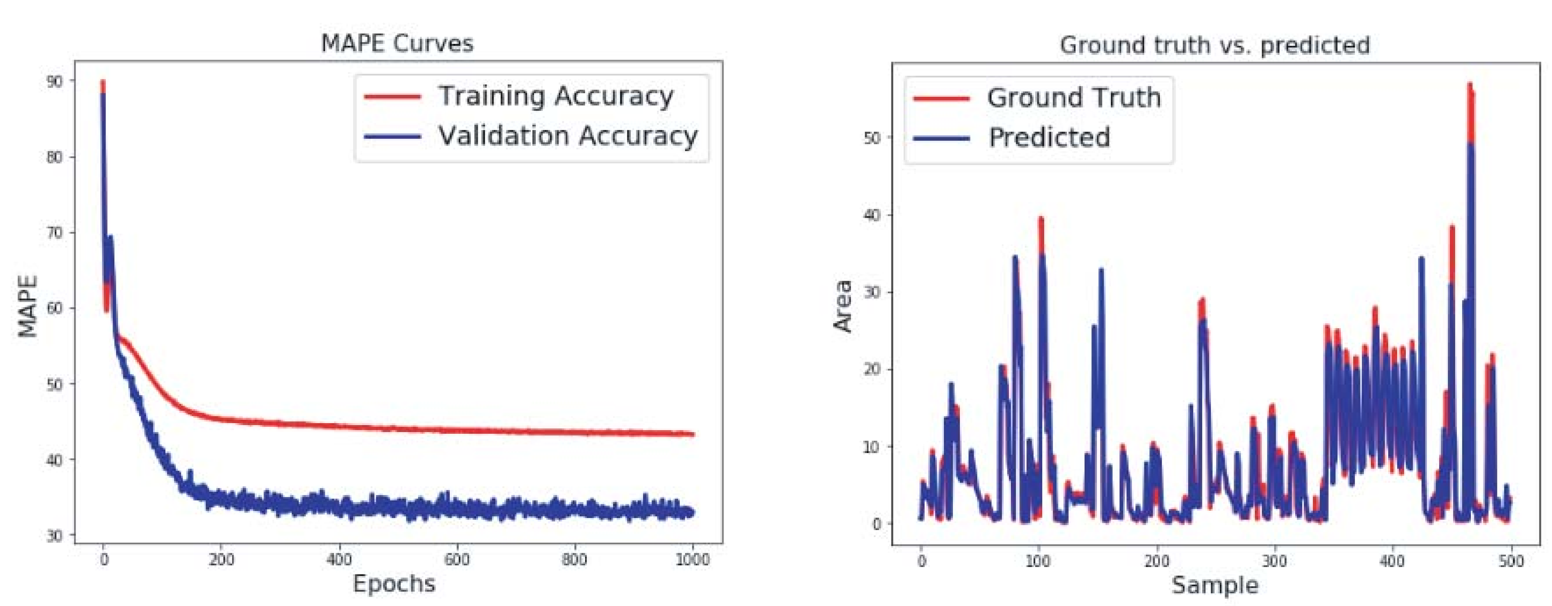
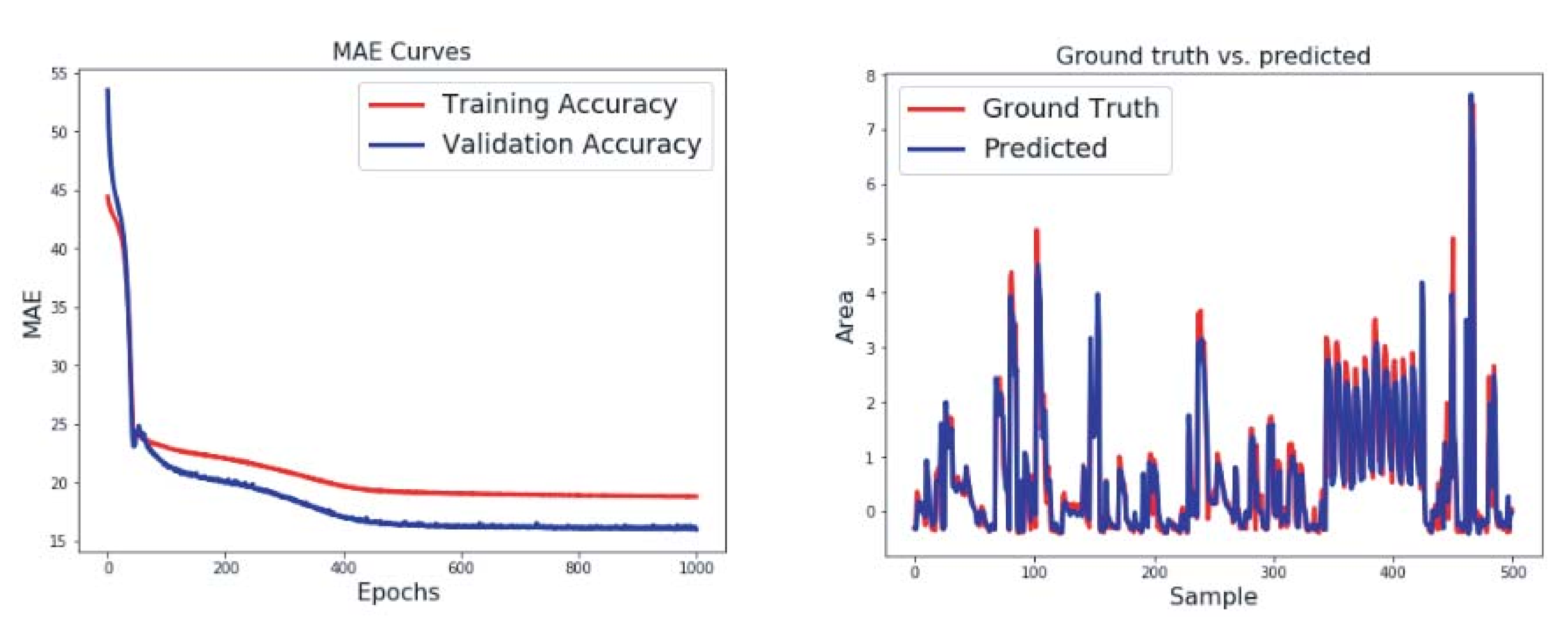


Figure 3: Model Results incorporating image data. MAPE plateaus at ~16%.

Left: Prediction accuracy (measured in MAPE) vs. training iterations (Epochs).
Right: Predicted value vs. Ground Truth value.

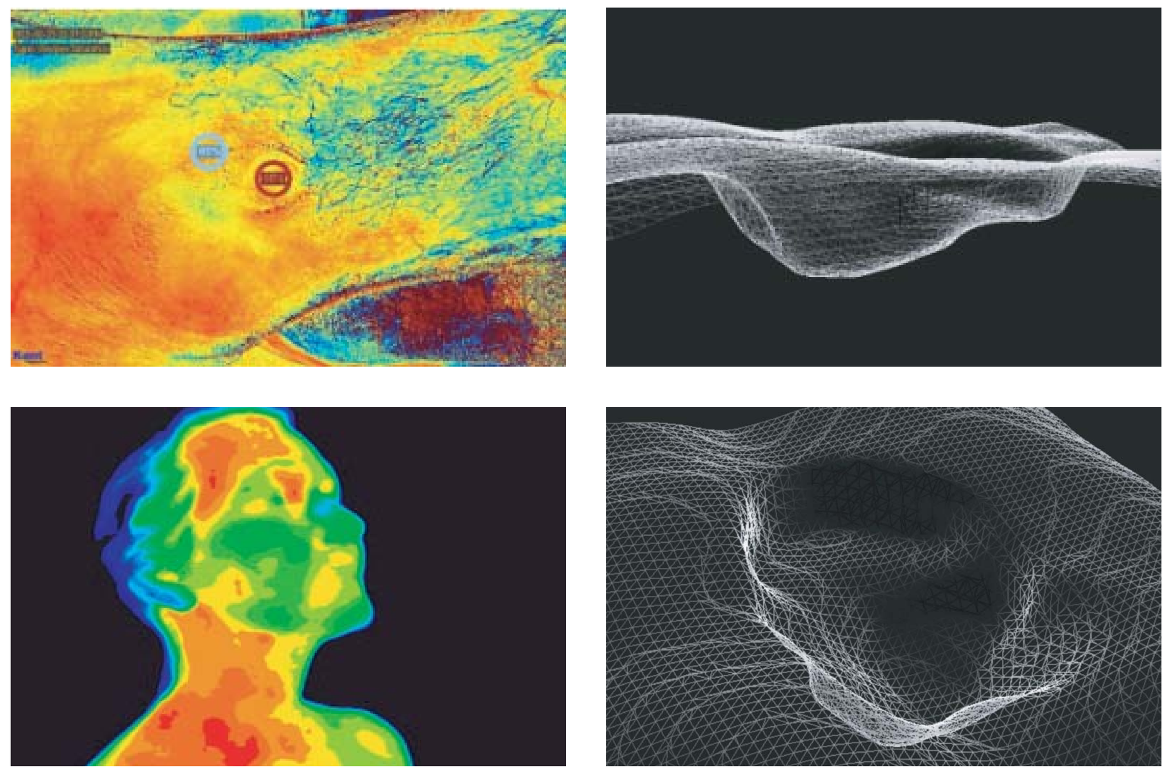


CONCLUSION

The proposed novel LSTM network enables the use of wound image, patient demographic data, and historical healing trajectories to perform robust sequence learning. This application of artificial intelligence may enable more robust healing prediction, thereby facilitating better risk stratification and, subsequently, treatment decisions.

Combining CNN with LSTM architecture required more then 10000 images to achieve acceptable accuracy. Utilizing 13000+ images and demographics allowed for a successful training session.

Future work will focus on improving the robustness and generalizability of the hybrid LSTM cell with more images and data augmentation to include other imaging modalities, including thermal, perfusion, oxygenation, as well as 3D imaging.



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