Machine Learning-Driven Support Algorithm for Skin Ulcers Preliminary Diagnosis: A Lightweight Approach for Digital Images Semantic Segmentation and Color-Based Classification

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About me

Debora Beneduce

BIRTH DATE: 04/20/1998

CONTRY: Italy

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2021 – Bachelor's Degree in Biomedical Engineering
Thesis Title: "The role of wall shear stress in atherosclerotic plaques rupture"

2023 – Master's Degree in Biomedical Engineering
Thesis Title: "Design of a wideband wearable antenna for head microwave sensing applications"

Since 2024 – Researcher in Biomedical Systems Development
Topics: Bio-signals and bio-images processing, Artificial Intelligence and Machine/Deep Learning in biomedical applications

Publications

- Gugliermino M., Rodriguez-Duarte D. O., Beneduce D., Tobon Vasquez J. A., Vipiana F., "Compact wearable broadband antenna for head microwave sensing and imaging", IEEE CAMA, 2023.
- Pagana G., Beneduce D., Cutarelli M., Terranova S., Sabbatini M., Imperiale A., Khalili Param A., Lubrano F., Caragnano G., "Telehealth and telemedicine web-app for skin ulcers remote monitoring", IEEE Xplore, 2025.

Teamwork and current projects

Debora Beneduce

Junior researcher in biomedical applications

Guido Pagana

Medical Doctor and senior researcher in biomedical applications and ICT

Fabrizio Bertone

Senior researcher in cloud computing and web development

Giuseppe Caragnano

Program manager and senior researcher in Advanced Computing

Topics:

- High Performance Computing
- Artificial Intelligence (AI), Machine/Deep Learning
- Cloud Computing

Projects:

- **SALUTEDERM** (funded by Aosta Valley Region, Italy) aims to enhance skin health by developing an innovative diagnostic device for skin ulcers and an active patch to improve wound healing.
- **ENACT** (funded by European Commission) aims to monitor pollution influence on health and cardiovascular diseases insurgence in urban areas.
- **EMERALD** (funded by Aosta Valley Region, Italy) aims to develop of a system for environmental monitoring and the circular economy through the adoption of multispectral technologies combined with the use of artificial vision and automation, AI algorithms and edge computing.

Teamwork and current projects

Debora Beneduce

Guido Pagana

Funded by the European Union

Persimmon

Personalized
Sustainable Smart
Patch Omnificence

SCAN ME

New sensor bio-degradable materials

+

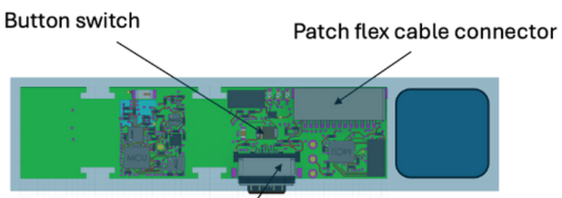
Digital surface mount technology

+

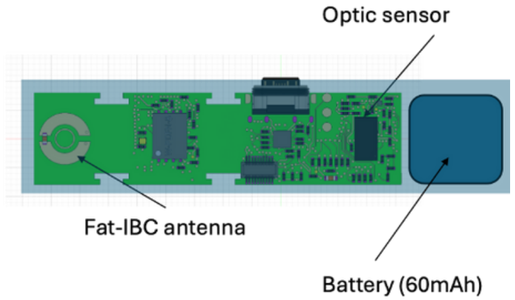
Body-worn networks

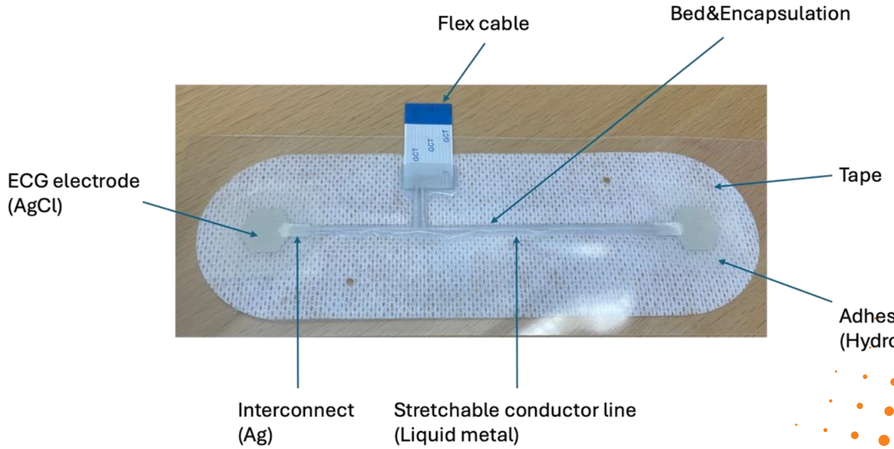
Smart sensors-based patches for decentralized personal health monitoring

Top



Bottom (skin side)





Background & Motivation

Chronic skin ulcers burden

- Different causes, **different types** ✸
- **Slow healing**
- Risk of infection
- Hospitalization
- Amputation

Challenges

- Need for **regular monitoring**
- Barriers in rural or underserved areas
- Lack of standardized tools

Telemedicine benefits

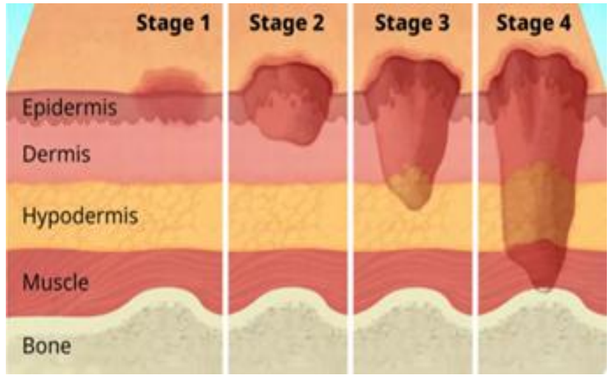
- **Remote, objective** and **consistent monitoring**
- Improve healing rates
- Reduced admissions

AI Opportunity

- Automatic wound detection
- Automatic wound severity assessment
- **Preliminary diagnosis as medical support**

✸

- **Diabetic foot ulcers**: ~6.3% of diabetic people (~40M-60M globally)
- **Venous leg ulcers**: ~1% of adults, up to 3–4% of elderly (> 65 years)
- **Pressure ulcers** (bedsores): 8-26% of hospitalized/long-term care patients



https://www.verywellhealth.com/pressure-ulcer-7549469

European Pressure Ulcers Advisory Panel (EPUAP) classification

Research gap

- Manual wound assessment is **subjective** and **time-consuming**
- **Misclassification** and inter-observer variability affect treatment
- **Limited AI applications** for ulcer diagnosis
- High **annotation costs** and **dataset scarcity**
- Few **lightweight**, interpretable, **real-time** solutions
- Lack of **tissue analysis**

Our goal & our approach

Develop a machine learning-based system for automated **ulcer segmentation** and **severity assessment**

- **Accurate**
- **Lightweighted**
- **Tissue evaluation**

Sequential pipeline

1. Pre-processing — Enhancing image quality
2. Ulcer segmentation — Wound detection through a trained Neural Network (NN)
3. Post-processing — Segmentation errors correction
4. Tissue evaluation — Color analysis

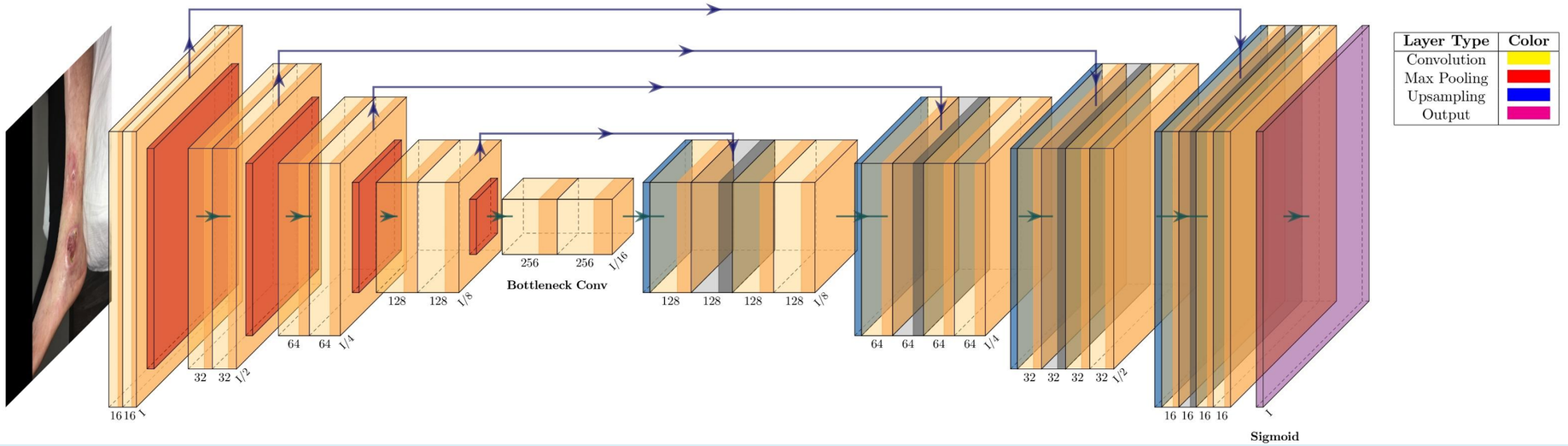
Methods: segmentation task

PRE-PROCESSING

- **Resize** at 512×512 resolution
- Color-space from RGB to **grayscale** (GS) → less sensitive to illumination artifacts
- **Local contrast** enhancement (CLAHE)
- Brightness normalization → $[0, 1]$

TRAINING

- **Modified U-Net model**, encoder-decoder symmetric structure + skip connections
- # epochs = 50, batch_size = 2
- 1010 pairs images- binary segmentation masks*
  - Training set 70%
  - Validation set 10%
  - Test set 20%



The NN is trained to **directly recognize the wound borders** without identifying a Region Of Interest (ROI) before:

- **Avoiding propagating errors**
- **Less pre-processing stages**
- **Learning global contextual cues and local boundary information for a reliable segmentation**

*University of Wisconsin-Milwaukee Big Data Lab. (2024). Wound Localization Dataset. Retrieved December 2024, from https://github.com/uwm-bigdata/wound-localization

Methods: segmentation task

POST-PROCESSING

- **Removal of very small objects**, $area < area_{max}/6$
- **Background removal**

WHY?

- Heterogenous light conditions
- Different positions and image acquisition angles
- Disturbing elements with colors similar to the wound ones

HOW?

- From RGB color-space to $\mathbf{YC_rC_b}$ →
  - $\boldsymbol{Y}$ Luminance → image brigthness level
  - $\mathbf{C_r}$ red chrominance → shift of R channel from Y
  - $\mathbf{C_b}$ blue chrominance→ shift of B channel from Y

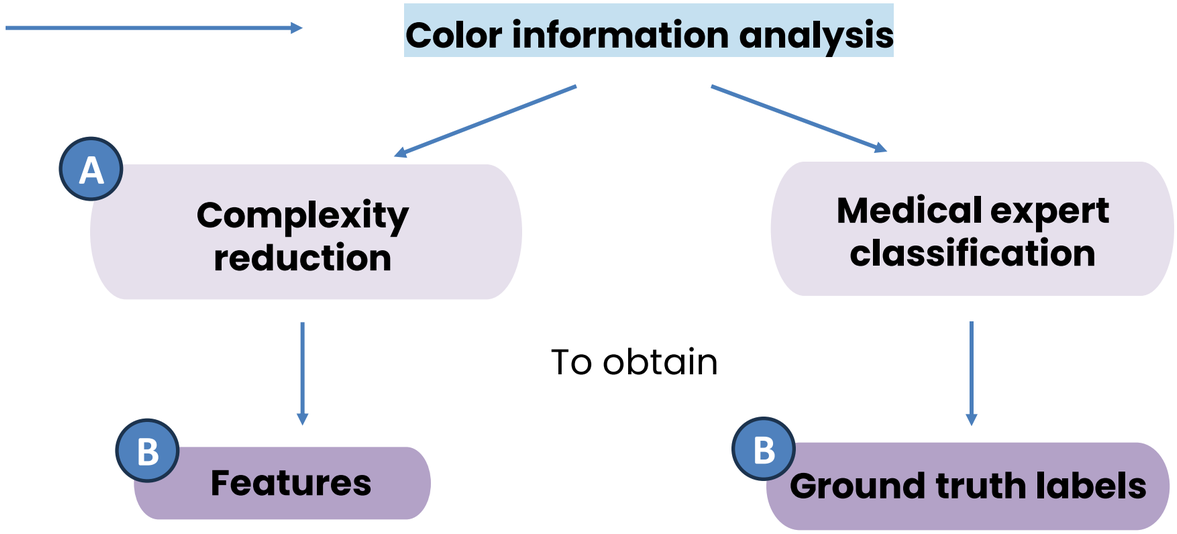
RGB image | $\mathbf{YC_rC_b}$ image | $\boldsymbol{Y}$ channel | $\mathbf{C_r}$ channel | $\mathbf{C_b}$ channel

The skin area is highlighted→thresholding to isolate it

Methods: tissue classification task

➢ **Crucial role of color information for exposed tissues classification**

Color	Clinical meaning
White	Exposed bone or fibrinous tissue
Pink-Red	Healthy granulation tissue or early-stage damage and tissue inflammation
Yellow	Slough or devitalized tissue
Brown/Black	Necrotic tissue or eschar formation



A Complexity reduction → Simple Linear Iterative Clustering (SLIC) algorithm

The color analysis is not pixel-based (computationally demanding) but **superpixel-based**

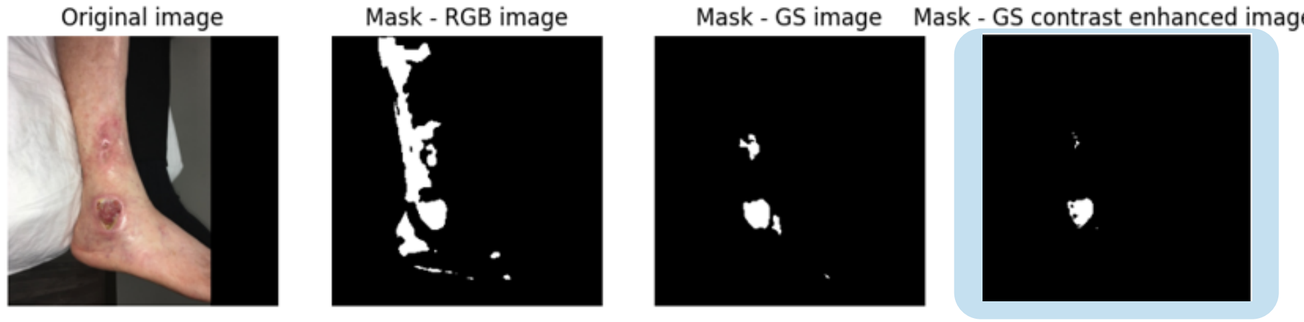
↳ Cluster of pixels with similar color and delimiting areas shape

B Multiple Logistic Regressor

- Input = [extracted features; ground truth labels]
- Training set 80%, test set 20%

Results: segmentation task

COLOR-SPACE AND CONTRAST ENHANCING



SKIN ISOLATION

FINAL SEGMENTATION

METRICS

$$IoU = 82\%$$
$$Precision = 93\%$$
$$Recall = 89\%$$
$$Dice\ Coefficient = 88\%$$

Good performance also on under-represented **darker phototype** (0.5% of the dataset)

Only **1.9M trainable parameters**

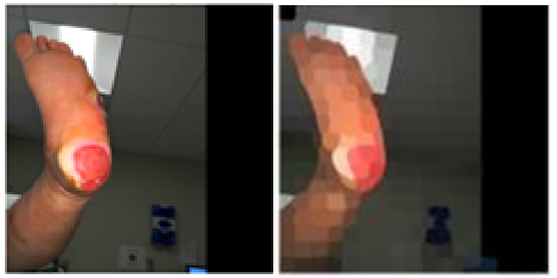
Results: classification task

SLIC ALGORITHM

N # $pixels$, K # $superpixels$

$S^2 = \frac{N}{K}$ Superpixel approx. size

$S = \sqrt{\frac{N}{K}}$ Grid interval, distance between each centre



$K = 290$

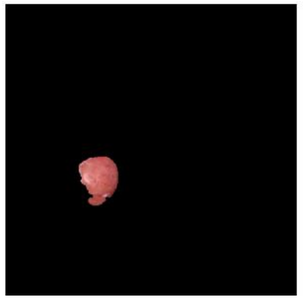
$m = 20$

↓

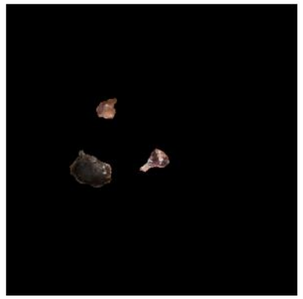
Compactness measure

COLOR ANALYSIS

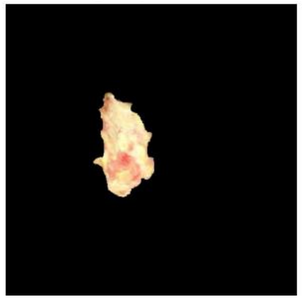
Early-stage ulcer

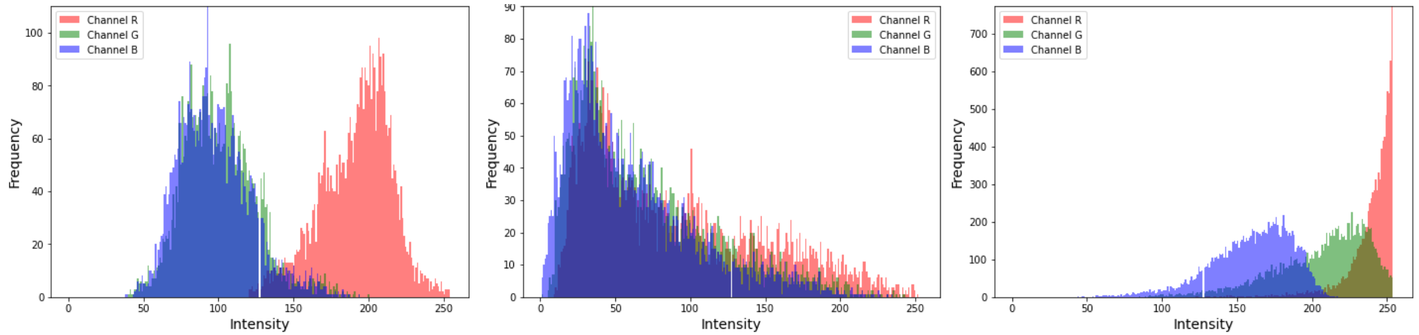


Necrotic ulcer



Slough presence



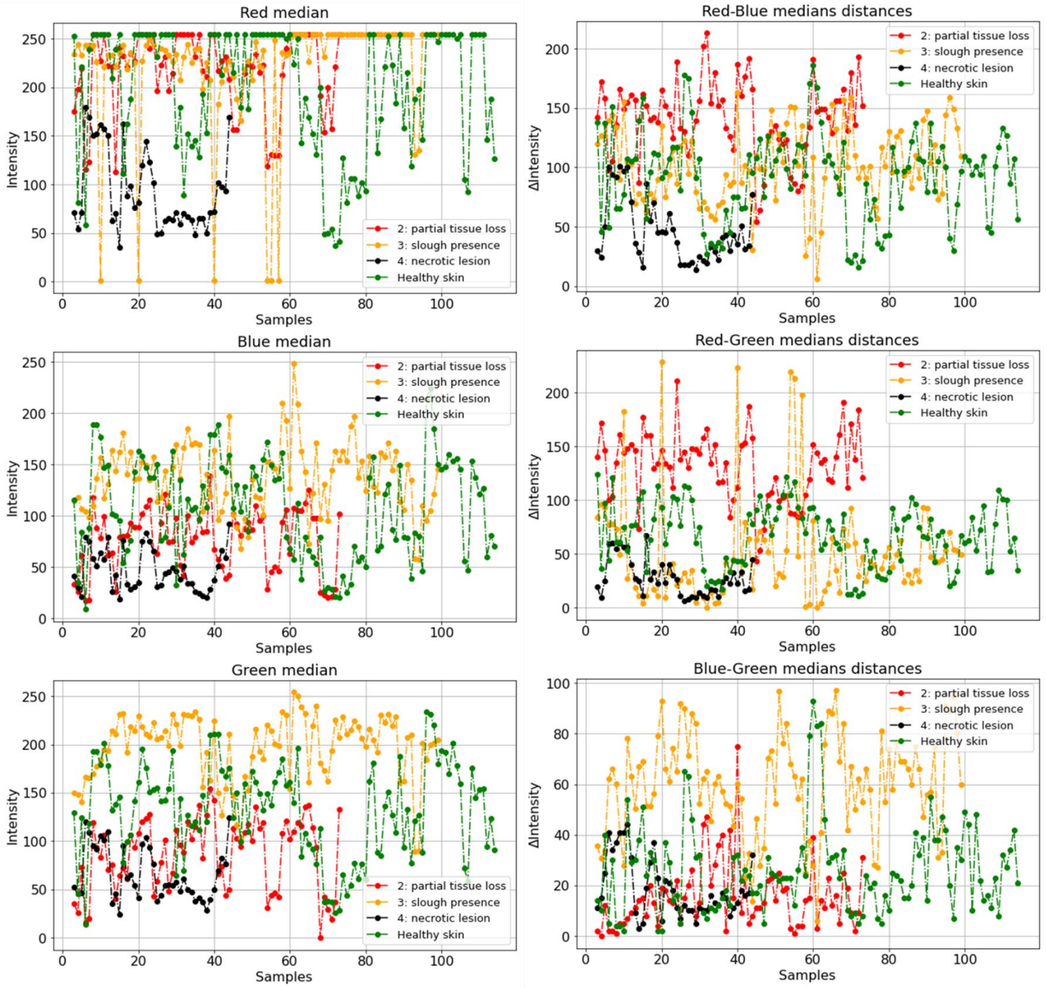


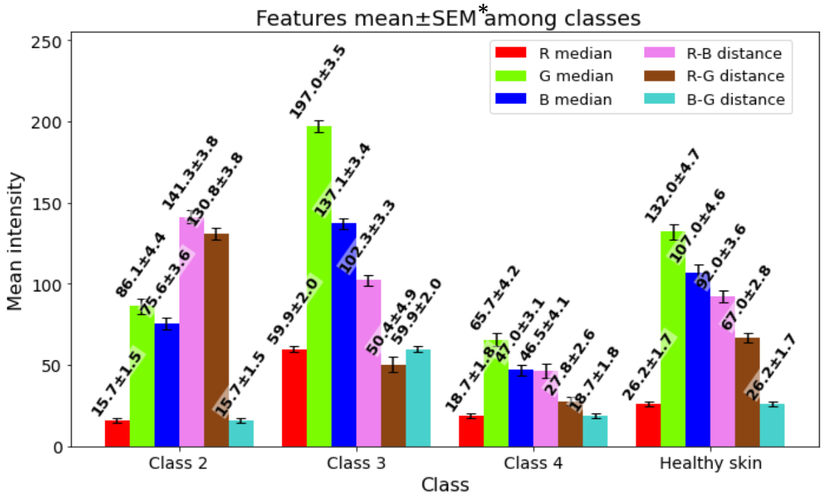
R, G and B brightness histograms

Results: classification task

FEATURES EXTRACTION

6 most discriminative parameters

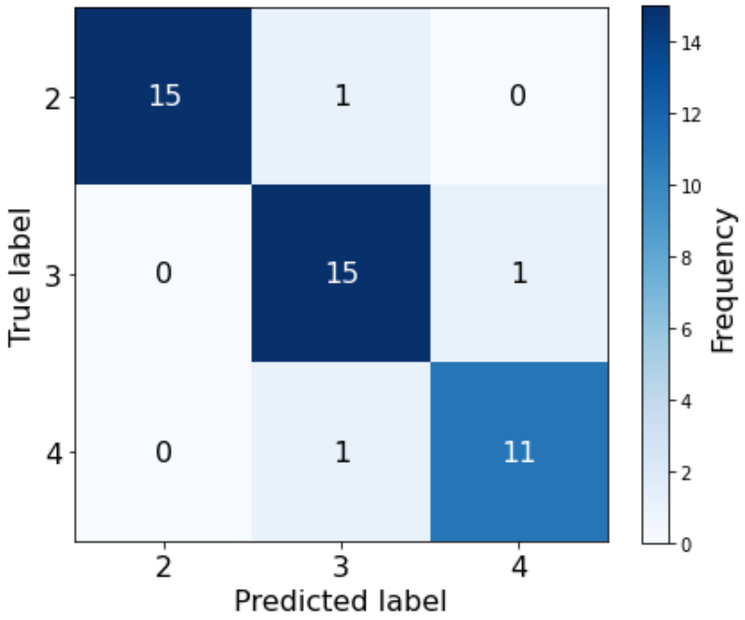




*Standard Error of the Mean

Results: classification task

CLASSIFICATION RESULTS



2, 3, 4 EPUAP ulcer stages
(class 1 is not represented in the database→not considered)

94% accuracy

Errors in higher classes are conservative!

TOTAL INFERENCE TIME

$300\ ms$ → **real-time** application

Conclusion and future work

WHY?

Need for **medical support** in skin ulcer monitoring and lack of **AI-driven** solutions

WHAT?

Lightweight **machine-learning** method for **real-time skin ulcers diagnosis**

HOW?

- **U-Net** model with symmetric encoder-decoder structure and skip connections
- **Grayscale images**, locally contrast enhanced
- **Skin recognition**
- Lesion **borders detection**
- **Color analysis** among different classes
- **Ulcers classification**

QUALITY?

SEGMENTATION TASK

- $\boldsymbol{IoU = 82\%}$
- $\boldsymbol{Precision = 93\%}$
- $\boldsymbol{Recall = 89\%}$
- $\boldsymbol{Dice\ Coefficient = 88\%}$
- **1.9M trainable parameters**

CLASSIFICATION TASK

- $\boldsymbol{accuracy = 94\%}$
- Errors are conservative

NEXT?

- Custom dataset with images containing reference objects to retrieve size expressed in cm and cm^2
- Retrieve a unified metric as **severity score** by combining size and color information
- Integration with a **portable device** (already in progress)
- Testing in real-world scenarios

Thank you for your attention

QUESTIONS?

Reach me at

debora.beneduce@linksfoundation.com

or on

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