Review of AI-Based Algorithms for Pressure Ulcer Assessment and Decision Support

Fateme Fayyazbakhsh [1], Lisa Gould [2], and Ming C. Leu [1]

[1] Missouri University of Science and Technology (Rolla, Missouri), [2] South Shore Hospital (Weymouth, Massachusetts)

Pressure Ulcer

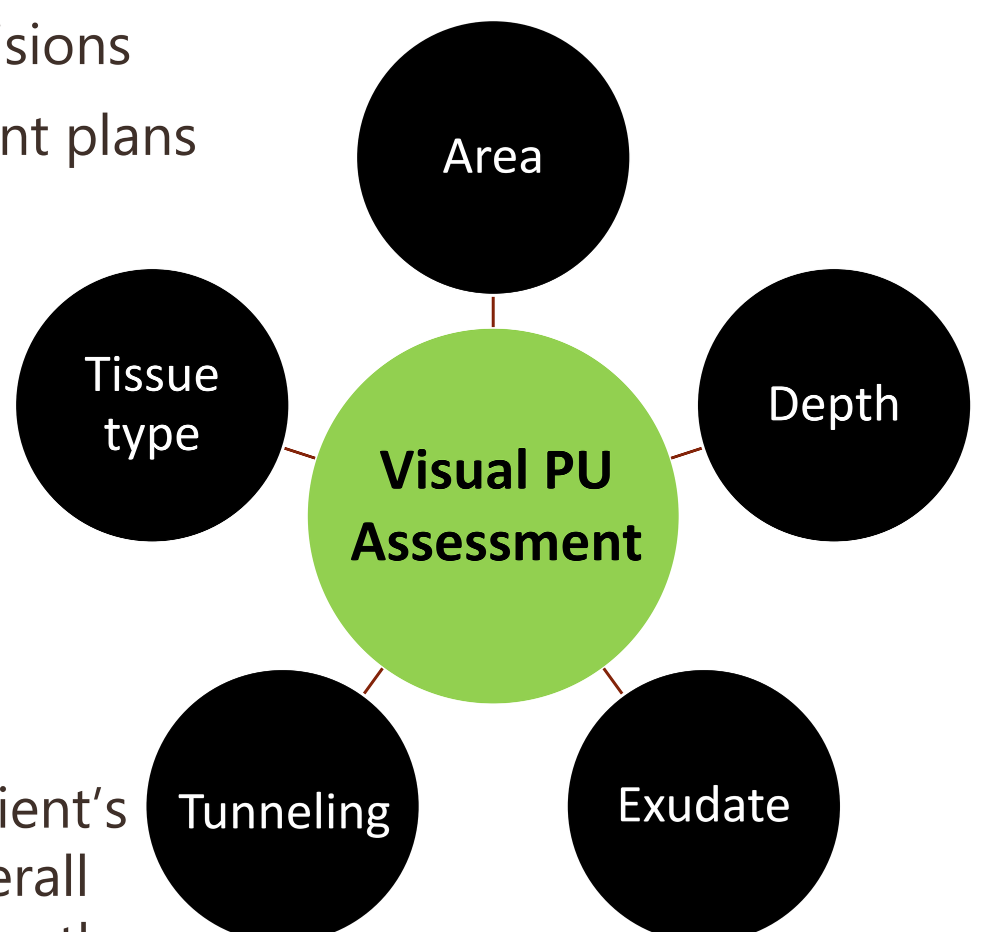
Pressure ulcer (PU), also known as decubitus ulcer or bedsore, is an injury caused by shear, friction, and prolonged pressure leading to inadequate tissue perfusion, ischemic necrosis, and progressive damage to the skin and underlying tissues.

PU prevalence in U.S. hospital ICUs vary from 13.1% to 30%. Each year 2.5 million Americans develop pressure ulcers, with over 60,000 deaths due to sepsis and osteomyelitis, with an estimated annual cost of $9–$11 billion.

Wound Assessment

Wound assessment is an integral component of wound management:

- Provide detailed information on the extent of tissue damage
- Foundation for the timely diagnosis of vulnerable areas
- Informed clinical decisions
- Personalized treatment plans



Challenge

- **Time-consuming**
- **Inconsistency**
- **Inaccuracy**
- **Human bias**
- **Subjectivity**

Factors such as the patient's skin color, age, and overall health can also influence the visual appearance of a PU, making it difficult to classify the wound.

AI Algorithms for PU Assessment

Physical wound examination using rulers and other foreign objects that may cause pain or infection. Thus, there exist a critical need for a contactless, accurate wound assessment tool.

- **Deep learning**

A subtype of machine learning inspired by the human brain, has shown potential in image analysis by automatically learning complex patterns.

Various types of AI algorithms have been used for chronic wound assessment:

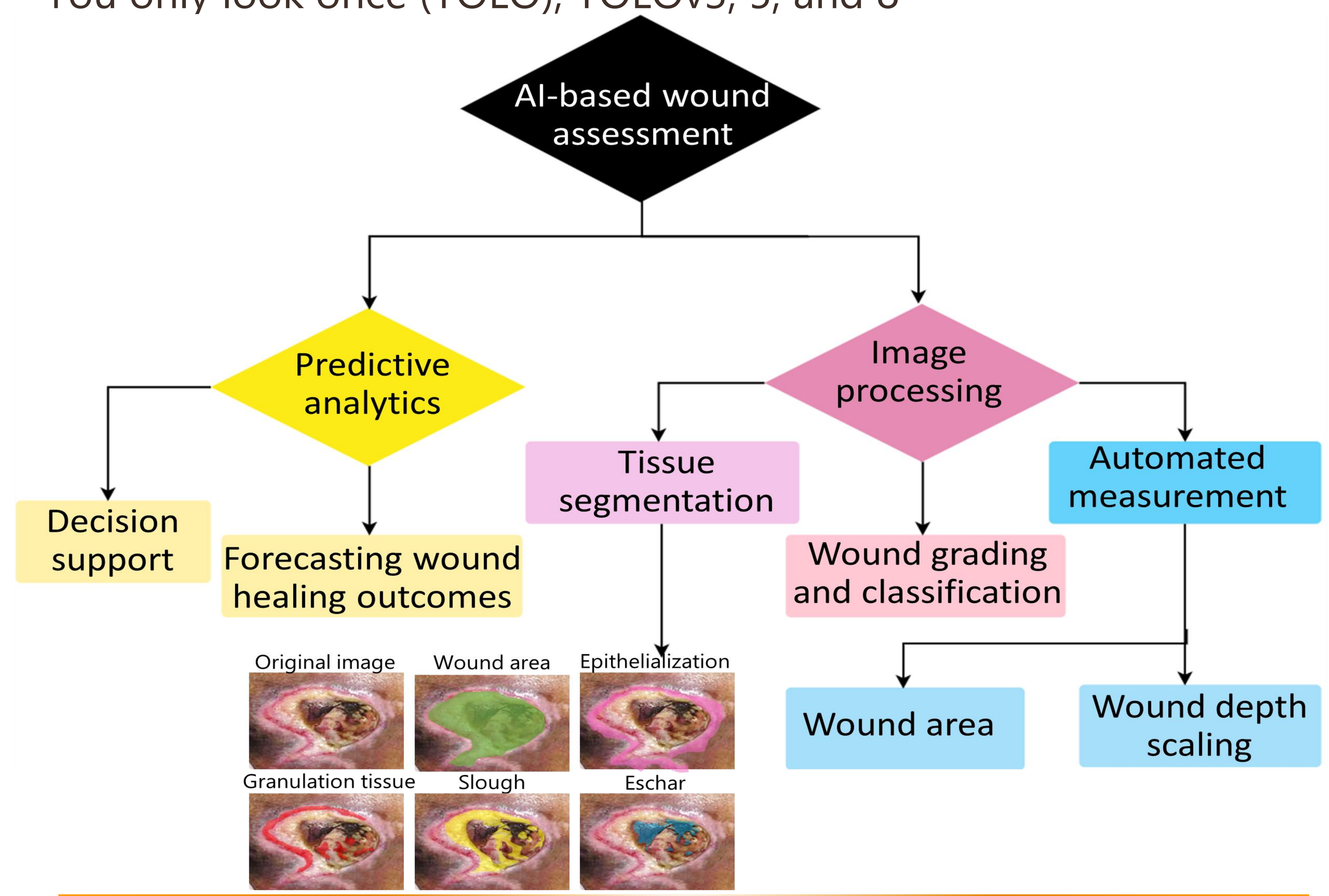
Over 50% of the published papers used a variety of Neural Networks algorithms

- **High accuracy with low speed**
- **Requires post-processing techniques including thresholding, hole filling, and noise removal**

Convolutional neural networks (CNN), Mask R-CNN, Deep neural network (DNN), constrained confidence neural network (AuxCN), etc.

Digital Twin: less complicated with low accuracy

Automated object detection: fast immerging and high speed: You only look once (YOLO), YOLOv3, 5, and 8



Algorithms Performance Metrices

To evaluate the performance of algorithms we need a dataset annotated with clinicians.

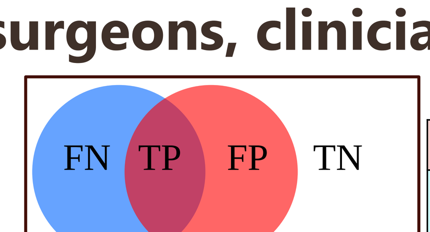
- **Grand Truth: The clinical diagnosis made by human intelligence, i.e. nurses, surgeons, clinicians. etc.**

$$Recall = \frac{TP}{TP+FN}$$

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP}$$

$$Specificty = \frac{TN}{TP+FP}$$

$$F1\ Score = \frac{2 * (Precision * Recall)}{TP+FN}$$

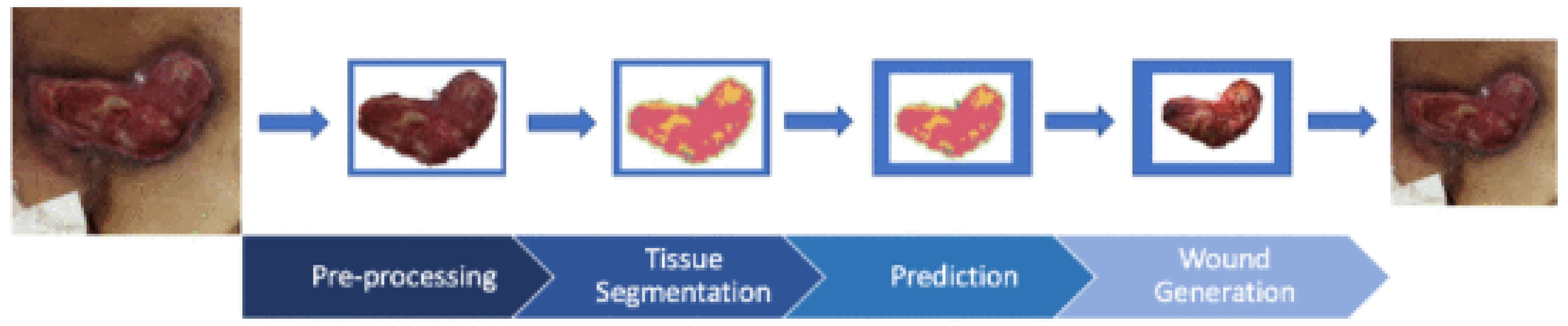


		Predicted	
		Wound detected	Wound not detected
Ground truth	wound exist	TP	FN
	wound doesn't exist	FP	TN

A higher F1 score indicates that the algorithm achieved a good balance between minimizing FPs and FNs, resulting in more accurate and reliable predictions overall.

Healing Status and Prediction

Deep learning algorithms can utilize the wound data obtained from images to determine the wound current status and predict the healing trajectory by generating synthetic wound image for future time points.



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Main Limitations and Knowledge Gap

- **Low accuracy and slow performance**

Optimization of algorithm design, training methodologies, and computational resources.

- **Limited availability of large, diverse datasets comprising diverse wound images**

A desired dataset composed of 500 smartphone images. 70-90% of the annotated images are used for training the algorithms while 10-30% of them are utilized for verification of the algorithm performance. on.

Inconsistent distribution of pressure ulcers of various stages. For example the majority of wound images are for unstageable PUs.

- **Validation, regulatory approval, and clinical use**

AI algorithms for wound care must undergo rigorous validation at to ensure their accuracy, reliability, and safety before clinical deployment.

Future Directions

- **Data augmentation using Generative Adversarial Networks (GANs)**
- **Algorithmic advancements:**
- **Address algorithm and dataset bias**
- **Clinical integration and validation**
- **User-friendly interfaces and minimal human intervention**
- **Integration with existing healthcare equipment**

For questions or a full reference list, please contact: f.fba@mst.edu