Human Parsing Based on Deep Learning for Analyzing the Body Pressure Distribution to Be Used in Pressure Ulcer Risk Management and Prediction

Mohammad Mohammad Amini, Ahmad Reza Heravi, Paulo Alves, Davood Fanaei Sheikholeslami, Sajjad Aemmi, and Fatemeh Hariri

Abstract— Pressure ulcers, commonly referred to as pressure injuries, are prevalent skin injuries that occur in hospitalized patients. This paper investigates the utilization of deep learning-based models to detect human body parts from pressure heatmaps captured by sensor sheets. The primary contribution involves training and fine-tuning a human body parser capable of analyzing binary, gray-level, and colored heatmaps representing body pressure. The fine-tuned body parser exhibits satisfactory accuracy for the analysis of pressure ulcers. Furthermore, an action recognition architecture based on deep learning is applied to analyze the movement of each body part. This innovative approach establishes a reliable criterion for making informed decisions regarding the likelihood of pressure ulcers developing in organs subject to higher pressure and reduced movement.

Keywords— Artificial Intelligence, Pressure Ulcer, Deep Learning, Pressure Heatmap, Human Parsing, Action Recognition.

I. INTRODUCTION

The prevalence of pressure ulcers or injuries is growing at an alarming rate, being recognized as one of the most common chronic medical conditions in hospitals. While different terminologies exist for these conditions, such as pressure injury (PI) in Australasia, the US, and Canada, this paper will refer to them as pressure ulcers (PUs) [1,2].

As defined by the European Pressure Ulcer Advisory Panel (EPUAP), the National Pressure Injury Advisory Panel (NPIAP), and the Pan Pacific Pressure Injury Alliance (PPPIA), PUs are characterized as 'Localized damage to the skin and underlying soft tissue usually over a bony prominence or related to a medical or other device. They can present as intact skin or an open ulcer and may be painful. These injuries are generally caused by intense and/or prolonged pressure, or in combination with shear [3,4].

PUs are chronic wounds arising from continuous pressure over time, leading to ischemia of the underlying skin structure [5]. These injuries most frequently occur at bony prominences such as the sacral area and the heel. Various factors contribute to the formation of PUs, including prolonged contact with a bed or chair without frequent repositioning, exposure to urine or stool, medical conditions like diabetes that affect blood flow, injuries that limit body positioning, and the patient's nutritional status or medications. PUs are associated with tissue damage resulting from sustained mechanical loading, namely deformations in compression, tension, or shear, or a combination of these loading modes [5, 6].

This paper proposes research methodologies aimed at enhancing future investigations in predicting PU risks. Digitalization in healthcare can improve diagnostics and predictions of health issues. Particularly for PUs, this potential was highlighted by Ch. Shi et al [7] in their comprehensive review of over 156 studies focusing on the digitalization of wound care management.

Despite rigorous prevention measures, PUs can still occur. The risk of developing PUs during hospitalization is three times greater than the risk of a car accident [4]. Pressure or tissue deformation interrupting blood flow can lead to the death of healthy skin, muscle, or fat tissue. The different categories or stages of PUs, summarized by the EPUAP/NPIAP/PPIA [3], are defined based on the ulcer's depth and the type of tissue affected. A higher-stage ulcer indicates more profound tissue damage and possibly a more severe injury [8].

There are six categories of pressure ulcers/injuries such as: Category/Stage I: Nonblanchable Erythema Intact skin with non-blanchable redness of a localized area. Category/Stage II: Partial Thickness Skin Loss Partial thickness loss of dermis presenting as a shallow open ulcer with a red-pink wound bed,

Category/Stage III: Full Thickness Skin Loss - Full thickness tissue loss. Subcutaneous fat may be visible, but bone, tendon or muscle are not exposed. Category/Stage IV: Full Thickness Tissue Loss - Full thickness tissue loss with exposed bone, tendon, or muscle. Unstageable: Depth Unknown – Full-thickness tissue loss in which the base of the ulcer is covered by slough (yellow, tan, gray, green, or brown) and/or eschar (tan, brown or black) in the wound bed. Suspected Deep Tissue Injury: Depth Unknown Purple or maroon localized area of discolored intact skin or blood-filled blister due to damage of underlying soft tissue from pressure and/or shear. The area may be preceded by tissue that is

Mohammad Mohammad Amini, Ahmad Reza Heravi, Davood Fanaei Sheikholeslami, Sajjad Aemmi, Mahdi Faghihi, Fatemeh Hariri (Authors) Sensomatt Lda., Castelo Branco, Portugal, Email: info@sensomatt.com

Paulo Alves (Author), School of Nursing, Universidade Católica Portuguesa-Porto, Porto, Portugal, Email: pjalves@ucp.pt

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painful, firm, mushy, boggy, warmer, or cooler as compared to adjacent tissue.

PUs can appear in several areas such as the back or sides of the head, rims of the ears, shoulders, hipbones, lower back, backs or sides of the knees, heels, ankles, and toes. Certain patient factors, such as age and comorbidities like diabetes, can slow the healing of pressure injuries. Therefore, some wounds may not heal before a patient's death, creating a significant economic burden for healthcare services. PUs are painful and susceptible to infection, necessitating vigilant monitoring by medical staff.

Non-invasive wound monitoring techniques, such as imaging, are preferred to mitigate patient discomfort. These techniques enable an accurate analysis of wound features without contact. Mobility and pressure are two key factors in the formation of bedsores. This paper introduces a new patient analysis technique using a pressure map of the patient's body. A sensor sheet placed underneath the patient allows for continuous monitoring of mobility and pressure. This approach provides a non-intrusive, continuous monitoring facility and respects privacy laws.

However, interpreting the pressure heatmaps presents challenges, including:

1. Understanding the relationship between pressure output and the patient's body figure
2. Matching each body part with the pressure heatmap
3. Predicting which body parts are static or sufficiently mobile
4. Integrating these factors into the standard decision-making process for bedsores

This paper addresses the first two issues, with the remaining two, pertaining to decision-making, to be considered in future studies.

We employed a deep learning-based body-parser, trained on binarized and gray-level heat-map outputs, to predict body parts from the pressure heatmap. The model demonstrated accuracy comparable to imaging in predicting the patient's position and body part. We also undertook a localized analysis of each body part's pressure using the body-parser, enabling the identification of body areas enduring more pressure and those sensitive parts requiring individual examination. The sequence of pressure heatmaps was used to monitor the movement and displacement of body parts over time. This novel, fine-tuned human parser can be integrated into standard routines to predict pressure ulcers more effectively.

To estimate the mobility of the whole body and each body part, we utilized a Conv2D+LSTM model. This approach allows for distinguishing between body parts with acceptable mobility and those that remain static.

The rest of this paper is structured as follows: Section II reviews the related work, Section III discusses different categories of pressure injury assessment using image processing, including wound segmentation, measurement, tissue classification, and healing prediction. We also include a discussion of other types of skin wounds from the selected papers to broaden the wound imaging analysis techniques. Section IV outlines deep learning techniques used in biomedical image processing. Section V discusses the utility of deep learning for assessing pressure injuries efficiently using image processing. Section VI concludes the paper, and finally, Section VII suggests directions for future research.

II. Literature Review

This section reviews some relevant works regarding human parser algorithms and pressure ulcer detection methods.

A. Approaches to Pressure Ulcers

A study by S. Caggiari et al. in 2021 [9] demonstrated that pressure mapping technology could be employed to assess the risk of developing a pressure ulcer. This is especially crucial for individuals with spinal cord injuries, as their movements are typically limited to small-scale motions. Therefore, pressure distribution can be utilized as a measure of movement. They successfully verified that it is possible to predict posture and mobility in a sleeping patient through continuous pressure monitoring combined with the application of AI algorithms. In the present study, we additionally employed body segmentation, as it plays a significant role in preventing pressure ulcers, particularly for patients admitted to intensive care units.

B. Human Parser Models

Tao Ruan et al. [10] proposed a human parsing method called CE2P to segment human body parts. The paper identifies several useful properties, such as feature resolution, global context information, and edge details, and carries out thorough analyses to understand how to leverage them to benefit the human parsing task. These useful properties ultimately yield a simple yet effective Context Embedding with Edge Perceiving (CE2P) framework for single human parsing.

In another work, Peike Li et al. [11] put forward a new human parsing method known as SCHP for segmenting human body parts. This method uses ResNet101 with ImageNet pretrained weights. To address the problem of learning with label noise, the researchers introduced a purification strategy, known as Self-Correction for Human Parsing (SCHP), to progressively improve the reliability of the supervised labels and the learned models.

In a different approach, Henry M. Clever et al. [12] proposed a 3D Human Pose and Shape Estimator. Their physics-based method simulates human bodies at rest on a bed equipped with a pressure-sensing mat. They also presented PressurePose, a synthetic dataset with 206K pressure images with 3D human poses and shapes, and PressureNet, a deep learning model that estimates human pose and shape given a pressure image and gender. Despite being trained solely on synthetic data, PressureNet performed well with real data from participants in diverse poses.

Ye Liu et al. [13] presented a multi-scale structure-aware network for robust human parsing. The proposed network, named MSSA-Net, harnesses multi-scale features and joint structural cues in a coarse-to-fine strategy for effective human parsing. MSSA-Net also employs a novel structure-aware loss function to enhance the segmentation accuracy of challenging regions, such as limb junctions and fine-grained parts.

C. *Pressure Ulcer Prediction Using Image Processing*

T. Chen et al. [14] presented an automated pressure ulcer classification method based on an adaptive region growing and fuzzy support vector machine (ARF-SVM). This method extracts the features of the pressure ulcer regions using a multiscale adaptive region-growing algorithm and employs a fuzzy SVM for classification. The proposed method achieved an accuracy of 95.5% on a dataset of 200 pressure ulcer images.

III. Methods

Informed by the literature review and utilizing a physical sensor sheet, we introduce a novel approach for human body segmentation using collected data. Initially, we prepared the necessary dataset within the MLOPs pipeline by performing body segmentation on RGB images. This process resulted in a comprehensive dataset, comprising the sensor sheet data and its corresponding segmented body. The model was trained on this provided dataset. Subsequently, we trained the dataset using ResNet101 to learn body segmentation from the sensor sheet's binarized and gray-scale converted 2D data. Finally, we derived the pressure of each body part from the sensor sheet data and the novel deep learning model, which predicts the user's body position from the pressure heatmap. In this section, we detail the various datasets used to train the distinct stages of our algorithm.

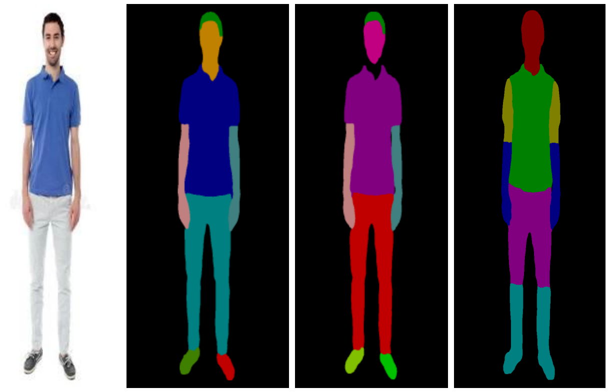
A. *Human Parsing Datasets*

For the first step, we require a pre-trained network to parse the body in standard images. We consider three popular datasets with distinct labeling systems.

LIP [15] is the largest single-person human parsing dataset, comprising over 50,000 images. This dataset primarily focuses on complex real-world scenarios. LIP consists of 20 labels such as Hat, Hair, Glove, Sunglasses, Dress, Coat, Socks, Pants, Scarf, Skirt, Face, and so forth.

ATR [16] is another large single-person human parsing dataset with over 17,000 images. It places greater emphasis on fashion AI. ATR includes 18 labels like Hat, Hair, Belt, Left-shoe, Right-shoe, Face, Left-leg, Right-leg, Left-arm, Right-arm, Bag, Scarf, among others.

Pascal Person Part is a smaller single-person human parsing dataset with over 3,000 images. This dataset is particularly focused on body parts segmentation. Pascal Person Part has 7 labels: Background, Head, Torso, Upper Arms, Lower Arms, Upper Legs, and Lower Legs.



a b c d

Fig 1. (a) normal image. (b) LIP output. (c) ATR output. (d) Pascal output.

B. *Bodies at Rests Dataset*

The Pressure Pose real dataset comprises 10 males and 10 females with 1K labeled real pressure images and paired heatmap mats of size 64 x 27 [17,18].

a b

Fig 2. (a) normal image. (b) pressure map

C. *Our generated Dataset*

For the purposes of this research, we utilized a sensor sheet on the patient's bed to collect the necessary data to train the deep learning model. The sensing portion of the real pressure mat does not cover the entire mattress. We measured a non-sensing border of 6 cm on the sides of the bed and 9 cm at the top and bottom. The synthetic pressure mat covers the entire bed (68 x 33), but only an inner subset (64 x 27) that represents the sensing area of the pressure image array is recorded. This dataset includes 14K RGB images and unpaired heatmap mats.

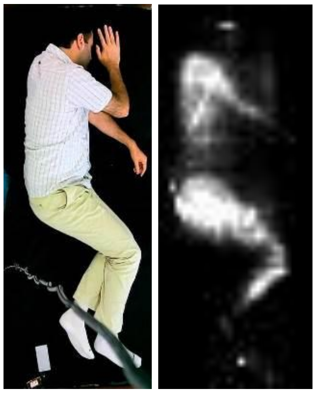


Fig 3. (a) normal image. (b) pressure map

IV. Our approach

In this section, we delineate the steps involved in using a body parser to segment different body parts from heatmap images.

A. *Initial Results*

The Human Parser ResNet101 [19] Network is designed to convert RGB images into parsed body images. However, when binary or grayscale heatmap images are used as inputs, this network does not perform optimally. The outcome of this process is displayed in Figure 4.

Fig 4. (a) normal image. (b) normal image output. (c) binary image output.

B. *Binary Fine-tuned Results*

We employed the Human Parser to transform RGB images into parsed body images. Additionally, we converted RGB images into binary to generate a paired dataset comprising binary images as inputs and segmented images as outputs. Following this, we fine-tuned the Human Parser model using the paired dataset to create a binary segmentation converter. The results of this process are illustrated in Figure 5. This new Human Parser model was fine-tuned by altering the model's input and making certain modifications to the output layer.

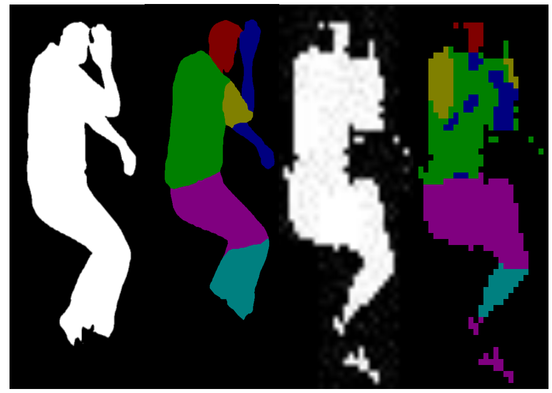


Fig 5. (a) binary image. (b) binary image output. (c) binary heat map. (d) binary heat map output.

C. *Gray-scale Fine-tuned Results*

To attain improved results, we used grayscale heatmap images as inputs in a paired dataset. The Human Parser model was then fine-tuned once more with this new paired dataset to create a grayscale heatmap-to-segmentation converter. The results from this process are depicted in Figure 6.

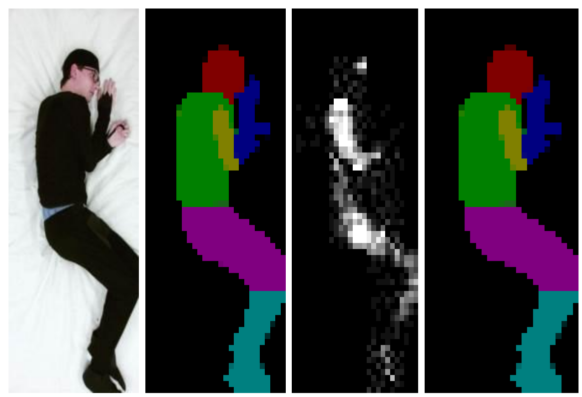


Fig 6. (a) normal image. (b) normal image output. (c) heat map. (d) heat map output.

D. *Pressure Ulcer Detection for Body Parts*

Upon acquiring parsed heatmap images, each body part can be analyzed to detect potential pressure ulcer issues. The pressure on each body part is scrutinized individually, with the maximum amount of pressure recorded in that specific body region being selected as the representative value. Thereafter, by setting an appropriate threshold, we can identify and report body parts that are subjected to abnormal pressure. The results from this analysis are displayed in Figure 7.

a b c d

Fig 7. (a) normal image. (b) heat map. (c) parsed image. (d) heat map output.

V. RESULTS

To conduct an in-depth analysis of the trained deep learning models, we employed the mIOU (mean Intersection over Union) metric. This was used to compare the performance of the proposed models against the segmented body output. The mIOU metric provides a comprehensive measure of the models' segmentation performance. Table 1 presents the results of this comparison. Notably, the accuracy achieved using gray-level input data from the sensor sheet was about 0.97% (mIOU above 0.5), indicating a satisfactory level of precision for the body segmentation task.

TABLE I
THE MIOU RESULT OF THE TRAINED MODEL ON THE SENSOR SHEET DATA

	mIOU	***mIOU with 0.5 threshold Subhead***
Our Dataset (Binary)	0.56	0.82
Our dataset (Grayscale)	0.63	0.97

VI. CONCLUSION

In this paper, we propose a deep lear ning-based human parser for analyzing body pressure tasks. This parser constitutes a significant advancement over existing methods and sets a new standard. The self-co rrection mechanism utilized in our approach is a versatile strategy that can be integrated into any framework, leading to additional performance improvements.

The findings of this study will be instrumental in developing a pressure ulcer prediction platform as a primary pose management system. By performing body segmentation and pressure analysis, we examine the maximum pressure exerted on each body part and the duration of the pressure presence, factors that directly influence the risk of developing pressure ulcers.

In future research, our aim is to enhance our method to achieve superior results for human parsing tasks involving images and videos of body pressure. Our forthcoming endeavors will concentrate on precise measurement and predictive analysis of body movements, which can be segmented into different organs to devise the most effective method for predicting pressure ulcers.

VII. FUTURE WORKS

The current research proposes a deep learning-based human parser for the analysis of body pressure tasks, marking a significant improvement over existing methods and establishing a new benchmark. The self-correction mechanism incorporated in our method is a universal strategy that can be applied to any framework, potentially leading to performance enhancements.

The outcomes of this st udy will be applied to the development of a pressure ulcer prediction platform as a foundational pose management system. By conducting body segmentation and pressure analysis, we scrutinize the maximum pressure on each body part and the duration of pressure presence, which has a direct bearing on the risk of pressure ulcer development.

In future investigations, we plan to refine our method to yield superior results for human parsing tasks involving body pressure images and videos. Our upcoming initiatives will concentrate on precision measurement and predictive analysis of body movements, subdivided into different body parts, to devise the most efficacious method for pressure ulcer prediction.

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About Author (s):

Mohammad possesses a deep-seated passion for health-tech. He has spearheaded the development of numerous solutions aimed at enhancing the quality of life for the elderly, wheelchair users, and other vulnerable individuals. As an innovation manager, he has led R&D departments for the past 15 years.

Ahmad is a proficient AI developer with over 12 years of experience in creating smart solutions for a variety of industries. He has developed numerous generative neural networks using deep learning, each tailored for different purposes, that are now being utilized in various industries.

Paulo, the Dean of the Nursing School at UCP-Porto University, has served as a pivotal figure in chronic wound management, particularly in the treatment of pressure injuries, for over 15 years. He has an avid interest in the application of high-tech solutions to wound treatment, consistently for the integration of cutting-edge technology in medical care.

Davood, serving as a business developer in this project, plays a crucial role in bridging operational gaps and ensuring the smooth execution of project tasks. His responsibilities extend to leading the team of volunteers, managing data collection, and implementing stringent data safety measures in compliance with the (GDPR).

Sajjad is a highly skilled programmer with a broad knowledge base spanning numerous programming languages. His role in this project involves the development of back-end code for the artificial intelligence engine. Furthermore, Sajjad's responsibilities include the management of newly generated datasets.

Fatemeh, a medical doctor, ensures that the project outcomes align with clinical standards and are within medical limitations. With more than five years of experience working as a technical assistant for medical device manufacturers, she brings a crucial perspective to the team.