Instituto Politécnico
de Castelo Branco
Escola Superior
de Tecnologia

Solução para Classificação de Posturas de Pessoas Acamadas Baseada em Mapas de Pressão

Pressure Map-based Solution for Lying-people Posture Classification

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Dezembro de 2023

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Resumo

O campo das tecnologias de informação está em constante evolução, e é notável a sua expansão no campo da saúde. Esta dissertação foca-se em demonstrar como os métodos de classificação de posturas baseados em mapas de pressão de pessoas acamadas podem contribuir para melhorar não apenas os cuidados prestados aos pacientes, mas também aliviar a carga de trabalho dos profissionais de saúde.

Este relatório descreve as várias fases do desenvolvimento do trabalho, as quais são apresentadas em cinco publicações. Duas revisões sistemáticas, uma focada em conjuntos de dados relativos a mapas de pressão e outra focada em diferentes métodos utilizados para a classificação de posturas baseados em pressão. As restantes três publicações focam-se no desenvolvimento das diferentes partes necessárias para uma solução de classificação de posturas. Assim, relativamente aos dados, uma publicação descreve um conjunto de dados de mapas de pressão, com 3 diferentes camadas, das quais apenas uma é usada, nomeadamente a camada relativa aos dados adquiridos através da utilização de uma manta de pressão posicionada em cima de uma cama hospitalar. Uma segunda publicação, relativa às várias experiências escolhidas para demonstrar a utilização do conjunto de dados desenvolvido, é também incluída neste trabalho. Os resultados apresentados nesta publicação incluem os treinos de vários modelos de aprendizagem máquina (*machine learning*) a ser utilizados para classificação de posturas, além de retirar conclusões com as experiências realizadas, nomeadamente sobre a influência dos dados adicionais (características dos participantes), recolhidos durante o desenvolvimento do conjunto de dados, ou sobre como a resolução dos mapas de pressão pode afetar os modelos treinados. A última publicação incluída descreve uma plataforma desenvolvida com o propósito de suportar uma solução de classificação de posturas para o cuidado de pacientes acamados, nomeadamente para a monitorização e prevenção de úlceras de pressão. Esta plataforma utilizaria os resultados provenientes dos modelos já mencionados para gerar informação importante, como sejam a duração de pressão em certas partes do corpo ou a geração de alarmes quando necessário.

Esta dissertação apresenta uma solução para classificação de posturas baseada em mapas de pressão com os diferentes passos necessários abordados nas diferentes publicações. O sistema tem o potencial de auxiliar profissionais de saúde além de pacientes, e mostra como a utilização destas tecnologias pode influenciar diferentes campos como a área da saúde.

Palavras-chave

Classificação de posturas, *Machine learning*, Mapa de pressão, Pessoas acamadas

Abstract

Information technologies are in constant evolution, and there have been significant expansions into the healthcare field. This dissertation intends to demonstrate how posture classification methods based on lying-people pressure maps utilizing machine learning could enhance patient care and alleviate the workload of healthcare professionals.

This study encompasses the various stages of the work's development in five publications, including two systematic reviews, one focused on existing pressure map datasets and the other focused on posture classification approaches using pressure-based methods. These reviews aimed to solidify the work included in this study by supporting it with the work done by fellow researchers in the field. The remaining three publications focus on the development of the different parts required for a posture classification solution. Regarding the data, a publication depicting a pressure map dataset, with 3 distinct layers is introduced, from which only one of the layers is used, which is gathered using a pressure sensor sheet placed on top of a hospital bed. An additional publication containing various experiments aiming to demonstrate the utilization of the aforementioned dataset is included in the dissertation, which results in the training of various machine learning models that can be used for posture classification. This study also studies the influence of different factors such as the influence of additional data (participant characteristics) gathered upon dataset development and how the resolution of the pressure maps used in training affect the resulting models. A final publication is included, depicting a platform developed with the aim of supporting a posture classification solution for bedded patient care, namely for pressure ulcer monitoring and prevention. This platform would take the output from the previously trained models and gather important information from them such as pressure duration in certain body areas, and alert generation whenever deemed necessary.

This dissertation presents a solution for posture classification based on pressure maps, with the required steps detailed in the different publications. The system envisioned in this study has the potential to aid healthcare professionals and patients alike and showcases how information technologies and machine learning specifically can influence different fields such as healthcare.

Keywords

Lying people, Machine Learning, Posture classification, Pressure map

Index

1. Introduction

This dissertation aims to demonstrate a solution for lying people monitoring making use of posture classification methods. To this end a total of 5 publications are presented which pose as part of the end solution, from the development of a pressure map dataset with all the necessary steps included, to the utilization of said dataset for training Machine Learning (ML) classification models to a demonstration of a platform that could make use of posture classification methods.

The state-of-the-art study that is usually done within the dissertation study is also included in two publications, having a systematic review of the literature for both existing datasets and existing posture classification methods.

A part of this study was conducted under the SensoMatt project (grant agreement no. CENTRO-01-0247-FEDER-070107, co-financed by European Funds (FEDER) by CENTRO2020) namely the work described in the publications related to the PoPu dataset in [1], and the system for monitoring pressure ulcers described in [2].

1.1. Topic Description

The field of information technologies is always growing, and its influence in other fields or sectors is growingly noticeable and the health sector is no different. Sleep studies or in-bed related conditions are in high demand for patient's health supervision and there have been improvements regarding the monitoring and prevention of such conditions. The use of ML assisted systems is ever growing, especially in cases where the patients can be monitored as to their status in any way. These systems aim not only to improve the patient's wellbeing, but also to aid healthcare professionals by reducing their workload whenever possible.

For bedded patients, their positions can be monitored, and this information alone can be used for many applications. An example of the ease of burden this sort of application could allow for is in pressure ulcer prevention. As patients remain bedded for long periods of time, prolonged pressure in specific body areas can lead to the development of pressure ulcers. By detecting the position of the bedded patient using classification algorithms, the healthcare professionals can be alerted whenever it is required, namely when prolonged pressure is detected in a certain body area so the patients can be shifted, and the risk of pressure ulcers is reduced. For this specific use case, the patient's posture can be mapped to the body parts that are currently under pressure and an assessment can be made accordingly (e.g.: a person lying on their back will likely have their buttocks being pressured).

Apart from this, there are other studies that can make use of posture classification such as sleep studies, which relate the patient's position to sleep related disorders. Among other studies that rely on data from people that are bedded or in a lying position.

The work in this dissertation aims to study a posture classification application, from gathering the data required for the underlying ML algorithms, along with the methods for data gathering and the procedures required for it, to training and validating models using said data as well as depicting possible applications for the utilization of the solution.

1.2. Objectives

The work included in this study is driven by a set of objectives, with each contributing to the result of a pressure-map based posture classification solution that would be useful for healthcare professionals when bedded patients are in consideration.

First and foremost, for a classification solution of any kind, there are common requirements, such as data in the form of a dataset, and the machine learning models that account for classifying the data.

A review of the existing datasets that could be used for a posture classification system was the logical first step as it would lead to identifying a potential dataset to be used for the next steps. This leads to understanding what the requirements for a successful dataset are, what data is included in them and how they can be used.

A dataset was necessary to train the machine learning models responsible for posture classification. This step was driven by not only the objectives of this work but also by the SensoMatt project. The intention for this dataset was to gather data from two sensor sheets simultaneously, one placed over, and one placed under a hospital mattress. A third layer was also added regarding body part segmentation. However, for the purposes of this study only the layer related to the sensor sheet on top of the mattress is considered.

Before training the classification models required for a posture classification solution, a second review, this time regarding the existing posture classification solutions, was a necessary step to examine the state of the art and determine which methodologies were taken when developing similar solutions, along with what algorithms were used and how effective they were in posture classification solutions.

Once the algorithms to be used in ML training were selected, the dataset developed previously was used to perform various experiments to test the accuracy of the models trained with it. Experiments were added according to the output of the previous stages described in this chapter.

Since the system envisioned in this dissertation aims to be of use to healthcare professionals, there needs to be a means of interaction between the system and the end user (medical professionals), therefore, a platform was designed and developed to accommodate this system in the form of a pressure ulcer monitoring and prevention application that allows users to easily obtain the outputs from the system.

With the objectives described, the solution developed should represent a viable solution, able to use appropriate data and generate useful information that can be represented in a number of ways to aid healthcare professionals in the field.

1.3. Work Contribution

This document contains the study done within a set of publications that result in a solution in the field of bedded or lying-people posture classification. This sub-chapter contains the publications listed and how they contributed to the dissertation.

1.3.1. Publication List

First the publications that are included in the dissertation study:

L. Fonseca *et al.*, “Integrated System for Pressure Ulcers Monitoring and Prevention,” in *Lecture Notes in Networks and Systems*, 2023. doi: 10.1007/978-3-031-26852-6_5.

L. Fonseca, F. Ribeiro, and J. Metrôlho, “Lying-People Pressure-Map Datasets: A Systematic Review,” *Data 2023, Vol. 8, Page 12*, vol. 8, no. 1, p. 12, Dec. 2022, doi: 10.3390/DATA8010012.

L. Fonseca *et al.*, “PoPu-Data: A Multilayered, Simultaneously Collected Lying Position Dataset,” *Data (Basel)*, vol. 8, no. 7, 2023, doi: 10.3390/data8070120.

L. Fonseca, F. Ribeiro, and J. Metrôlho, “Pressure-Based Posture Classification Methods and Algorithms: A Systematic Review,” *Computers*, vol. 12, no. 5. 2023. doi: 10.3390/computers12050104.

L. Fonseca, F. Ribeiro, and J. Metrôlho, “Effects of the Number of Classes and Pressure Map Resolution on Fine-Grained In-Bed Posture Classification,” *Computation 2023, Vol. 11, Page 239*, vol. 11, no. 12, p. 239, Dec. 2023, doi: 10.3390/COMPUTATION11120239.

There is also another publication related to the work but not considered a part of the dissertation:

Silva, A., Santos, O., Reinaldo, F., Fidalgo, F., Metrôlho, J., Amini, M., Fonseca, L., Dionísio, R., & Pt, R. (2022). Innovation and knowledge transfer for monitoring, predicting and preventing ulcers: the Sensomatt Approach. ICOPEV 2022 - 5th

International Conference on Production Economics and Project Evaluation, 233–244. https://doi.org/10.53681/2023.L03/03

1.3.2. Publications Relation and Description

This document includes five studies that were published over the course of the research work for this dissertation, and each of them provides different information towards the goal of providing a posture classification solution based on lying people pressure map data. Although these publications are not in chronological order, all of them have a purpose in the development of the system.

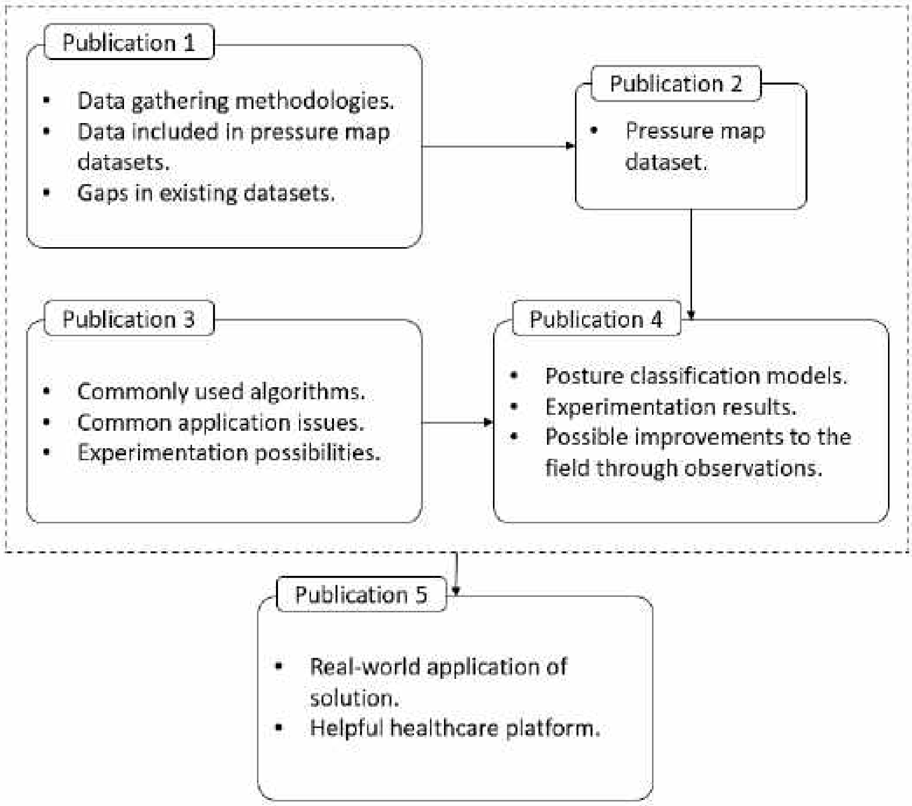

Figure 1. Relation between publications based on outputs.

Displayed in Figure 1 is a representation of the relation between the different publications, with each publication having their output used to some end. Publication 5 (Integrated System for Pressure Ulcers Monitoring and Prevention [2]) has no direct influence from the other publications, but their output provides an informed overview on what is necessary for a platform to be helpful and functioning considering the healthcare field and the posture classification applications.

Following the explanation on the relation between publications, the work done for this dissertation included in the various publications is presented in detail for a better understanding of how they result in a solution as a whole.

Starting with the publication titled Lying-People Pressure-Map Datasets: A Systematic Review [3], a study that acts as the initial state of the art study as it is a systematic review in the field of pressure map datasets, the purpose of this study is to find existing datasets that use pressure data, what data they include apart from the pressure data, how that data is organized, and what the data gathering process was. Through the information output from this study, the following publication will have a basis to work on and a sort of guideline not only in terms of the data to be collected but also regarding the procedures that need to be undertaken for a dataset to be successfully developed.

The following publication [1] PoPu-Data: A Multilayered, Simultaneously Collected Lying Position Dataset presents the dataset developed and used in this dissertation. Inputting the information gathered from the systematic review done to previously existing datasets, the dataset herein provided includes the data from 60 participants, with relatively well distributed characteristics (height, weight and sex), with various positions labeled (28) resulting in the highest number of positions amongst the literature and a high number of samples to facilitate future machine learning usage.

This publication includes data from three different layers: first, from a sensor sheet placed on top of a hospital mattress. Second, from a sensor sheet placed beneath the same mattress, these two were collected simultaneously. Lastly, the data from the sensor sheet on top of the mattress was used to develop a segmentation data layer, which splits the pressure image into the various body parts observed in it.

For the purposes of this dissertation only the pressure data from the first layer (top sensor sheet) is used.

The third publication [4] Pressure-Based Posture Classification Methods and Algorithms: A Systematic Review, acts once again as a state-of-the-art study, but this time in the field of machine learning methods used in posture classification. Aiming to find not only the most common algorithms used when developing posture classification solutions and how they perform but also to find common issues in this sort of application, to provide a more informed review for possible future applications.

The main takeaways from this review are that the most influencing factor in worsening the classification accuracies come from considering multiple postures, with the best results coming from solutions that use 3 or 4 postures, however, it is noted that high grained classification is useful as it provides precise information that is important for medical usage. There are also indications that the quality of the pressure data itself is a contributing factor for best results, however, there seems to be no apparent distinction between works that use a high number of sensors versus a smaller number of sensors.

The fourth publication, titled Effects of the Number of Classes and Pressure Map Resolution on Fine-Grained In-Bed Posture Classification [5] presents the usage of the dataset in [1] towards the development of posture classification ML models and measure how they perform. Considering the output from [4] a set of 5 algorithms was used to train models throughout various experiments included in the publication.

The experiments begin by testing how the models trained using the data as is would perform. This experiment shows that the models reach high accuracies when considering 4 postures, but considerably lower accuracies when using the 28 postures included.

Following the initial experiments, and to increase the accuracy of the high-granularity experiments, the main posture is input into the algorithm as part of the training data, to display if having the main posture classified beforehand would affect its accuracy, but it was to no avail as the accuracies remained relatively similar.

The next experiment intends to demonstrate the influence of the additional participant characteristics in the classification accuracies, and after removing the weight, height, and sex data from the training data it seems they are not highly affecting factors and thus show that the most important data in posture classification is the pressure data.

The last few experiments include the reduction of the pressure data resolution to simulate sensor sheets with a smaller number of sensors. These experiments have great results as they show that even with the resolution scaled down to 16x7 from 64x27 the accuracies remain very high (up to 95%).

The fifth and final publication, [2] Integrated System for Pressure Ulcers Monitoring and Prevention includes the demonstration of a platform that could make use of a posture classification solution to aid healthcare professionals in the field of pressure ulcer monitoring and prevention. The platform includes many functions such as patient information storage and access, graphical representations of the patients' state, among others.

Posture classification comes in by providing the platform with the patient's current posture, from this information, the body parts that are under pressure can be determined and various alerts can be generated, namely when there is prolonged pressure in one or various body parts, when movements that cause friction are detected or when there is no pressure detected indicating a fall.

This sort of application is a helpful tool for healthcare professionals as the patients affected by this type of condition need careful supervision to make sure their condition does not worsen.

The five publications in this dissertation present a solution all the way from the data collection procedure to model training and validating, to demonstrating a possible use for posture classification solutions. Bedded related conditions such as pressure ulcers or sleep disorders among others can be aided by using an approach similar to the one present in this work.

1.4. Document Structure

This document is organized into seven different chapters.

Chapter 1 contains a description of the overall topic of the document to summarize what is the reason behind this work and its purpose. It also introduces the results from the research study including a brief description of how the resulting publications are related, namely how their findings influence not only this work but also the rest of the publications.

Chapters 2 through 6 all account for one publication each, having an introduction to the publication, to summarize the objectives and findings of each study, along with the full publication.

The seventh and last chapter contains the conclusions taken from the study exposed throughout this document and some future work proposals that could be undertaken after the research stage of this study, be it in terms of further improving the herein presented solution or as part of a real application.

2. Publication 1: Lying-People Pressure-Map Datasets: A Systematic Review

2.1. Publication Summary

The aim of this publication is to assess the state-of-the-art in the field of lying people pressure map datasets, as the title suggests a systematic review was done to find all the studies on the matter and select the ones most suitable to the goal of the study. From a total of 405 individual studies, 9 were selected for inclusion and they were analyzed to answer a set of research questions to guide the withdrawal of information from them.

The reasons for such a difference between the number of individual studies and the ones selected were mostly due to the differences in what was considered a pressure map dataset, and there were also a few studies that had information regarding the same dataset but were not actual duplicates to start with.

The study reveals that although there are quite a few datasets with pressure map data available, there are some issues with the ones available, namely regarding the number of postures considered in them, the additional data gathered alongside the pressure data, and the number of samples contained in them.

Some of the datasets also had some reasons that make the datasets imbalanced for model training, namely low numbers of participants and a small participant variation regarding their physical attributes (weight, height and sex).

2.2. Full Publication

data

MDPI

Review

Lying-People Pressure-Map Datasets: A Systematic Review

Luís Fonseca [1], Fernando Ribeiro [1,2,*] and José Metrôlho [1,2]

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Abstract: Bedded or lying-people pressure-map datasets can be used to identify patients' in-bed postures and can be very useful in numerous healthcare applications. However, the construction of these datasets is not always easy, and many researchers often resort to existing datasets to carry out their experiments and validate their solutions. This systematic review aimed to identify and characterise pressure-map datasets on lying-people- or bedded-people positions. We used a systematic approach to select nine studies that were thoroughly reviewed and summarised them considering methods of data collection, fields considered in the datasets, and results or their uses after collection. As a result of the review, six research questions were answered that allowed a characterisation of existing datasets regarding of the types of data included, number and types of poses considered, participant characteristics and size of the dataset, and information on how the datasets were built. This study might represent an important basis for academics and researchers to understand the information collected in each pressure-map dataset, the possible uses of such datasets, or methods to build new datasets.

Keywords: in-bed posture; pressure-dataset characterization; pressure-map dataset; systematic review

Citation: Fonseca, L.; Ribeiro, F.; Metrôlho, J. Lying-People Pressure-Map Datasets: A Systematic Review. *Data* **2023**, *8*, 12. https://doi.org/10.3390/data8010012

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1. Introduction

Sleep studies and in-bed related conditions are in high demand for patient's health supervision and can be improved through the use of Machine Learning (ML)-assisted systems with the ability to detect when a specific patient needs assistance. Features such as these allow reduction in the effort of healthcare professionals. However, systems that would allow such an easing of burden require trained datasets. As health-related systems require critical accuracy, the data included in these datasets are crucial and all their parameters are very important when developing systems in this field. In such a scenario, solutions that combine the Internet of Things (IoT) and ML can help monitor patients' posture and can provide support to caregivers' activities, avoiding unnecessary overburdening and/or caregiver burnout. Usually, these solutions rely on the use of some type of sensor-based solutions (e.g., beds equipped with sensors [1], physiological signals and polysomnography [2]), camera-based solutions [3], or pressure mattresses [4]. In this context, solutions based on pressure maps are not intrusive for patients and have been successfully used in numerous healthcare applications. Pressure maps represent the pressure distribution under in-bed patients' body parts in different in-bed postures, and they are typically built using matrix-pressure-sensor sheets placed over the mattress. They have been used for in-bed body posture estimation [5,6], measurement of physiological signals (e.g., respiration [7,8]), pressure ulcer prevention [9–11], sleep studies [8,12,13], and bed-fall detection [11]. However, to develop, train, and validate many of these solutions, datasets are required that include pressure maps of a significant number of participants, with different characteristics and in different body positions.

However, the construction of these datasets is not easy, and many researchers often resort to the existing datasets to aid their studies. Therefore, finding a quality dataset, or building a new dataset, is a decision that must be made and is a fundamental requirement to build and validate any posture recognition-based healthcare application.

The purpose of this review was to find datasets about lying people's or bedded people's positions and characterise the existing datasets with respect to the methods used for data collection, the fields considered in the datasets, and the result or their possible uses after collection. The foci for these approaches would then result in a set of research questions that describe not only what the datasets included but also how they were built, what they were, and what they could be used for. The data gathered would then be used to answer the following set of research questions:

RQ1: What was the purpose of using pressure datasets?

RQ2: What data were included in the dataset?

RQ3: How was the participant population distributed?

RQ4: How many poses were considered for the dataset?

RQ5: What was the size of the resulting dataset?

RQ6: What information is available regarding the pressure data?

The answers to these questions would help identify the most common and most important aspects and identify the essential attributes in a lying-posture dataset.

The review was organised according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [14]. This process included identifying the purpose and the intended goals of the review, searching for the literature, formulating the inclusion and exclusion criteria, data extraction and analysis, discussion, and writing of the review.

The remainder of this article is organised as follows. In Section 2 we describe and apply the methodology chosen to perform this review, and we present the search strategy, the inclusion and exclusion criteria and the results, which are subsequently analyzed in Section 3 and discussed in Section 4. In Section 5 we identify the strengths and limitations of this review and finally, in Section 6, we draw some conclusions.

2. Methodology

This section contains a systematic review of studies/papers that address either the making of or the use of a pressure-distribution dataset for various purposes, including position/posture classification.

The review was conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [14]. Thus, the steps implemented in the search strategy were described to map the number of identified, included, and excluded works and the reasons for exclusions. It included the following steps, which corresponded to the section or subsection of this article listed after each step:

1. Identifying the purpose and intended goals of the review (Section 1)
2. Search strategy (Section 2.1)
3. Screening for inclusion (Section 2.2)
4. Screening for exclusion (Section 2.3)
5. Data extraction (Section 3)
6. Analysis (Section 3)
7. Discussion (Section 4)
8. Writing the review

2.1. Search Strategy

The literature search was conducted using Scopus, Web of Science, and PubMed as the databases. To perform the search, search terms related to the goal of this review were set, mostly considering pressure datasets. After the initial experiments and according to a preliminary quick search. the terms to be considered in the search were identified. First, with a focus on datasets, any words derived from the word dataset were considered. Second, although an initial search revealed that the use of pressure would result in the inclusion of other subjects, the attempt to tune the pressure search term resulted in the exclusion of a few relevant studies and was therefore left unchanged. Third, the terms were associated with the fact that the patient was lying on a bed. Thus, the complete string for the search was defined as follows:

dataset* AND pressure AND (bed* or lying)

The search was performed in November 2022 and resulted in 614 total studies: 263 from Scopus, 308 from Web of Science, and 43 from PubMed (403 after removing duplicates).

In addition, two more studies were identified through other sources.

2.2. Screening for Inclusion

The collected set of studies was examined by title and, when necessary, by abstract, to decide whether, for the purposes of this review, they were worth reading further or if they had to be excluded. This screening considered studies to be included in the review only if they met the following criteria: (1) studies that presented the collection or use of a body-pressure dataset or similar, (2) studies that focused on bedded or lying subjects, (3) studies that were published in a scientific peer-reviewed publication, and (4) studies that were written in English. Studies that did not meet all of these criteria were excluded.

At this stage, the works were not judged for their quality nor was the information evaluated in each study.

After the application of these criteria, 384 studies (352 based solely on their title and 32 after a review of their abstract) were excluded. This resulted in 21 studies.

2.3. Screening for Exclusion

The final list of studies was then assessed to validate whether they could be included in the final analysis. At this stage, the full text of each article/work was analysed to assess in detail the purpose, strategy, and outcomes of each study. Studies that did not present sufficient information about the data used or collected were excluded.

After a full-text analysis, 12 more studies were excluded. Six of them were trained using a dataset that was already included in the final selection, two focused on data gathered though sensors placed on the participants' bodies, one focused on patient activity such as respiration, another was focused on legislation regarding clinical data collection without specific information on the data itself, another was not focused on the data and had no information on the dataset used, and the last had no full text available.

The resulting list consisted of nine studies, which is a low number considering the initial search results; it also included various types of datasets. This showed that datasets for lying-people studies are not readily available and those that are available still vary in the type of data included, which might be an issue for researchers when they use the datasets.

2.4. Results

As presented in Figure 1, after the literature search, 405 studies were obtained (after removing 211 duplicates), referred to as the 'identification' stage in the diagram; after application of the inclusion criteria identified in Section 2.2. 'Screening for Inclusion' and in the 'screening' section of the diagram, 384 studies were excluded, resulting in 21 studies. A full-text evaluation of the remaining 21 studies was performed, excluding 12 studies that did not match the intended focus, presented usage of a dataset with a different source paper, or had no full text available; this stage is represented in the figure as 'eligibility'. The remaining nine studies were then presented in the synthesis and were the 'included' studies in the flow diagram.

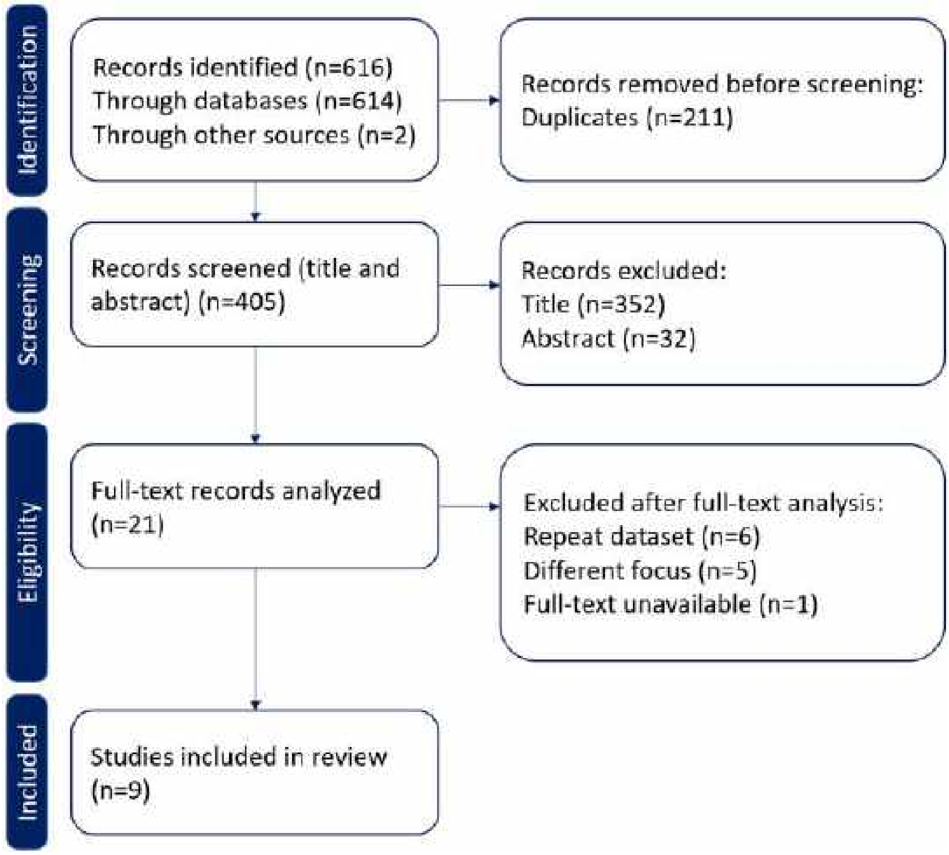

Figure 1. Flowchart of the systematic review process that determined the papers selected for the present study (adapted from the PRISMA 2020 flow diagram [14]).

Although the intent of this work was to find work focused on pressure-map information, two studies without any pressure data were included as the work in these was found to be relevant to the purpose of this paper. Furthermore, it helped to identify a common ground in all lying-people datasets. The other seven studies had pressure-data collection with varying levels of importance, as five out of the seven had the pressure map as the main focus of the dataset, apart from the participant characteristics. The last two studies included additional data gathered from hardware: one using post processing data that measured the perimeter and area of the pressure map to help pinpoint the lying person's position; and the other using three different types of imaging units for RGB, thermal, and depth image captures, which were later used for posture recognition.

2.5. Characteristics of Included Studies

The nine studies that were included in the review were published between 2017 and 2022 and were undertaken in China (three studies), the United States (three studies), Czechia (one study), Korea (one study), and Slovakia (one study).

All of the studies included in the review addressed the use of lying-people datasets for multiple applications but mainly for posture recognition. The description of the datasets used was sometimes derivative and some lacked information regarding the way the data were acquired or subject/participant characterisation.

3. Analysis of Included Studies

With the list of studies to be included in this review decided, in this section, these studies were analysed in depth with respect to their content, focusing on the information required to answer the aforementioned research questions. The information displayed in table 1 answers most of the questions with each row representing one of the papers included in the review. The Dataset Title (Availability) column displays the title of the dataset and whether it is available for public use according to the authors of the specific paper.

Table 1. Summary of the articles selected for analysis and synthesis.

Ref.	Part.	Poses	Data Collected	Participant Characteristics	Sample Size	Data Collection Hardware	Dataset Title (Availability)
[15]	109	15	Pressure map RGB image Thermal image Depth image	Height Weight Gender Body measurements	15,000	Pressure sensing mat RGB imaging unit, LWIR (Long wavelength infrared) imaging unit Depth imaging unit	SLP dataset (Available)
[4]	13	8	Pressure map	Height Weight Age	26,000	Pressure sensing mat	PMatData (Available)
[16]	N/A	99	Pressure map	Height Weight Gender	206,000	3D software	Bodies at rest/pressure pose (available)
[17]	21	4	Pressure map	Weight Gender	2520	Pressure sensing mat	Not available
[18]	6	4	Pressure map	Height Weight	736	Pressure sensing mat	Not available
[19]	12	1	Pressure map	Weight	60	Pressure sensing mat	Not available
[20]	20	4	Pressure map Geometric feature values	Height Weight Age Gender	1280	Pressure sensing mat	Not available
[21]	66	7	RGB image Thermal image	Height Weight Age Gender	1400	RGB camera Infrared thermal camera	Not available
[22]	32	20	RGB image Depth image	Age Gender	19,800	Kinect camera	Human in-bed posture data (Available)

For each of the papers listed in the table above, a small summary was created and is presented below in the same order as shown in the table. The major focus of the summary was to find the purpose of the work, the data used for achieving it, how those data were gathered and the participants' distribution, the parameters chosen by the authors, and lastly, the results of the work.

With the consideration that the datasets developed and used in the studies analysed were used for recognition purposes using machine-learning algorithms, the resulting accuracy of the algorithms using the said datasets was included in the analysis of each work when available; this accuracy (represented as a percentage) displayed how likely the algorithm developed was of accurately predicting the position or posture of a certain bedded individual, having used a dataset for its training, which was analysed in detail for each of the papers considered in this review.

Simultaneously Collected Multimodal Lying Pose Dataset: Towards In-Bed Human Pose Monitoring under Adverse Vision Conditions [15] intended to gather important data for pose estimation and monitoring for in-bed scenarios specifically, as the authors found that the existing datasets in the 2D human-pose datasets field had ambiguity issues. The data were gathered using multiple methods: through RGB imaging (pictures); thermal imaging; depth imaging; and pressure mapping. They were then paired with the relevant clinical data, including height, weight, sex, bust size, hip size, and limb sizes.

The authors presented a very complete dataset gathering data from 109 different individuals, with slightly distributed parameters throughout the data having 78 male and 31 female subjects ranging from 150 to 190 cm in height and from 30 to 120 kg in weight, implying that the resulting dataset had a good representation of different body types and led to better pose estimation.

This work considered 15 different poses for the data collection, evenly distributed between three main poses, namely supine, left facing, and right facing, having five random poses for each of these main poses. There were different samples taken for uncovered, covered with a thin sheet, and covered with a heavy blanket, resulting in 15,000 pose samples for in-bed study use.

The data were collected without a pillow, considering only the covers which did not affect the pressure maps. The hardware used for data collection was not specified in the paper, and the pressure maps specifically were collected with a pressure-sensing mat, but there was no information regarding the size of the mattress or the sensor count. The poses considered for this work were counted to be 15, but when it came to pose estimation, only three could be accounted for as there were five different poses for each of the three main poses, and they were chosen at random by the participant.

A pressure-map dataset for posture and subject analytics [4] presented the development work for, according to the authors, the first publicly available dataset of lying-pose pressure maps. The data were collected in two different experiments by using two different pressure sensing mats; the first experiment used a mat consisting of a 64 × 32 pressure sensor matrix, and the second experiment used a smaller matrix mat with a 64 × 27 configuration.

The dataset was developed with the participation of 13 individuals, and their height, ranging from 169 to 186 cm; weight, ranging from 66 to 100 kg; and age, ranging from 19 to 34 years, were gathered as additional participant data, proven useful by the authors. The sex of the participants was not mentioned in the paper.

The postures were also gathered differently in the experiments, with the first experiment having eight postures considered, with some of them being variations of some of the main postures considered in the lying pressure-map field, namely supine, left facing, and right facing. The second experiment had only the three main postures included. In all of the frames captured, the participants had a standard pillow under their head.

The sampling was taken every second for around 2 min for each posture recorded, which generated a large sample size of 26,000, but some of them were repeats as the participants did not shift their position during the 2 min period. The authors of this paper decided to gather the participants' age, which was not commonly found in other similar work, but the authors used the participant data in subject identification, attempting to classify the different subjects, according to their information and the pressure maps gathered, with satisfactory accuracy, thus proving that the authors gathered discriminative information.

Bodies at Rest: 3D Human Pose and Shape Estimation from a Pressure Image using Synthetic Data [16] presented an interesting approach to the dataset collection methods used in pressure-map dataset-development. The authors created a dataset with computer-generated data, using a simulated environment where a 3D model of a human lay on a pressure mat. This approach solved the challenge of real data collection, which could be difficult at scale.

Without real participants, the dataset included different body shapes, and the weight, height, and gender were still considered parameters in the dataset. The weight and height ranges were not discussed in the paper.

The postures for this dataset were divided into five groups, having 20 different postures for supine positions, 20 for prone positions, 20 for each left and right facing, and finally, 19 postures acquired through human interaction, where a group of 10 male and 10 female participants were asked to lay comfortably in these 19 different positions.

The dataset had only one sample for each of the postures, having one for every 99 for every different simulated 'subject'.

To test the usefulness of the dataset, the authors developed a posture-recognition system which obtained only the generated pressure maps and the subject's gender as the input and attempted to create a 3D model of the predicted posture; the results showed an accurate prediction from the input data, which indicated the importance of the selected parameters.

A smart IoT system for detecting the position of a lying person using a novel textile pressure sensor [17] aimed to assist bedded-patient healthcare providers with an IoT bedside system that detected whether the patient was lying in a specific position for long periods, so that the health staff could be warned accordingly and the patient could be turned. This system was proposed in some other papers as pointed out by the authors in [23], but the authors in this study proposed an approach using only a pressure map of the individual's torso for posture classification.

Included in this work was the development of a dataset which included data from 18 male and 3 female participants with weights ranging from 45 to 125 kg. The data considered for the dataset were the pressure maps, consisting of 8 × 8 matrices with values ranging from 0 to 140, and the participants gender and weight, although only the weight and pressure maps were used in the posture classification.

The postures considered for the dataset were supine, prone, left facing, and right facing, and the participants were asked to shift their position slightly 30 times for each posture, which in total resulted in 120 different samples taken for each participant.

The parameters taken from the individuals did not include height, which was taken into consideration for most work in the field; however, as the pressure maps were only of the individual's upper body, the individual's height might not have influenced the results of the posture classification system.

The result of the posture-classification algorithm on the collected dataset ended up with an overall accuracy score of 82.22%, which was mostly lowered by the difference in the participant's body weight according to the authors, because of the weight range of the participants.

In-Bed Posture Classification Based on Sparse Representation in Redundant Dictionaries [18] used pressure maps for posture classification without using other parameters such as height or weight, in an attempt to find the differences between using the classification systems known as sparse representation classification and standard classification methods.

The dataset used to demonstrate the authors' work gathered 736 different pressure images of six test subjects of various weights and heights that were undescribed with respect to their range. The pressure maps used were obtained from a pressure-sensing mat consisting of a 30 × 11 pressure-sensor matrix.

Four postures were considered for this work, namely supine, prone, left lateral, and right lateral.

Although the authors decided against the use of other participant characteristics such as weight, the resulting posture classifier still showed promising results, although lower than similar applications that included individual parameter use such as weight.

The prediction of the body weight of a person lying on a smart mat under non-restraint and unconsciousness conditions [19] had a different goal than that of most of the work found in the search, attempting to predict the weight of the bedded individual that the authors gathered pressure maps for, as well as the weight of the lying person.

The gathered dataset had only 60 samples, from 12 participants, whose only parameter stored was their weight; as the goal of the work was to predict the weight specifically, no other data were required. The weight of the participants ranged from 56 to 89 kg, averaging 73 kg. The pressure sensing mat used was developed by the authors and contained a matrix of 8 × 16 pressure sensors evenly distributed along a 2.05 m × 0.85 m mattress to simulate a hospital environment.

As the goal was only to predict an individual's weight using only their pressure information, no other parameters were gathered, and the dataset only accounted for one lying position (supine). The limited data gathered for the dataset made it usable in a more finite range of studies as most of the available datasets have other relevant information and additional samples.

The authors did go on to test the applicability of the weight prediction algorithm on the dataset and concluded that the array size of the pressure sensing mat resulted in a number of 'dead zones' where no pressure was detected which caused errors in the predictions. Furthermore, the authors stated that the results of the algorithm could be improved by using a larger dataset.

Pressure Image Recognition of Lying Positions Based on Multi-Feature Value Regularised Extreme Learning Algorithm [20] presents a lying-position recognition system that uses not only the pressure data from the participant's torso but also geometric values such as the perimeter and area of the pressure image for increased accuracy.

For testing their algorithm, the authors gathered a dataset consisting of 1280 samples, taken from 20 (10 male and 10 female) participants, including the pressure maps, represented in a 16 × 16 matrix with the pressure values, and the individual parameters included height, ranging from 160 to 180 cm; weight, ranging from 45 to 80 kg; and age ranging from 20 to 27 years. The authors also included post-processing data in their dataset, calculated using the pressure maps, and recorded the perimeter and area of the pressured body area for later use.

Apart from the use of only the pressure image of the torso, the data gathered for this work were very complete as they included the parameters that were gathered for most work in the field. The dataset also considered four different positions, namely supine, prone, left facing, and right facing.

The purpose of this work was to precisely predict the lying posture for the prevention of possible sleep- or bed-related diseases, particularly for long-term bedded patients. By using the proposed algorithm (RELM algorithm), the authors could predict the individual's lying position with a 98.75% accuracy, which according to the authors resulted from the use of the multiple parameters for the prediction, both pressure related and those related to the individuals.

Blanket Accommodative Sleep Posture Classification System Using an Infrared Depth Camera: A Deep Learning Approach with Synthetic Augmentation of Blanket Conditions [21] had the objective of accurately classifying different sleeping postures by using thermal image data, irrespective of the cover on the individual.

The dataset used for training and testing the proposed method, gathered by the authors, consisted of 1400 sample images, taken from 66 (40 male and 26 female) participants, accounting for different parameters, including their age (averaging 35.7 years with a standard deviation of 17.4 years), height (averaging 167 cm with a standard deviation of 18 cm), and weight (averaging 63 kg with a standard deviation of 12.23 kg).

Each sample contained the participant's information along with a thermal image of the patient in one of seven different positions and in four different cover or blanket conditions. The different lying positions considered were supine, prone (one with the head facing the right and another the left), log (left and right), and foetal (left and right). The blanket conditions indicated the type of blanket on the participant for that sample, varying in thickness and material.

Although the dataset described in this work did not have any pressure information included, the inclusion of the different postures was relevant to their findings and could be helpful in pressure-map studies.

The methods for classification used by the authors were then divided into two different sets: one for classifying the position out of the seven postures gathered, and the other for classifying only four postures (supine, prone, left facing, and right facing). The four-posture classifier exhibited excellent results with 97.1% accuracy; in contrast, the seven-posture classifier had 88.9% accuracy, leading to the conclusion that using a larger dataset would improve the outcome of this work.

Human Posture Recognition Using a Hybrid of Fuzzy Logic and Machine Learning Approaches [22] had two main purposes: first, creating a posture recognition system capable of not only recognising the posture of a certain lying individual but also determining the position of their limbs; second, gathering a dataset that could be used for the training of a posture-recognition system and made available to other researchers.

The dataset presented in this paper contained 19,800 different samples taken from 32 (16 male and 16 female) participants; the samples included the individual's gender and age (ranging from 21 to 57 years) along with the RGB and depth images of the participants in one of the 20 different postures.

The postures selected for this work was derived from the statistical analysis of lying patients in hospital beds and were the result of categorising more than 1800 possible postures into the 20 most common ones.

The dataset was very complete with respect to postures but lacked some of the parameters that other datasets made available such as height and weight. Although the data collected were not related to pressure, the number of postures was relevant to this work as were the results of the study.

The author's methods of classification achieved 97.1% accuracy, which was impressive considering that unlike most other works included in this review, this work classified 20 different positions; these positions were mostly variations of the four main positions used in most works (namely supine, prone, left facing, and right facing) but were differentiated in the classification procedure. Other fine-grained works in the field did not obtain high results. The reason for the high accuracy might be the use of depth imaging over pressure mapping.

4. Discussion

As the analysis of the included studies followed the research questions, the discussion is also sub-divided into six different paragraphs, each representing the discussion regarding the information taken from the analysis results for the research questions.

For a better understanding of how the different studies included in the review answered the questions, they were compared, and to further clarify how the majority of the works were developed, they were presented using a quantitative representation (out of nine, with nine being the total number of studies included), grouping the studies according to the similarities found.

The purpose of using pressure datasets (RQ1), according to the studies included in the review, was mostly lying-posture recognition, with seven out of nine focusing on lying-posture classification. Out of these, two aimed to aid sleep quality studies with posture recognition, two were concerned with pressure-ulcer prevention, and four aimed to predict a lying person's posture so it could be used later. Of the two studies that did not intend to classify lying postures, one focused on weight prediction using pressure data alone and the other focused mostly on the data-gathering procedure.

With respect to the data included in the datasets (RQ2), eight out of the nine included the participants' weight, six out of the nine studies included their height, six out of the nine included the sex (gender) of the participants, four of the nine included studies also used the participants' age, and one study used body measurements (e.g., waist width and thigh width) for their datasets. On the basis of this information, and particularly after analysing each paper, the authors concluded that none of these characteristics stood out as more important with respect to the lying-position classification as each work regarded the characteristics gathered, albeit different from one another, important for their specific study. However, as different studies used different parameters and all of them ended with highly accurate results, they did not seem imperative to the resulting classification algorithms' precision. All of these should still be considered in the development of new datasets when their collection is possible, considering that other works might use them for different purposes, as in the work in [19], which predicted body weight and therefore requireed weight data to be included in the dataset. The purposes of these datasets are, however, not limited to posture recognition, and some studies suggest the usage of other factors for different purposes; for example, the authors in [24] mentioned the use of age and weight for their study, and the study published in [25] concluded that there were noticeable differences in the pressures registered from the trochanteric zone (hip area) depending on anthropomorphic factors and the participants' gender. Thus, the inclusion of various individual characteristics is recommended as it will allow new and more complete studies to emerge from it.

Participant population distribution characteristics (RQ3) also allow future researchers to inspect how representative the dataset is, as having no information regarding the participants' different body parameters has use for classifier demonstration, but if the goal is health related, the algorithms cannot be expected to perform as well on different people. This implies that not only is the participant count relevant but how diverse their characteristics are is also relevant. The authors of the studies included accurately described the population of their dataset, although some did not include information on how representative it was, stating only the minimum and maximum for a specific characteristic.

The poses considered for the dataset (RQ4) were one of the most important aspects of the works included in this review, as the possibilities for a human position while lying on a bed could be endless depending on how finely grained the considered postures were. With respect to the different poses, most of the works in this review (six out of nine) considered a smaller number of poses, up to eight, mostly represented by the four main lying postures (supine, prone, left facing, and right facing); however, one work included 15 postures, another included 20, and lastly, the study that used computer-generated data considered 99 different poses. The works that included fewer poses in their posture classification tended to achieve higher precision than those aiming for a finer-grained classifier, but a higher number of poses might be important for different medical uses, where knowing the exact position of a lying person might determine how a system reacts.

The size of the dataset (RQ5) or the number of samples in one is important when used for training machine-learning algorithms such as classifiers. The datasets considered in this study varied in size with five having 2500 or less, and the other four datasets having more than 15,000 samples. The accuracy of the resulting classifiers was not noticeably lower for the studies using smaller datasets necessarily, but these had a lower number of postures, which led to the conclusion that the larger the number of postures considered in the classification was, the larger the number of samples needed to be.

With respect to the information available regarding pressure data (RQ6), one of the most important aspects of pressure maps is their resolution, and the resolutions considered in the studies included in this review ranged from 64 sensors displayed in an 8×8 resolution to 2048 sensors in a 64×32 resolution. The precision of the pressure maps and the algorithms trained using such pressure maps increased according to how high the resolution was; however, studies with lower resolutions achieved high accuracy classifiers, either by using different parameters (weight, height, etc.) or by gathering the pressure of a specific body part, usually the torso for posture recognition. Furthermore, regarding pressure maps, more specifically, the hardware used to gather them, the position of the sensor sheets is on top of the mattress or bed, directly below the participant or with a sheet covering it for all the studies included in this review because the weight distribution dissipates through mattresses or other soft surfaces.

Although all the works included answered the research questions thought of for this review, there were a few gaps found while analysing each of the studies, namely (in the order they are listed in Section 3):

- Lack of hardware specification: this information can be useful for future researchers, not only the ones using already developed datasets but also researchers developing new datasets, by knowing the hardware used for the data collection procedure.

Information such as resolution (image or pressure matrix resolution) or hardware dimensions could lead to researchers making informed decisions on the hardware used.

- Regarding pressure maps, some of the studies did not include information on the resolution of the pressure maps in the datasets. As some studies aim for finer-grained posture classification, they need a higher resolution for accurate results, and if this information is not displayed, researchers will have a hard time finding an adequate dataset.
- The postures chosen for the datasets vary depending on how many postures the researchers are attempting to classify. However, after an analysis of the studies in this review, the postures included in the lying-people datasets should include at least the four postures that are mostly used, namely supine, prone, left facing, and right facing, as these are the most common lying positions found in medical studies.
- All of the studies included in this review included participant characteristics in their datasets. However, some of them did not describe their range, stating only that they used the participants' weight, for example, but not describing how they varied; the inclusion of this information is important for clinical applications, as they can display how accurate the resulting applications will be, considering different anatomic proportions. With respect to participant characteristics, the participant distribution as to the characteristics is not always taken into consideration, and as human bodies have a nigh infinite number of different proportions, datasets that can be used in the clinical field of study should have a representative distribution in mind.
- Another gap found was the dataset size. Some authors consider the main reason for low accuracy of the classification algorithms to be the limited sample size of the datasets, and this is mostly because of the difficulty of finding willing participants for data collection. Although one of the papers suggested using computer-generated data, the usage of such data might not be suitable for clinical applications.
- Furthermore, the physical setup of the data collection procedure could be described in studies that present a new dataset to demonstrate not only what material or equipment is required for new dataset development but also the techniques used for it, such as the use of a graphical user interface or how the participants are informed of what they need to do for the data-collection procedure.

The analysis of the studies included in this review help highlight the important factors when developing a dataset in the considered field or choosing one for lying-people-related research. With the use of the predefined research questions, the information gathered showed how the datasets were used, what data were considered in them, how many participants were included in the making of the datasets, and which of their characteristics had to be considered. With the overall analysis complete, the gaps found were also addressed with the intent of informing researchers on information that was sometimes left undiscussed and should be included for the reasons described above.

5. Strengths and Limitations of this Review

This review followed the PRISMA methodology. It provides a comprehensive review of the existing pressure-map datasets involving lying people or bedded-people positions. This review is important because it presents a characterisation of the datasets, namely the methods for data collection, the fields considered in the datasets, and the results or their use after collection. It represents an important basis for academics and researchers to understand the information collected in each dataset, how they can be used, or even how to proceed to build new datasets.

However, it also has some limitations. The search for literature was carried out using three databases (Scopus, Web of Science, and PubMed). Although these databases cover several domains and span many individual databases, this decision may have influenced the number of relevant articles obtained. The use of other databases, such as IEEE Xplore, ACM Digital Library, ScienceDirect, or BMC, could possibly have increased the number of analysed articles and contributed to the improvement of the overall analysis. Furthermore, the search strategy was deemed to restrict the number of non-relevant articles (e.g., the string used in the search might have influenced the number of results; only articles written in English). These options might have discarded relevant articles, e.g., those written in languages other than English or others that might not have been covered by the search string used. These limitations might have significantly affected the number of records obtained and might have had some impact on the number of retrievals of relevant articles. However, we believe that these constraints did not have a significant effect on the discussion and the conclusions.

6. Final Remarks

By following the PRISMA methodology, this systematic review aimed to find studies on the development and usage of datasets that included pressure maps in their compositions, synthesising the ones found appropriate for the purposes of this review and analysing them in full to gather the most useful information from them.

The literature search was conducted using three databases (Scopus, Web of Science, and PubMed), and after the literature search, 405 distinct studies were obtained, resulting in 21 studies after the application of inclusion and exclusion criteria. Finally, after the full-text evaluation of the remaining studies, 12 studies were excluded. The resulting list contained nine studies that were published between 2017 and 2022.

The results of this review revealed that most applications found for the field of pressure-map datasets were for posture recognition or simply pressure-level detection, which then would have numerous uses for clinical applications. The most commonly gathered participant parameters were analysed, and most studies seemed to include weight and height, but these parameters did not seem to make a relevant difference as the works that did not use them reported similar results. They should still be considered in the development of new datasets however, as they can be used for different studies. With these parameters, the population distribution can also be identified, which ensures that the resulting system will still function accordingly for different people.

The techniques used for gathering pressure data, such as the different poses considered, were analysed, and the results of the studies that included more postures tended to have greater difficulty in the posture-classification process, but considered the finer granularity to be worth the decrease in accuracy. Other parameters such as the sensor position, amount, and resulting resolution of the pressure maps were included, revealing many different approaches with all of them exhibiting high accuracy in the classification, albeit most had a low number of postures considered for recognition.

The dataset sizes were also included in the review, which is important for machine-learning algorithm-training, as more data usually results in a better model.

This review also made it possible to identify a set of gaps that, in some way, made a deeper analysis difficult, namely lack of information on hardware specification and on the physical setup of the data collection procedure, lack of information on the resolution of the pressure maps in the datasets, differences in the postures chosen for the datasets, lack of relevant information on participant characteristics, and, in some cases, a small number of participants in the dataset. It is therefore recommended that these gaps be analysed by future researchers in detail when developing new datasets or related work in the field.

The initial literature search resulted in a significant number of studies. However, after the application of inclusion and exclusion criteria, the final number of studies was relatively small. All of the analysed studies addressed the use of lying-people datasets, but they included various types of datasets. This might suggest that the availability of datasets for lying-people studies are not readily available and those that are available still vary in the type of data included, which might be an issue for researchers when using the datasets. Thus, the aim of this study was not only to conduct a review on pressure-map datasets to display the state-of-the-art datasets available, but also to give future researchers important information regarding the development of new datasets in the field of bedded or lying-people studies.

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3. Publication 2: PoPu-Data: A Multilayered, Simultaneously Collected Lying Position Dataset

3.1. Publication Summary

This publication includes the information regarding the dataset that was developed having helpful inputs from the systematic review made in the publication presented in chapter 2.

Information regarding the data collection methods, setup and materials are included in the publication.

This study presents the dataset itself, with a description of the data format used and what the data gathered represents. Along with pressure map data from two separate sheets (one placed on top and one below a hospital mattress), the dataset also includes the participants' weight, height and sex. There is also an additional layer in the dataset consisting of manually labeled segmentation data, with each segment representing a part of the participant's body.

The PoPu dataset includes data from 60 volunteers distributed along the different characteristics (weight, height and sex) in the hopes of getting a balanced dataset for future model training. There are 28 different positions included in the dataset with 7 positions for each of the main postures considered in the literature (supine, prone, facing left and facing right), with 8 of these positions including the use of pillows.

3.2. Full Publication

data

MDPI

Data Descriptor

PoPu-Data: A Multilayered, Simultaneously Collected Lying Position Dataset

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Abstract: This study presents a dataset containing three layers of data that are useful for body position classification and all uses related to it. The PoPu dataset contains simultaneously collected data from two different sensor sheets—one placed over and one placed under a mattress; furthermore, a segmentation data layer was added where different body parts are identified using the pressure data from the sensors over the mattress. The data included were gathered from 60 healthy volunteers distributed among the different gathered characteristics: namely sex, weight, and height. This dataset can be used for position classification, assessing the viability of sensors placed under a mattress, and in applications regarding bedded or lying people or sleep related disorders.

Dataset: The dataset is available on GitHub: https://github.com/rdionisio1403/PoPu/.

Dataset License: The dataset is available under Creative Commons (CC0).

Keywords: in-bed posture; lying posture; pressure dataset; pressure-map dataset

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1. Summary

Bedded or lying-people pressure-maps can be used to identify patient positions and behaviors and can be very useful in numerous healthcare applications. The development of these applications normally requires the training and validation of algorithms based on datasets with a high number of pressure maps that represent different people in different positions and conditions. However, building these datasets is a laborious and time-consuming task, as it is necessary to involve a large number of participants who have to carry out a set of predefined behaviors and movements that are recorded and classified. For this reason, researchers tend to use public datasets to carry out their experiments and validate their solutions. However, to be useful, these datasets should have certain criteria: namely, regarding the quality of the data and containing sufficient samples to characterize a given population.

A study on pressure-map datasets [1] conducted a review through three databases (Scopus, Web of Science, and PubMed). Compared to the other datasets referenced in this study, this dataset includes a greater number of positions that are labelled accordingly, a high number of samples, and well-distributed, relevant participant characteristics.

This study aims to create a dataset that contains the data not only from a commercial sensor sheet placed directly below the subjects, but also from sensors below a mattress, along with relevant participant characteristics and body part segmentation information.

The resulting dataset includes data from 60 individuals lying in 28 different positions, with 7 variations of each of the 4 main positions that are found in most of the literature—supine, prone, facing left, and facing right. Additionally, for all variations, the participants were asked to shift their body slightly twice, in order to increase the variety of the data samples, which ultimately resulted in 50,400 pressure data samples and 1680 segmentation images.

This dataset can be used for assessing the viability of sensors placed under a mattress, and all its layers can be used for classification algorithms similar to the work researchers conducted in [2–5], as well as health studies related to pressure ulcers [6], sleep disorders [3], and fall prevention, among others.

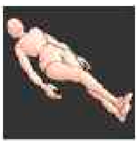
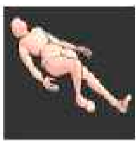
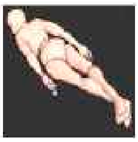
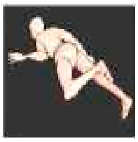
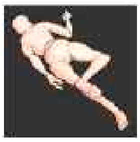
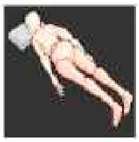
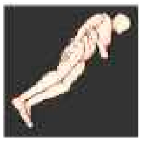
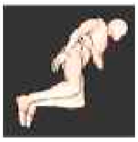
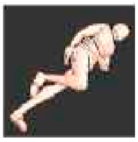
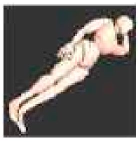
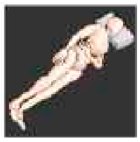
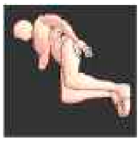
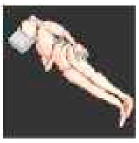
2. Data Description

This section contains the information regarding the data included in the dataset. First the different positions considered for the data gathering process, then a description of the participants and the distributions of the data gathered and finally a description of the organization of the data, from the different files to the format of the data in each file.

2.1. Pressure-over- and Pressure-under (PoPu)-Mattress Dataset

Prior to the collection of the pressure data, the most common sleeping or lying positions were searched; most literature includes four positions (supine, prone, facing left and facing right); therefore, for this dataset, the positions were organized into these four main positions and the rest were considered variations. Table 1 displays all of the 28 positions considered and how they are organized. For each of the main positions, two variations also included pillow placement with the intent of analyzing its influence on the pressure data.

Table 1. Different positions and variations considered.

Position Variations	1	2	3	4	5	6	7
Supine							
Prone							
Facing left							
Facing right							

2.2. Participant Characteristics

A total of 60 healthy individuals participated in the data collection process and had their weight, height, and sex registered along with the pressure data. The weight of the participants, with their distribution shown in Figure 1, ranged from 45 kg to 127 kg (the average weight was 74.25 with a standard deviation of 17.6), the height ranged from 145 cm to 195 cm (the average was 171.9 with a standard deviation of 10.3) with the distribution shown in Figure 2, and the sex distribution was 24 females (40%) and 36 males (60%).

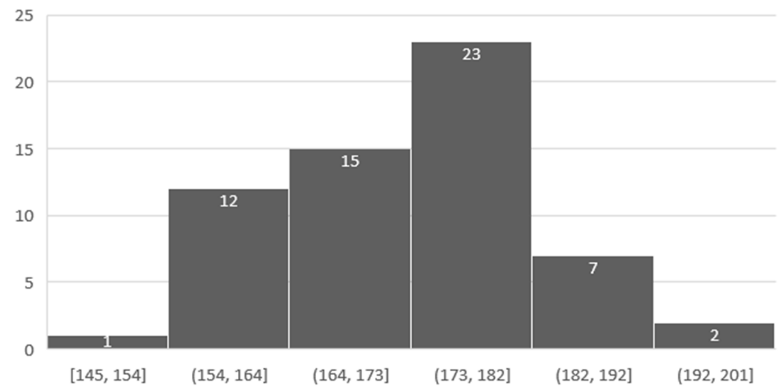


Figure 1. Participants' weight distribution.

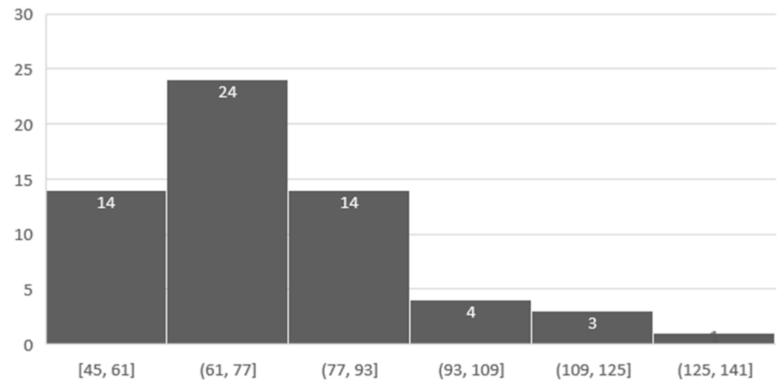


Figure 2. Participants' height distribution.

2.3. Dataset Format Description

This dataset's files use the JSON (JavaScript Object Notation) format, as it is widely used and can easily be formatted by researchers if necessary. The dataset is split in three folders that represent each of the layers, with each containing one folder for each of the 60 volunteers. The three initial folders represent the pressure data from the sensors under the mattress ("*sensomatt_data*" folder), the pressure data from the sensors over the mattress ("*tactilus_data*" folder), and the segmentation results ("*segmentation_data*" folder).

Regarding the pressure data folders, each of the volunteer folders contains three files for every position considered, named after the position (for a total of 84 files), with an indication for each shift in the same position. For example, for data concerning the supine position in the first variation, the file will be named "*supine1_0*"; the file for the same variation after a slight shift from the volunteer will either be named "*supine1_1*" or "*supine1_2*". Each of the files contains 10 samples.

Other than the files corresponding to each position, there is also a file, named "*empty1*" which contains samples taken while there was no volunteer on the sensors, which can be used to remove any initial noise from the data. There is also a file named "*others*" which contains samples that were taken throughout the data-gathering process but which are not labeled as to the position the participant was in.

In the "*segmentation_data*" folder, each of the volunteer folders contains one file for every position considered, named similarly to the pressure data folders, with the slight difference that there is only one file for each position, so for the same position above, there would be one file named "*supine1*". There is also a folder with images obtained from the segmentation files—one for each of the positions.

The structure of the folders is represented in the following tree:

```
└── PoPu_data/
    ├── sensomatt_data/
    │   ├── 1(volunteer_id)/
    │   │   └── <position+variation_json_data_files_with_bottom_pressure_data>
    │   ├── (...)
    │   └── 60(volunteer_id)/
    │       └── <position+variation_json_data_files_with_bottom_pressure_data>
    ├── tactilus_data/
    │   ├── 1(volunteer_id)/
    │   │   └── <position+variation_json_data_files_with_top_pressure_data>
    │   ├── (...)
    │   └── 60(volunteer_id)/
    │       └── <position+variation_json_data_files_with_top_pressure_data>
    └── segmentation_data/
        ├── 1(volunteer_id)/
        │   ├── <position+variation_json_files_with_segmentation_results>
        │   └── <segment_images_folder>/
        │       └── <position+variation_segment_image>
        ├── (...)
        └── 60(volunteer_id)/
            ├── <position+variation_json_files_with_segmentation_results>
            └── <segment_images_folder>/
                └── <position+variation_segment_image>
```

Each of the pressure map file's content is organized as follows:

```
{
  volunteer_id: <identifier_for_volunteer>,
  sex: <sex_of_volunteer>,
  height: <height_of_volunteer_in_cm>,
  weight: <weight_of_volunteer_in kg>,
  <sensor_sheet_name>_columns: <number_of_columns>,
  <sensor_sheet_name>_rows: <number_of_rows>,
  position: <position_of_volunteer>,
  variation: <variation_number>,
 snapshots: {
   0: {
       id: <identifier_generated_for_specific_sample>,
       <sensor_sheet_name>_readings: [<list_of_values_from_sensor_sheet>
   }
   ( . . . )
   10: {
       id: <identifier_generated_for_specific_sample>,
       <sensor_sheet_name>_readings: [<list_of_values_from_sensor_sheet>
   }
}
```

The "others" file on the pressure data folders has a similar structure but without the position and variation labels.

The segmentation files have one file for each position, using the pressure data from the top sensor sheet's data (tactilus_data). The organization of the segmentation files is as follows:

```
{
   id: <image_name>,
   annotations: [
       {
```

```
            id: <body_part_number_in_image>,
            completed_by: 1,
            result: [<list_of_polygons_found_in_image>
              {
                original_width: <image_width>,
                original_height: <image_height>,
                image_rotation: <image_rotation>,
                value: {
                  points: [ <list_of_polygon_vertices_(ordered_clockwise)>
                    [<x>,<y>],
                    (...)
                    [<x>,<y>]
                  ],
                  closed: <true_if_polygon_closed_false_otherwise>,
                  polygonlabels: [<name_of_body_part>]
                },
                id: <randomly_generated_id>,
                from_name: "label",
                to_name: "image",
                type: "polygonlabels",
                origin: "manual"
              },
              (...rest_of_polygons . . . )
            ],
            <info_regarding_segmentation_process_(omitted)>
          }
        ],
        file_upload: <segmentation_image_name>,
        <info_regarding_image_(omitted)>
      }
```


Since the "*others*" file has no associated position, it is not included in the "*segmentation_data*" folder.

With these files, a pressure image can be generated, as seen in Figure 3, and the different pressure values can be observed along with the different segments on the data files.

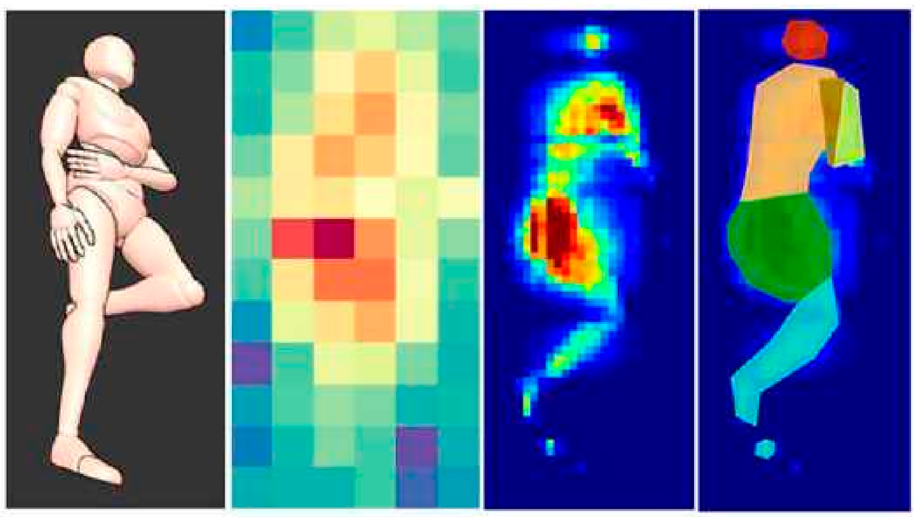


Figure 3. Different images from data included in PoPu dataset, from left to right: example 3D-modelled position, bottom sensors pressure map, top sensors pressure map, segmentation image.

Figure 3 shows 3 different images from the same volunteer in the facing-left position and in variation 3.

3. Methods

This section contains the methods used to collect the data. The materials used will be described, along with a description of how they were used during the data collection, in terms of hardware and the software developed for the data-gathering procedure. Then, a description of the experimental setup is provided. Lastly, the experimental procedure's details are given.

3.1. Equipment

For this experiment, two different sensor sheets were used: one placed on top of a standard viscoelastic, single-piece, foam hospital mattress (195 cm × 85 cm × 16 cm) and the other placed under it.

The sheet placed over the mattress was a commercially available, 180 cm × 78 cm Tactilus sensor sheet [7] with a total of 1728 piezoelectric sensors evenly distributed in a 27 × 64 matrix. Each of the sensors output a pressure value between 0 and 100 mmHg.

The Sensomatt sensor sheet, placed under the mattress, contained 72 single cells, designed to detect omnidirectional contact pressure induced by soft contact such as mattress foam contact. The sensor cells are registered under Portugal Intellectual Property law with the patent number: 117507.

Sensor cells could be arranged in any different configuration, but in this experiment, they were arranged in 12 × 6 matrix distributed over the 170 × 84 surface of the sheet.

Apart from the sensor sheets, both a hospital bed and mattress were used throughout the process. When required by the predetermined positions, different-sized pillows were used, with dimensions of either 50 cm × 70 cm or 30 cm × 50 cm. A scale was used to measure the weight and a tape measure was used to measure the height of the volunteers.

3.2. Setup

The bed was placed in a room, shown in Figure 4, where only the volunteers and the researchers responsible for data gathering were present. The sheets were placed over and under the mattress as shown in Figure 5 and secured to avoid excessive movement as the volunteers shifted their position as instructed. The sheets were connected to a computer on which the data were recorded.

Figure 4. Data-gathering procedure material and environment.

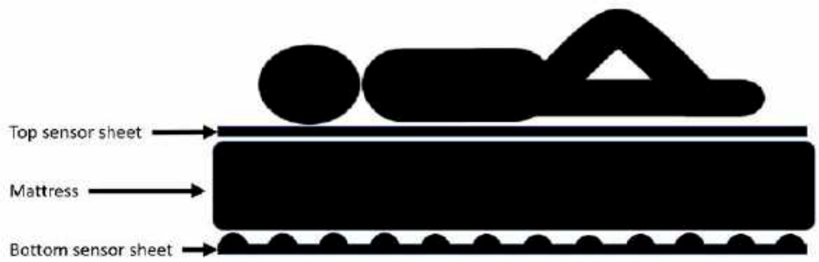


Figure 5. Sensor sheet placement diagram.

To ensure the data were synchronized, a program was developed to collect the data from both sensor sheets at the same time, and they were saved into 10 frames over a short period—only after it has been observed that the volunteer had shifted to the correct position. The program was developed to ensure that the data were gathered at the same instant by using multithreaded programming.

3.3. Experimental Procedure

All volunteers were asked to lie down in the same positions and in the same order to guarantee the dataset was accurate and usable by future researchers, and to ensure these conditions were met, the volunteers were first given a consent form and informed of the actions they would need to perform. Furthermore, they were informed prior to the experiment that they should not be wearing thick clothing, to ensure that the pressure images would not contain any noise related to it.

The following step consisted of the volunteers removing any items from their pockets along with any protruding items of clothing (i.e., belts, bracelets, watches) and removing their shoes. The weights and heights of the volunteers were then taken and registered in the software. After these steps, the volunteers were asked to lie down on the bed and assume the first of the 28 total positions comfortably.

Once they assumed the first position, the researcher in charge of data collection would initiate the data-gathering program and once it was completed the volunteer was then instructed to shift their position slightly twice and wait for the data to be gathered before moving on to the next position. When the position required the usage of pillows, they were given to the volunteers and placed wherever necessary by one of the researchers with healthcare knowledge.

To ensure the validity of the data, all the volunteers went through the exact same process, with the order of the positions being established prior to the data collection procedure.

The body segmentation, which was added after the data gathering was complete, was achieved via manual annotation by a minimum of 2 researchers (maximum 3) to ensure its validity, assisted by a commercially available annotation tool [8]. The annotation process was performed based on a colorized pressure heatmap for each volunteer in each position. These annotations were considered based on analyzing different layers with varying contrasts, to increase the accuracy. The annotation was conducted for a maximum of 6 body zones, along with a background zone (which is not reported), depending on the visibility of the body from the pressure heatmap. The accuracy of the data ground truth relies on the visibility of pressure induced by body elements on the pressure sensor. It was also ensured by the 28 predefined positions in which volunteers were requested to position themselves in specific ways.

4. Limitations

Despite attempting to generate a diverse dataset that would represent all body types, for better algorithmic results when applied to machine learning or similar studies, it should be noted that there are some limitations as to the dataset's range of applications.

The data gathered from both the sensor sheets might not be representative of populations in distinct geographical regions, as the vast majority of the volunteers in this study were local to the country where the study was conducted.

The bottom-layer data are dependent on the mattress used in the data-gathering process; although this procedure used a standard hospital mattress, as described in Section 3.1, mattresses that change in density, for example, will dissipate the pressure differently and will achieve different results.

Regarding the segmentation layer, the amount of data available is limited to one per position instead of thirty different samples.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Ethics Committee of the Polytechnic Institute of Castelo Branco (protocol code 36 CE-IPCB/2021).

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Data Availability Statement: The data presented in this study are openly available in GitHub: https://github.com/rdionisio1403/PoPu/ access on 1 July 2023.

Conflicts of Interest: The authors declare no conflict of interest.

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4. Publication 3: Pressure-Based Posture Classification Methods and Algorithms: A Systematic Review

4.1. Publication Summary

This publication aims to study the state of the art in the field of classification methods used in pressure-based posture classification to aid fellow researchers in the field by analyzing the different studies available in the literature attempting to find patterns that indicate the best usage of pressure data in classification solutions. The study identified 187 unique studies regarding the matter and selected 22 to be included in the review.

A set of research questions were setup to guide the review towards what differences in the initial data resulted in the best classification accuracies, and by answering this question the study concludes that these associations are very difficult since most of the studies use different methods, either considering the actual datasets and the data included in them or how the data is treated prior to model training.

The study also concludes that the seemingly most influential factor when it comes to the accuracy of the classification solutions is the number of positions considered, which comes to no surprise, since it is a common machine learning issue.

There are also indications that the pressure data itself is a determining factor in the outcome of the studies included in the review, but apart from the data quality the number of sensors in the data gathering procedure, which result in a higher resolution pressure matrix might affect the classification results.

4.2. Full Publication

computers

MDPI

Review

Pressure-Based Posture Classification Methods and Algorithms: A Systematic Review

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Abstract: There are many uses for machine learning in everyday life and there is a steady increase in the field of medicine; the use of such technologies facilitates the tiresome work of health professionals by either automating repetitive tasks or making them simpler. Bed-related disorders are a great example where tedious tasks could be facilitated by machine learning algorithms, as suggested by many authors, by providing information on the posture of a particular bedded patient to health professionals. To assess the already existing studies in this field, this study provides a systematic review where the literature is analyzed to find correlations between the various factors involved in the making of such a system and how they perform. The overall findings suggest that there is only a significant relationship between the postures considered for classification and the resulting accuracy, despite some other factors such as the amount of data available providing some differences according to the type of algorithm used, with neural networks needing larger datasets. This study aims to increase awareness in this field and give future researchers information based on previous works' strengths and limitations while giving some suggestions based on the literature review.

Keywords: posture; classification; lying; bedded; pressure; algorithms

check for updates

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1. Introduction

The use of machine learning (ML) techniques in health research is becoming more common nowadays and it has the possibility of alleviating health professionals' busy schedules. A popular use of these techniques made popular recently is posture classification; using different ML techniques, researchers intend to accurately classify a certain patient's lying posture to aid in sleep or other in-bed related conditions. Although there are some studies that show satisfyingly accurate results of such applications, there are some data that seem to relate to the accuracy of these sort of applications. Examples of these altering features are, for example, the dataset used for the training of the ML model chosen by the researchers and the number of postures the algorithm is capable of classifying, among others.

With the purpose of making a more informed study and to better understand which factors might lead to a more accurate classification system, research on the technologies involved in the subject of posture classification was carried out. In this research, the topics found most often were all related to ML, the data used for the training of the ML algorithm, what steps were taken to process that data, and most importantly what method was used and its accuracy.

The data used for posture classification studies usually includes pressure data; these are gathered in a few different ways but mostly with the use of pressure (piezoelectric) sensors. In this case, a matrix of sensors of varied dimensions is placed under a bedded subject and each of the sensors will output the pressure value; these values result in a sort of pressure image which is tagged with the actual posture the subject is in and can then be used in training different ML algorithms.

Despite some studies using these pressure data directly for classification method training, there are some extra pre-processing techniques that can not only improve the accuracy but also the performance of the resulting system. These techniques include centering the pressure image, which increases the similarity between the multiple images available in a dataset; the images can also be further processed by a feature descriptor such as HOG (histogram of oriented gradients). This technique will focus on the shape of an object and yields better results when compared to the use of raw images; it also lowers the computation costs for training and classification.

Probably the most important factor in a classification system is the algorithm performing the actual classification, and these algorithms have evolved even in the subject of posture classification with studies using *k*-nearest neighbors (*k*NN) algorithms all the way to state-of-the-art neural network algorithms. The latter have many variations and show an increase in accuracy when compared to simpler approaches such as *k*NN or naïve Bayes.

This review aims to find any work that uses pressure data for posture classification, regardless of the type of data or the methods found in the reviewed articles. For organizing not only the information obtained from the studies included in this work, but also for better conclusions, the following set of research questions (RQs) was set:

RQ1: What is the number of samples in the dataset used?

RQ2: Is the dataset used available publicly?

RQ3: What data are gathered and used for posture classification?

RQ4: How many postures are gathered in the dataset and how many of them are later used for posture classification?

RQ5: What methods are used in posture classification?

RQ6: What is the accuracy of the proposed methods?

Answering these questions will result in a more informed discussion as their answers are used together to compare how the different approaches affect the outcome of the studies included in this review.

The review was organized according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [1]. This process included identifying the purpose and the intended goals of the review, a literature search, setting the inclusion and exclusion criteria, data extraction and analysis, a discussion and conclusions, and writing of the review.

The remainder of this article is organized as follows. Section 2 describes a search carried out to find related works and presents an analysis of some works that have some similarities with the work presented in this article. Section 3 contains the description and application of the methodology chosen to perform this review, and the search strategy, inclusion and exclusion criteria, and results are presented. Section 4 provides the data extraction and data analysis, and Section 5 presents the discussion. Finally, Section 6 presents the final remarks, the strengths and limitations of this work, and a discussion about challenges and opportunities.

2. Related Works

Research in posture classification, namely using pressure data obtained using pressure sensors under a lying person, has attracted considerable attention in recent years. Currently, numerous studies propose distinct algorithms to approach this problem. This growing interest can be seen in the results obtained in some databases of scientific articles. Despite this, there are no studies that have presented literature reviews on algorithms for lying people's posture classification based on pressure data. As of March 2023, there were 174 articles retrieved from Scopus when the query "(lying OR bed*) AND (posture OR position) AND classification AND pressure" was searched through the following fields: document title, abstract, and keywords. With the same query, 109 articles were retrieved from the Web of Science database. Of these, approximately 52% of them were published in the last 6 years. However, the same research did not result in any work that has carried out a review of the existing literature. In this sense, this work represents a step forward concerning other related works, thus representing a significant contribution to this study area.

Despite not finding an actual literature review on this subject, the works analyzed as this study was conducted included some comparisons between their methods and the ones published before theirs. For example, the authors in [2,3] analyzed multiple studies in some detail to illustrate how the differences in their approach change the accuracy of their results for the better when compared to similar works. In [4–6], the authors found some approaches that resembled the one developed in their work and compared them, highlighting aspects such as a higher number of classes predicted or simply a better result in accuracy. However, these comparisons tend to be biased to the purpose of the specific study as they intend to better in an already existing area instead of making an overall review of the existing literature as this work aims to do.

3. Methodology

This section contains a systematic review of studies/papers that address the use of one or multiple methods for posture classification, namely using pressure data obtained mostly using piezoelectric sensors under a lying person. The review was conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [1]. Thus, the steps implemented for this review, resulting in the indicated sections were as follows:

1. Identifying intended goals for the review (Section 1)
2. Describing how the search was conducted (Section 3.1)
3. Screening for inclusion (Section 3.2)
4. Screening for exclusion (Section 3.3)
5. Analysis (Section 4)
6. Discussion (Section 5)

3.1. Search Strategy

Attempting to find the most results, for this review, there were three databases used, namely Scopus, Web of Science, and PubMed. The search terms were set considering the main goal of this review, and after analyzing the results using different terms, the ones that wielded the best results were chosen, focusing on posture classification carried out on any kind of pressure data. The resulting string for the search was then defined as follows:

(Lying OR bed*) AND (posture OR position) AND classification AND pressure.

Furthermore, the results were filtered to include all work published after 2013 up to 2023.

The search was conducted in March 2023, through the document title and keywords fields, and resulted in a total of 257 studies: 104 from Scopus, 80 from Web of Science, and 73 from PubMed (187 after removing duplicates).

3.2. Screening for Inclusion

The step following the result of the initial search was examining the studies by their title and abstract to filter which of them were to be analyzed further with the purposes of this review in mind or which ones were to be excluded. For this screening, the studies to include were the ones that met the following criteria: (1) studies that presented the use of one or multiple methods for posture classification, (2) studies that focused on bedded or lying subjects, (3) studies that detail the accuracy of the method used, (4) studies that were published in a scientific peer-reviewed publication, and (5) studies that were written in English. All studies that met these criteria were included for further analysis.

After this step, 147 studies were excluded (mostly for their titles containing pressure data that were not relevant to this study such as water pressure), leaving 40 studies.

3.3. Screening for Exclusion

The remaining studies were analyzed to assess whether they could be included in the in-depth analysis. For this step, each article was read to extract the classification methods used, what data they used, and posture-related information. Studies without enough information about the methods or algorithms used or the results of the application of the classification system were excluded. In this step, 18 studies were excluded. Four studies limited their classification to sitting or lying positions, another four used wearable sensors which did not result in pressure data, three of them used blood or lung pressure data, two were repeats of another study already present (the most relevant was kept), two did not contain information regarding the performance of the method applied, one focused on three-dimensional joint estimations, another used recorded images, and the last had no full text available. The resulting list consisted of twenty-two studies.

3.4. Results

The steps taken for the review methodology are represented in Figure 1, which indicates that after the literature search on multiple databases, 187 studies were obtained (after the removal of 70 duplicates), referred to as the 'identification' stage in the diagram; after application of the inclusion criteria identified in Section 3.2. 'Screening for Inclusion' and in the 'screening' section of the diagram, 147 studies were excluded, resulting in 40 studies. A full-text evaluation of the remaining 40 studies was performed, excluding 18 studies that did not meet the required criteria or did not match the focus of this paper; this stage is represented in the figure as 'eligibility'. The remaining 22 studies were the 'included' studies in the flow diagram.

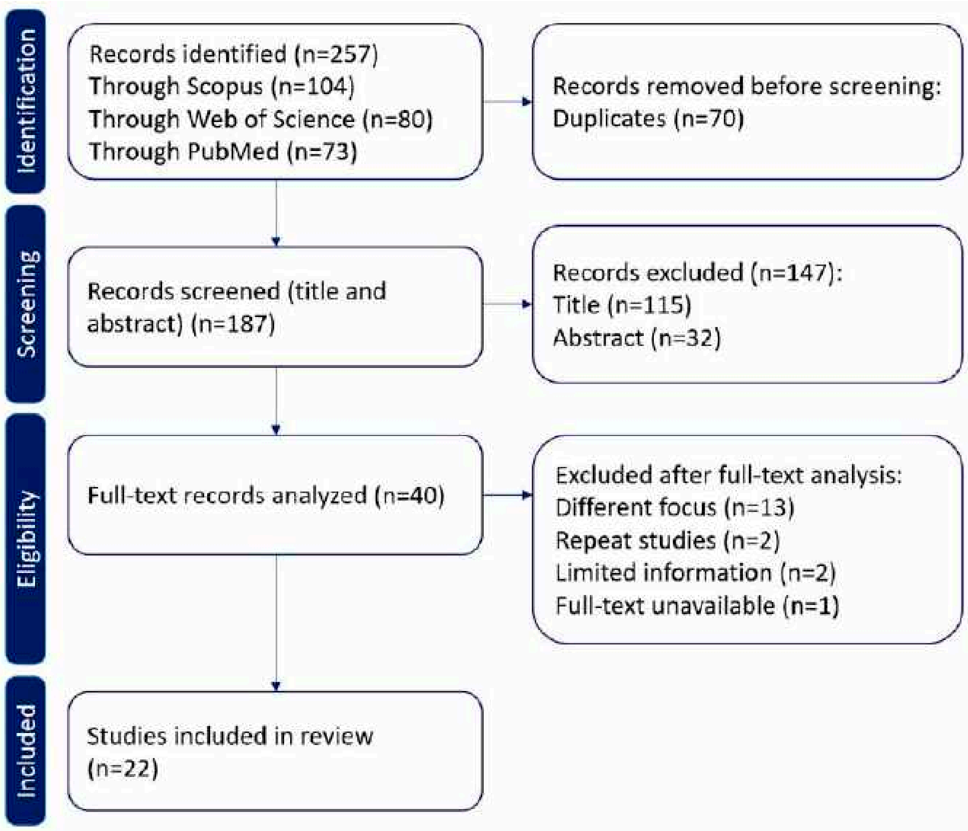

Figure 1. Diagram of the process that determined which papers were selected for this study (adapted from the PRISMA 2020 diagram [1]).

Most of the works selected for inclusion in this review use a dataset that includes a matrix of pressure values usually obtained by piezoelectric sensors; however, two studies were included with different approaches because the resulting classification method was similar to the ones that use pressure data. Although most of the studies examined throughout the screening steps used in-bed pressure data, a few works have high accuracy of different posture classifications with only a section of body pressure data and were also included.

3.5. Characteristics of the Included Studies

The studies chosen to be included in this review were published between 2013 and 2023. Although this was something that could be known from the initial query which limits the search to this range, it is still surprising that the studies that were included are distributed among the 10-year range.

The distribution portrayed in Figure 2 does, however, display an increase in the later years, with 50% of the studies having been published between 2021 and 2023.

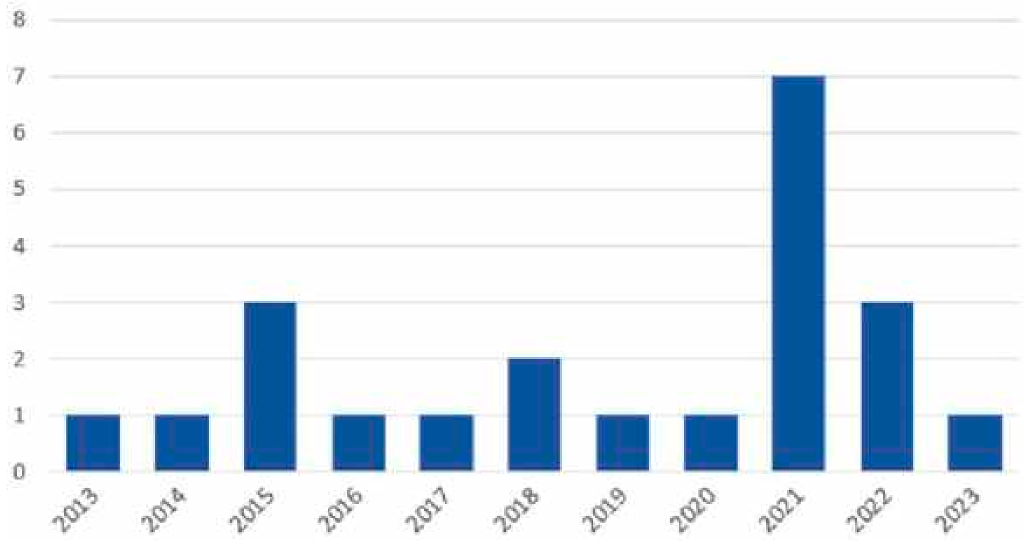

Figure 2. Publication date distribution for the studies included.

4. Analysis of the Included Studies

For easier analysis of multiple different studies, the most frequently found topics were found and withdrawn from the studies along with the information originally required to answer the research questions. These were then organized into a table including all the works selected for analysis. Each row represents one of the studies. The size column refers to the number of samples available in the dataset the authors used for their work; if this dataset is a publicly available one, the name of the dataset will also be included in the table cell. The data collected column has which data are included in said datasets. The poses available/used column displays how many postures the dataset originally has available followed by how many the researchers decided to use. The remaining columns refer to methods used either for pre-processing the data or actual classification and finally the accuracy of the developed system. Table 1 summarizes the data extracted from the selected articles.

Table 1. Synthetic analysis of the selected studies.

Ref.	Size	Data Collected	Poses Available/Used	Pre-Processing	Methods/Algorithms	Accuracy
[4]	26,000 PmatData	32 × 64 pressure matrix Age Weight Height	17/3 and 17	Median Filter Histogram Equalization	Spiking neural networks	99.99% (3 postures) 92.4% (17 postures)
[7]	1440	1600 pressure array	6/6	N/A	Decision tree Naïve Bayes Support vector machine (SVM) *k*NN	84.5% to 96.8%
[2]	3005	32 × 32 pressure matrix Age Weight Height	5/5	Histogram of oriented gradients (HOG)	SVM Convolutional neural network (CNN)	84.8% to 91.24%
[8]	2520	8 × 8 pressure matrix Sex Weight	3/3	N/A	CNN	95.2% to 99.56%
[9]	270	34 × 52 pressure matrix Age	9/9	Center alignment	SVM Naïve Bayes Neural network Random forest	77.1% (highest)
[10]	189	50 × 80 pressure matrix Age	6/6	Feature extraction (not described)	SVM CNN	80% 70%
[11]	2004	16 × 14 pressure matrix	4/4	HOG	SVM	99.01%
[3]	1116	64 × 27 pressure matrix Sex Age Weight Height	4/4	HOG Local binary patterns	Feed-forward artificial neural network (FFANN)	87.9%
[12]	26,000 PmatData	32 × 64 pressure matrix Age Weight Height	17/9	Principal component analysis	*k*NN Naïve bayes FFANN	94.9% 98.5% 99.6%
[5]	N/A	32 × 64 pressure matrix	8/8	Gaussian lowpass filter Binary filter	*k*NN	97.1%
[13]	448	80 × 40 pressure matrix Sex Age BMI	3/3 4/4	N/A	Deep neural network	99.7% 97.1%

Table 1. *Cont.*

Ref.	Size	Data Collected	Poses Available/Used	Pre-Processing	Methods/Algorithms	Accuracy
[14]	1051	32 × 32 pressure matrix Sex Age Weight Height	4/4	N/A	Deep neural network (ResNet-18)	95.08%
[15]	2004	32 × 16 pressure matrix Weight	4/4	Bilinear interpolation HOG Scale-Invariant Feature Transform	SVM	99.7%
[16]	N/A	64 × 27 pressure matrix Sex Age	13/3	Binary image extraction Center alignment	*k*NN	98.4%
[17]	736	30 × 11 pressure matrix Weight Height	4/4	N/A	Sparse representation	91.4%
[18]	N/A	32 × 64 pressure matrix	5/5	Median filter	Deep neural network with autoencoders	98.1%
[19]	26,000 PmatData	32 × 64 pressure matrix Age Weight Height	17/3	Reconfiguration of pressure maps into video files	Deep neural network (ResNet-18)	99.8%
[20]	26,000 PmatData	32 × 64 pressure matrix Age Weight Height	17/17	Median filter	Spiking neural network	90.56% to 99.9%
[6]	480	8 × 18 RFID matrix Sex Weight Height	8/8	HOG	Decision tree	96.14%
[21]	26,000 PmatData	32 × 64 pressure matrix Age Weight Height	17/5	No description	*k*NN	98.7%
[22]	26,000 PmatData	32 × 64 pressure matrix Age Weight Height	17/4	N/A	Quantized fully convoluted neural network	96.77%
[23]	2076	13 × 15 pressure matrix Breathing data	4/4	No description	Artificial neural network	89.9%

5. Discussion

With the analysis of the included studies concluded, the discussion will aim to relate the information found in the studies and all the factors involved in the classification methods proposed with their results. As with the analysis, this discussion will be organized according to the initial set of research questions, with each question having the possibility of affecting the outcome of the approaches in the studies included.

Regarding the amount of data used in each study and if they were obtained from a publicly available dataset (RQ1 and RQ2), six (27.3%) of the studies included using a publicly available dataset, namely PmatData [24] which includes the most (26,000) samples out of all the analyzed studies; the rest have their own data gathered with varying sample sizes (189–3005). The first noticeable difference is in the number of samples included in the studies' data. For algorithm training purposes, smaller datasets might lead to undertrained algorithms which will eventually lead to worse classification accuracy; the overall analysis of the work included in this review shows that the studies with smaller datasets have lower classification accuracy. However, the included studies do not always seem to have their results influenced by this matter. For example, the studies in [14,19] are similar in their method despite differences namely in the preprocessing stage and regarding the number of postures considered for classification; both show high accuracy (95.08% and 99.8%, respectively), with the first having a significantly smaller dataset to work on. This shows that the quality of the data has more influence on the classifier than the actual size of the dataset, as both datasets in these studies have about the same approach to the data gathering procedure, with [19] using the PmatData dataset. The fact that smaller data do not always lead to worse results has been studied in detail in [25], which displays the usage of different classification methods in the field of medical research on different-sized datasets and concludes that the performance of classifiers depends on how well the data represent the distribution and not on the amount of data available.

The quality of the dataset is dependent on what data are chosen to be included in it (RQ3), and with the focus of this review being pressure-related posture classification, all of the works include some kind of pressure image, with most using a matrix of pressure values acquired from piezoelectric sensors. The factors that might change the quality of the data are the dimension of the pressure image and what other information is gathered for each sample. Fourteen of the twenty-two (63.6%) studies have either the weight, the weight and height, or the body mass index (BMI) of the individual included in their data samples, but the accuracy does not seem to be directly influenced by the presence of body measurements as the studies that do not include any do not display a worse performance. This could be further explained by the possibility of the classifiers being able to predict these measurements, as the authors in [26] show by predicting the weight of a person using pressure maps as the input. Other characteristics such as age and sex are also gathered in some of the studies, but they do not seem to affect the outcome, and there is no seeming relationship noted between the dimension of the pressure maps and the accuracy either. This most likely indicates that the most important factor in pressure-related classification methods is the quality of the pressure data since all the studies using the public dataset have good classifier performance, and the ones that do not, vary in their results, even with some having higher resolution pressure images. This might be caused by excessive noise or misaligned data.

The postures considered for classification (RQ4) seem to be the factor most affecting the results in the studies, with some studies going to the extent of creating two different classifiers, with one considering a smaller number of postures, as in [4] where the authors end up with a significantly lower accuracy of 92.4% when 17 postures are considered compared to 99.99% accuracy based on only 3 postures. This fact might be related to the postures, as the postures considered usually include the four main postures found in most of the literature, and any posture beyond those is a variation of these, which are very similar postures that might be misclassified because of their similarity. However, the most probable reason is the number of classes, as with most classifiers, the higher the number of classes the lower the accuracy of the classifier. This seems to have an influence on the studies as some have a low number of postures considered for classification despite having more postures available in the dataset used. However, the better classification rate might not be worth the risk of misclassification of postures on clinical usage, especially for research carried out in the medical field.

As this study looks for classification methods, the method or algorithm used in the actual classification (RQ5) is one of the most important aspects of the research if not the most important, but there are also methods included in some of the studies that are used to preprocess the pressure images mostly for two different reasons: reducing the computational cost of the resulting classification algorithm or improving its accuracy. The usage of preprocessing techniques such as HOG was, according to the authors in [2,6,11], an important factor in improving the accuracy of their classifier and was proven to do so by comparing their approach to similar ones.

Regarding the actual classifier, researchers in the studies included point out that the usage of neural networks has increased over time while other algorithms such as *k*NN, despite still being used, are mostly included for comparison; this is because, in the field of classification methods, neural networks have shown better performance. The dates on the publications depict that 9 of the 11 (81.8%) studies published between 2021 and 2023 use neural networks for their classifier while only 5 out of 11 (45.5%) used neural networks from 2013 to 2021. The research for this study shows that, for the most part, only neural network implementations reach a high of 99% accuracy, with the only exception being the work in [15] which uses SVM. It is also interesting that the lowest accuracy found [10] used a neural network for their classifier; however, the cause of the low accuracy can be related to the small dataset, as neural networks tend to have better results with a higher number of training samples.

As every different factor was assessed as to its influence in the resulting accuracy of the classification methods (RQ6), the data to answer this research question were used to relate to the other questions and to understand how they might affect the outcome of the included studies. Furthermore, there could be an analysis of the accuracies for all of the studies, but as they range from 70% to 99.99%, although the majority tend to land in the 90–100% range, there is not a definitive conclusion regarding the accuracy without comparing it to the other factors involved.

6. Final Remarks

This systematic review aimed to find various methods for pressure-based posture classification, and by following the steps suggested by the PRISMA methodology, the studies found more appropriate for this purpose were selected and reviewed in full to gather information and compare how the various factors involved in the development of such methods influence their results.

By conducting the search in three different databases (Scopus, Web of Science, and PubMed), a total of 187 distinct studies were obtained, which resulted in 22 included studies after applying different inclusion and exclusion criteria and full-text analysis when necessary. Despite the conclusions drawn from this review, the limited number of studies in this field does not allow for more definitive conclusions, and with only a few examples of each method available in the literature, the discussion findings in this review should still help future research in the field.

After the paper analysis and cross-referencing of the various factors involved in the studies included in this review, a few observations were taken for discussion and future reference. Regarding the data, the relationship between dataset size and accuracy does not appear relevant for most applications, and the need for additional data other than pressure maps does not seem to affect the outcome of the classifiers by much either. Furthermore, the datasets used by the researchers are not always similar, a more standardized data-gathering method should be considered, for example, by including the four main postures found in the medical literature and by treating the rest of the postures as variations of the four initial postures.

The usage of preprocessing techniques should be considered as it is suggested to improve the computation requirements of the resulting classifier and in some cases to improve its accuracy; this relates to the importance of the pressure data as the preprocessing techniques focus on improving the pressure maps.

The factor that seems to influence the classification methods' accuracies the most is the number of postures considered for classification, and it has been noted by several researchers that it can also be easily explained as a machine learning issue: the more classes, the harder the classification. The studies have satisfying results even with a very low dataset size due to the reduction in the number of postures, with some studies even considering two of the postures mostly found in the medical literature (supine and prone) as one.

As machine learning evolves towards the use of neural networks, with deep neural networks being preferred, the sample number will be more important as deep neural networks tend to need more data to reach satisfying accuracy. The need for larger datasets will, however, address some of the issues described in the discussion, such as the posture numbers being a relevant factor for lower accuracy, as more data will allow researchers to use deeper neural networks and reach satisfying accuracy with a higher number of postures. The existence of more data would also lead to better comparison in the field, as most studies seem to attempt their use own data-gathering methods. If this was not the case and every study used the same amount of data or even the same dataset, comparing the results of their work would be far easier and more assertive conclusions could be taken.

Furthermore, as the pressure data were observed to be a determining factor in the outcome of the studies but the fact that it is not clear how pressure map dimensions affect them, it would be interesting to assess how the dimension would affect the resulting accuracy of the implemented methods. This way, a minimum optimal resolution could be found to lower not only the costs of the hardware (fewer sensors) but also the computational requirements for the classifiers.

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5. Publication 4: Effects of the Number of Classes and Pressure Map Resolution on Fine-Grained In-Bed Posture Classification

5.1. Publication Summary

This publication presents in-bed posture classification experiments using the PoPu dataset presented in the publication in chapter 3 and various state-of-the-art algorithms. The experiments aim to not only analyze if the usage of the PoPu dataset during model training yields positive results but also to test how the results are influenced by changing the data in the following ways:

1. Using the data as is considering only the 4 main postures and the total of 28 postures.
2. Evaluate if the higher granularity classification accuracy can be improved by classifying the main posture beforehand.
3. Assessing how the additional participant characteristics influence the classification accuracy.
4. Reducing the pressure map resolution by steps to evaluate how a higher number of sensors influences the classification outcome.

Through these experiments, the study concludes that the PoPu dataset can achieve a high accuracy of around 99% when used in lower granularity classification (4 postures) but a much lower accuracy of 68% when using every posture available in the dataset.

There were no significant changes observed in the experiment that evaluates if classifying the main position beforehand influences the classification accuracy of the high-grained classification, nor for the experiments regarding the additional participant characteristics.

The resolution reduction experiment however did produce some interesting results as the initial pressure map with a 64x27 resolution was reduced to 16x7 and the accuracy remained quite high, up to 95% and when reduced even further to 8x4 there were still accuracies in two of the used algorithms above 80%.

5.2. Full Publication

computation

Article

Effects of the Number of Classes and Pressure Map Resolution on Fine-Grained In-Bed Posture Classification

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Abstract: In-bed posture classification has attracted considerable research interest and has significant potential to enhance healthcare applications. Recent works generally use approaches based on pressure maps, machine learning algorithms and focused mainly on finding solutions to obtain high accuracy in posture classification. Typically, these solutions use different datasets with varying numbers of sensors and classify the four main postures (supine, prone, left-facing, and right-facing) or, in some cases, include some variants of those main postures. Following this, this article has three main objectives: fine-grained detection of postures of bedridden people, identifying a large number of postures, including small variations—consideration of 28 different postures will help to better identify the actual position of the bedridden person with a higher accuracy. The number of different postures in this approach is considerably higher than the of those used in any other related work; analyze the impact of pressure map resolution on the posture classification accuracy, which has also not been addressed in other studies; and use the PoPu dataset, a dataset that includes pressure maps from 60 participants and 28 different postures. The dataset was analyzed using five distinct ML algorithms (k-nearest neighbors, linear support vector machines, decision tree, random forest, and multi-layer perceptron). This study's findings show that the used algorithms achieve high accuracy in 4-posture classification (up to 99% in the case of MLP) using the PoPu dataset, with lower accuracies when attempting the finer-grained 28-posture classification approach (up to 68% in the case of random forest). The results indicate that using ML algorithms for finer-grained applications is possible to specify the patient's exact position to some degree since the parent posture is still accurately classified. Furthermore, reducing the resolution of the pressure maps seems to affect the classifiers only slightly, which suggests that for applications that do not need finer-granularity, a lower resolution might suffice.

Keywords: in-bed posture; posture classification; posture recognition; pressure map dataset

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1. Introduction

Over the last few years, several approaches to classifying postures in bedridden people have been proposed. Some of them are based on the use of pressure maps obtained through some type of sensor, normally positioned over the mattress, and the use of machine learning (ML) algorithms. These approaches are not very intrusive and allow classifying the in-bed person's postures with high levels of accuracy—usually above 90% going up to more than 99% in some studies—when only the four main postures (supine, prone, left facing, and right facing) or fewer postures are considered (e.g., [1–4]). A systematic review on methods for pressure-based posture classification [5], carried out in 2023, identified and analyzed 22 studies that followed this approach. The studies included in the review, despite being generally similar in the sense that they use pressure maps and ML algorithms, also present significant differences: they are based on datasets with different characteristics, they use different ML algorithms, and they often have different objectives in terms of type and number of postures they intend to classify. Additionally, existing studies mainly focus on searching for solutions to obtain better accuracy values in posture classification. However, there are some issues that need to be investigated in more detail. It is important to evaluate the accuracy of the algorithms in classifying a higher number of postures (in addition to the four main postures normally used) and to evaluate whether it is possible to classify them with high levels of accuracy. This will allow us to evaluate the use of these approaches in broader and more reliable healthcare applications. For example, in the case of applications for monitoring pressure ulcers, this will allow more precise monitoring of the body parts in contact with the mattress and identify the need for any action to be taken before further damage is done to the afflicted areas (e.g., shifting the patient's position). Furthermore, it is also important to evaluate to what extent the number of sensors in the pressure map (i.e., the sensor array resolution) affects classification accuracy, which may help to decide the best resolution of the sensor array to use, considering the purpose for which it will be used.

Thus, the main objectives of this work are as follows:

- Analyze and validate the use of ML algorithms in the classification of a large number of bedridden people postures, which will help to identify the real position of the bedridden person with high accuracy. Although these algorithms have already been used for posture classification with good results, their application to as many as 28 postures had not yet been evaluated.
- Analyze the impact of pressure map resolution on the accuracy of ML algorithms in classifying bedridden people postures. There are different studies conducted using varying amounts of sensors, but comparing the results of the different algorithms on the same dataset will allow for a better understanding of how the accuracy is affected by the number of sensors and demonstrate that a solution considering fewer sensors, which is not only cheaper but also computationally lighter, is a viable solution.
- Use the PoPu dataset [6], one of the datasets that presents a greater number of different postures and a greater number of samples obtained from real people. To the best of our knowledge, this is the first time the dataset has been used in a posture classification study.

2. Related Work

Recently, several studies have been carried out using pressure maps to detect and classify postures in bedridden people (e.g., [1,2,4,7–9]). In a systematic review with 22 studies on pressure-based posture classification methods and algorithms [5], published in 2023, several issues related to the characteristics of the datasets used were analyzed, the number of postures and the methods used in posture classification. It was concluded that most of the studies address the use of one or multiple methods for posture classification, namely using pressure data obtained mostly using piezoelectric sensors under a lying-down person. It was also found that most studies usually include the four main postures (supine, prone, facing left, and facing right) but there are some studies that considered a smaller number of postures (e.g., [1,2,4] three postures considered), obtaining an accuracy greater than 99%, and some studies with a higher number of postures, with a significantly lower accuracy of 92.4% when 17 postures are considered (e.g., [1]).

It is important to consider that the different values of accuracy presented in the studies were obtained under different conditions. The methods/algorithms used in addition to the datasets used are quite different, which makes it difficult to compare the results. Regarding methods/algorithms, there has been a growing use of neural networks. As far as datasets are concerned, the differences are very significant. Generally, datasets include some type of pressure image, with most using a matrix of pressure values, but the dimension of the pressure image differs considerably. Additionally, some datasets include additional information such as weight, height, or the body mass index of participants in their data samples. In fact, existing studies have mainly focused on evaluating the accuracy of proposed solutions for posture detection but the conditions under which studies are carried out differ greatly. The number of postures considered is often reduced and it is important to evaluate approaches that allow classifying a higher number of postures, which will increase the accuracy of identifying the actual position of the bedridden person and thus increase their potential interest in other applications. Furthermore, it has not been studied how the dimension of the pressure image would affect the resulting accuracy of the implemented methods.

3. Dataset Description

Bedded or lying-down people's pressure map datasets are increasingly being used to identify patients' in-bed postures and can be very useful for enhancing the development of numerous healthcare applications. To be an enabler of new healthcare solutions, the information they provide must be acquired through non-intrusive methods and must allow the rigorous identification of the bedded or lying-down people's postures. Although there are some publicly available datasets, they usually differ in the characteristics of the sensor array used to obtain the pressure map, the information they collect, and the size of the dataset. A systematic review of lying-down people's pressure-map datasets [10], published in 2023, identified and characterized nine datasets with pressure map data on lying-down people's or bedded people's positions. The datasets included in the review varied in size, with five having fewer than 2600 ([2,11–14]) and the other four ([15–18]) datasets having 15,000 or more samples. Six datasets ([2,11–15]) considered a smaller number of poses, up to eight, mostly represented by the four main lying postures. One work ([16]) included 15 postures; another ([18]) included 20. One study ([17]) that used computer-generated data considered 99 different poses. The resolutions of the sensor matrix ranged from 64 sensors displayed in an 8×8 resolution to 2048 sensors in a 64×32 resolution. Some significant differences between the datasets are related to the resolution of the pressure maps, differences in the postures chosen for the datasets, and the small number of participants in some datasets.

Considering these issues, in this study, a dataset of our authorship was used, the PoPu [6] dataset. The PoPu dataset contains simultaneously collected data from two different sensor sheets, one placed over and one placed under a mattress. In this case, only data from the sheet placed over the mattress sensor were used. The sensor sheet used was a commercially available 180 cm × 78 cm Tactilus [19] with 1728 piezoelectric sensors distributed in a 27×64 matrix. The dataset includes data from 60 individuals, namely sex, weight, height, and pressure maps corresponding to 28 different positions (as presented in Table 1), with 7 variations for each of the 4 main positions that are found in most of the literature (supine, prone, facing left, and facing right). For each of the main positions, two variations also include pillow placement. For each variation, 30 data samples representing small variations were acquired. This resulted in a dataset with 50,400 pressure data samples distributed evenly, with 1800 samples for each of the 28 positions. The high number of positions considered and the number of samples are some of the reasons that supported the choice of this dataset, as it will allow a more precise identification of the position of the bedridden person. The dataset also accounts for good distribution regarding the weight, height, and sex parameters, which should be valuable assets not only for the present study but also for any future applications, especially using real-time data. Additionally, to the best of our knowledge, this will be the first study that will use this dataset, which should serve as an important contribution to its validation.

Table 1. Different positions and variations considered (previously published in [6]).

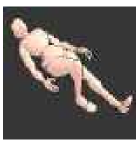
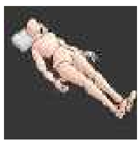
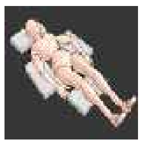
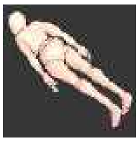
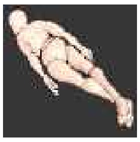
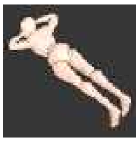
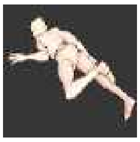
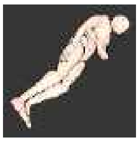
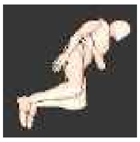
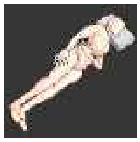
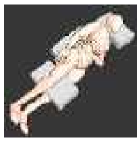
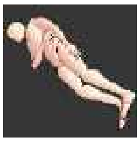
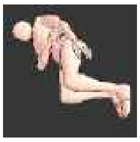
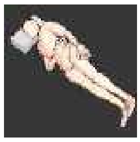
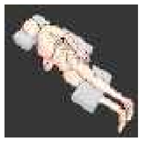
Posture Variations	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Supine							

Table 1. *Cont.*

Posture Variations	1	2	3	4	5	6	7
Prone							
Facing left							
Facing right							

4. Methodology

This section is divided into 2 subsections. The first subsection explores the different algorithms used in the literature and the ones selected for this study. The second subsection contains the information regarding the various experiments done for this study along with their results. The experiments and results (second) subsection is further split into different subsections representing the different experiments.

4.1. Algorithms

As recently published in [5], there have been several works that use artificial intelligence algorithms to detect patients' in-bed postures based on data collected from pressure sensors. This source of information varies in terms of the number of sensors that can range from 8 x 8 matrices to arrays of 1600 pressure sensors and considering variants of different postures of people in bed (4 to 17 different poses). The number of different identifiable postures also varies from approach to approach, ranging from the detection of just 3 poses to 17. To process this data and carry out the detection based on the collected datasets, several algorithms have also been used. Out of these, some stand out for their popularity and the accuracy they tend to achieve, such as k-nearest neighbors (k-NN), linear support vector machine (SVM), decision tree, random forest, or neural network. In the study published in [5], the relationship between collected pressure data (datasets), the algorithm or processing methods used, and the corresponding accuracy achieved was presented for several approaches published in the last decade. Of the different approaches, the use of neural networks has clearly increased in recent years and has achieved results with greater accuracy (99%). Although they can also achieve good results, other approaches, such as k-NN, are used for comparison purposes.

This work follows an approach in which five of the most commonly used algorithms in the field of posture classification ("Nearest Neighbors", "Linear SVM", "Decision Tree", "Random Forest", "Neural Network Multilayer Perceptron" (MLP)) are used on various combinations (number of poses (4 and 28) and resolutions (x to y)) of a dataset to analyze the accuracy achieved for different resolution scenarios of the input data and higher number of detectable postures.

4.2. Experiments and Results

This section contains the tests performed on the data in obtaining the most accurate models using the selected algorithms while keeping in mind that the number of data available could result in overfit models. The section is split into four subsections; the first contains the initial experiments using the selected algorithms and all the available data in two different scenarios—one with 4 classes and the other with 28 classes. The second subsection intends to further validate the results from the primary experiments as to demonstrate their validity, not only increasing the number of folds in the cross-fold validation experiments but also using the leave one subject out (LOSO) approach. The third subsection contains the experiment performed to the high granularity classifier, where the main position is given to test whether it will influence the resulting accuracy. The fourth subsection is relative to experimenting with the outcome of using the dataset to train new models using only the pressure data, this means that for this experiment, the additional characteristics (sex, weight, and height) were not used as input parameters. The fifth subsection contains the experimentation and results of lowering the resolution of the pressure data to assess the effectiveness of the resulting models.

For every experiment the library scikit-learn was used, not only for model training but also obtaining the metrics included in the experiments. Furthermore, to facilitate reproducibility of these experiments, the hyperparameters set for each of the selected algorithms were:

k-NN: k = 3;
SVC: kernel = linear, C = 0.025;
Decision tree: max_depth = 30;
Random forest: max_depth = 30;
Multilayer perceptron: alpha = 0.001, max_iterations = 1000

The calculated classification metrics include the model's accuracy, precision, recall score and F1 score. These are the most commonly used classification metrics, along with confusion matrices, that will also be included in some examples. Accuracy portrays how accurate the model is by comparing the accurate classification to the total number of predictions, and it was the metric used most when discussing the experimental results. The rest of the metrics used are averaged on account of the multiple postures considered for classification. Precision is the ratio of true positives compared to the number of total positives predicted. Recall is the ratio of true positives compared to the total positives in ground truth. The F1 score metric is the harmonic mean of the precision and recall scores.

4.2.1. Initial Experiments

Using the dataset and selected algorithms, the following steps include testing the effectiveness of the algorithms on said data. This will show how useful the dataset would be for posture classification. For this purpose, and following the methods used by other researchers, the dataset was first tested considering only the 4 main postures (supine, prone, left and right facing) and then using the 28 postures available in the dataset.

The data included in the dataset was modified to function with the proposed algorithms, namely by converting the parameter identifying the sex of the participants into binary values. Furthermore, the values in the pressure map were normalized previous to model training. This means the input data used for the experiments (unless mentioned otherwise) were:

Normalized (0–1) pressure values;
Participant sex;
Participant weight;
Participant height.

Since the dataset includes plenty of sample frames, the data were split 60/20/20 for all the following steps (60% of the data were used for training each of the models, 20% for testing, and 20% for validating the resulting models). The split was made so that none of the samples in the training split contained data from samples from volunteers that are found in the other splits. For validation purposes, the models go through k-fold cross-validation (k = 5), and the results presented in this section include the averages of the accuracy results from the cross validation. This means that for each algorithm, there will be 5 different models trained, each with different data splits.

The tables regarding the results of testing the different models will all follow the same format, with the average accuracy percentage, standard deviation for the accuracy, the average precision, average recall, and average F1 score. These values are gathered from applying k-fold cross validation to the model and correspond to the validation of the models.

First, the results for the models trained with only the 4 main postures considered are represented in Table 2.

Table 2. Results of 5-fold cross-validation with 4 classes.

Algorithm	*k*-NN	Linear SVM	Decision Tree	Random Forest	MLP
Average Accuracy %	92.11%	91.31%	80.07%	95.32%	95.60%
Standard Deviation	0.0071	0.0259	0.0331	0.0179	0.0196
Average Precision	0.9211	0.9131	0.8007	0.9532	0.9560
Average Recall	0.9211	0.9131	0.8007	0.9532	0.9560
Average F1 score	0.9211	0.9131	0.8007	0.9532	0.9560

It is worth noting that the highest accuracy registered for any of the models trained in this experiment was one of the MLP models, with a 98.40% validation accuracy. This is also the highest accuracy out of all of the experiments.

Apart from these results and to better illustrate the outcome of the models, as most have a high accuracy, the confusion matrix (code generated) for one of the algorithms—namely MLP—is displayed in Figure 1, in which each row represents the expected result and each column represents the predicted result for each position. For generating this and following confusion matrices, a model was trained simultaneously, using the same split of 60/20/20, and the values are from the validation of said model.

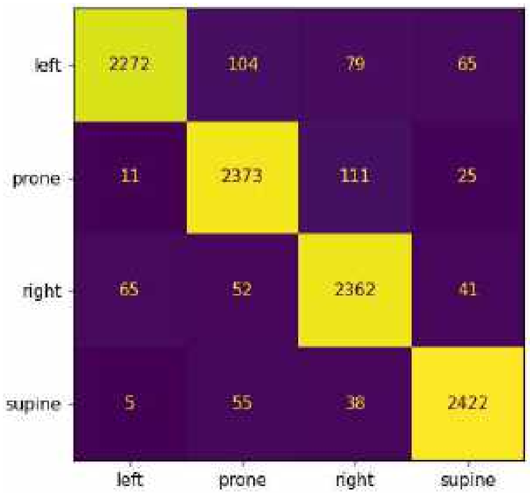


Figure 1. Confusion matrix of MLP classification with 4 classes.

As portrayed by Figure 1, there are not many incorrect classifications and there does not seem to be a pattern to the ones that are wrongfully classified.

After this, the next step was training different models, using the same algorithms, but considering all 28 postures available in the dataset. The results for this approach are represented in Table 3.

Table 3. Results of 5-fold cross-validation with 28 classes.

Algorithm	*k*-NN	Linear SVM	Decision Tree	Random Forest	MLP
Average Accuracy %	43.87%	58.40%	35.66%	63.58%	59.50%
Standard Deviation	0.0173	0.0245	0.0243	0.0240	0.0278
Average Precision	0.4387	0.5840	0.3566	0.6358	0.5950
Average Recall	0.4387	0.5840	0.3566	0.6358	0.5950
Average F1-score	0.4387	0.5840	0.3566	0.6358	0.5950

Unlike the 4-posture alternative, the results with 28 postures are quite lower as to their accuracy, with the highest average accuracy being around 64% and the highest model having a validation accuracy of 67.81% (random forest). Figure 2 shows the confusion matrix for the model resulting from the MLP algorithm. As the previous confusion matrix, the rows represent the expected result and the columns represent the result predicted by the model. Furthermore, the classes are represented in the same order (left, prone, right, supine), with 7 rows and columns representing the 7 variations for the main poisitions.

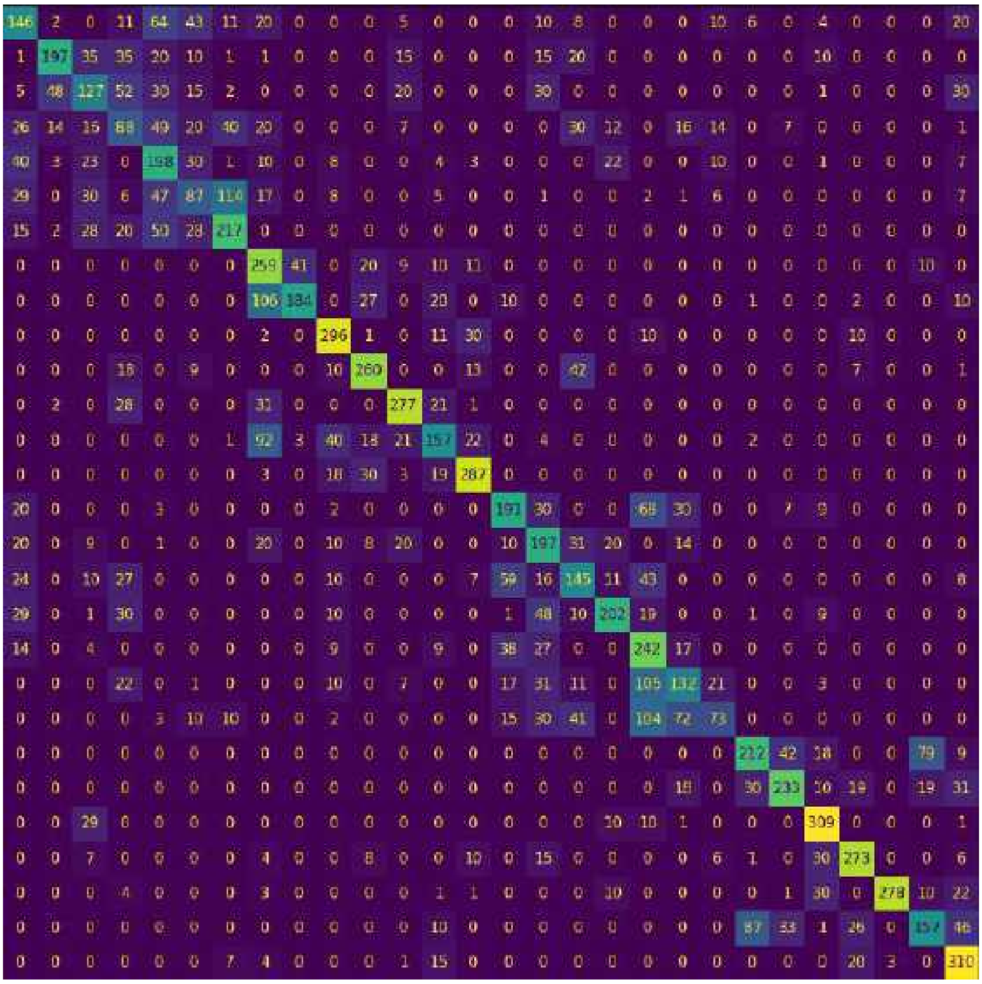


Figure 2. Confusion matrix of MLP classification with 28 classes.

The 28 posture experiment shows that even with a lower accuracy, most classifications are correct, and by observing the wrongfully predicted classes, there seems to be a pattern that indicates that even if the granularity of the postures is higher, the model mostly predicts classes that are of the same main class, as they are mostly encompassed inside the 7 variations.

4.2.2. Further Validation

To validate the results from the initial experiments further, additional experiments were conducted regarding the 4-posture classification experiments, namely increasing the number of folds in the cross validation to 10 and an additional experiment using the LOSO approach.

Since the highest average accuracy for 5-fold cross validation was attained using the MLP algorithm, the following experiments will also be using this algorithm.

Using 10-fold cross-validation, the results did not significantly change, as the average accuracy remained at around 96%.

The graph displayed in Figure 3 contains the validation accuracy for the 10-fold cross validation, with a lowest accuracy of 89.5% and a highest of 99.02%, which is a better result than any of those registered in the 5-fold cross validation. Furthermore, the metrics used in the other experiments are the following:

Average accuracy (%): 95.96%
Standard deviation: 0.0356
Average precision: 0.9596
Average recall: 0.9596
Average F1-score: 0.9596

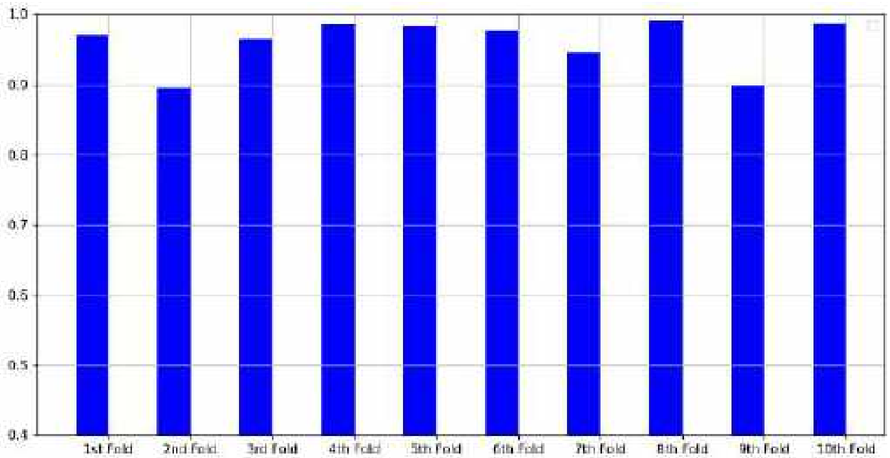


Figure 3. Tenfold cross validation accuracy results.

For the LOSO experiments, the models were trained using every sample except for the samples of one of the subjects, which was used for validation. This means that there were 60 different runs where a model was trained and validated as the dataset contains samples for 60 different volunteers.

For this experiment, the results are as follows:

Average accuracy (%): 96.25%
Standard deviation: 0.0741
Average precision: 0.9633
Average recall: 0.9625
Average F1-score: 0.9603

The results from this experiment further demonstrate that the resulting models will have a relatively high accuracy for most subjects. Although there were models with near-100% accuracy, there are some results from the LOSO experiment for which the accuracy is significantly lower, which explains the high standard deviation of the resulting accuracies. The individual results from this experiment will not be considered as the highest results, as they are heavily biased.

4.2.3. Pre-Calculated Main Posture Experiment

After observing the results from the previous section, an experiment was conceived which consists of using the outcome of the low granularity classifiers (which have high accuracy) as an input for the finer grained classificators. As such, for this experiment, the main posture is given as an input to the algorithms to assess how this influences the accuracy of the classifiers.

The results of these experiments are displayed in Table 4 like the rest of the experiments.

Table 4. Results of 5-fold cross-validation with 28 classes having the main posture as an additional input.

Algorithm	*k*-NN	Linear SVM	Decision Tree	Random Forest	MLP
Average Accuracy %	43.95%	58.84%	46.64%	64.10%	59.60%
Standard Deviation	0.0174	0.0260	0.0265	0.0178	0.0266
Average Precision	0.4395	0.5884	0.4664	0.6410	0.5960
Average Recall	0.4395	0.5884	0.4664	0.6410	0.5960
Average F1-score	0.4395	0.5884	0.4664	0.6410	0.5960

This experiment did not change the accuracy of the algorithms considerably, making only a significant difference in the decision tree algorithm, which improved its accuracy by 11%, but it still does not reach the 50% mark. The extra step of pre-classifying the main posture for finer granularity is found to not be relevant to the classifiers with finer granularity.

4.2.4. Pressure Only Experiment

The PoPu dataset includes not only pressure data but also participant characteristics, including sex, weight, and height. To test how this additional data influences the accuracy of the different algorithms, another batch of testing was conducted without including the additional parameters as input for the algorithms, and the same data are displayed in two tables—Table 5 with the results of the algorithms considering only 4 postures and Table 6 considering 28 postures—formatted like the tables in the previous experiments.

Table 5. Results of 5-fold cross-validation with 4 classes using pressure data only.

Algorithm	*k*-NN	Linear SVM	Decision Tree	Random Forest	MLP
Average Accuracy %	92.07%	91.25%	80.05%	95.37%	95.24%
Standard Deviation	0.0073	0.0258	0.0298	0.0156	0.0218
Average Precision	0.9207	0.9125	0.8005	0.9537	0.9524
Average Recall	0.9207	0.9125	0.8005	0.9537	0.9524
Average F1-score	0.9207	0.9125	0.8005	0.9537	0.9524

Table 6. Results of 5-fold cross-validation with 28 classes using pressure data only.

Algorithm	*k*-NN	Linear SVM	Decision Tree	Random Forest	MLP
Average Accuracy %	43.80%	58.25%	35.75%	63.06%	59.10%
Standard Deviation	0.0175	0.0240	0.0314	0.0304	0.0244
Average Precision	0.4380	0.5825	0.3575	0.6306	0.5910
Average Recall	0.4380	0.5825	0.3575	0.6306	0.5910
Average F1-score	0.4380	0.5825	0.3575	0.6306	0.5910

From this experiment, the immediate conclusion is that the additional participant information is not very impactful in the performance of the algorithms with the differences in accuracy percentages not reaching 1%.

4.2.5. Pressure Matrix Resolution Reduction Experiments

The following tests to the results from the usage of the PoPu dataset consisted of reducing the resolution of the pressure data to assess how it would affect the accuracy of the classification algorithms. For this purpose, the original pressure data, which is represented in a 64 × 27 matrix is transformed into a smaller matrix maintaining the shape of the original pressure data, this was accomplished by removing half of the rows and half of the columns and evaluating the accuracy of the algorithms for each split.

Figure 4 displays the different resolutions used for the model training in this section compared to the original (left) as images obtained directly from one of the pressure images available in the dataset.

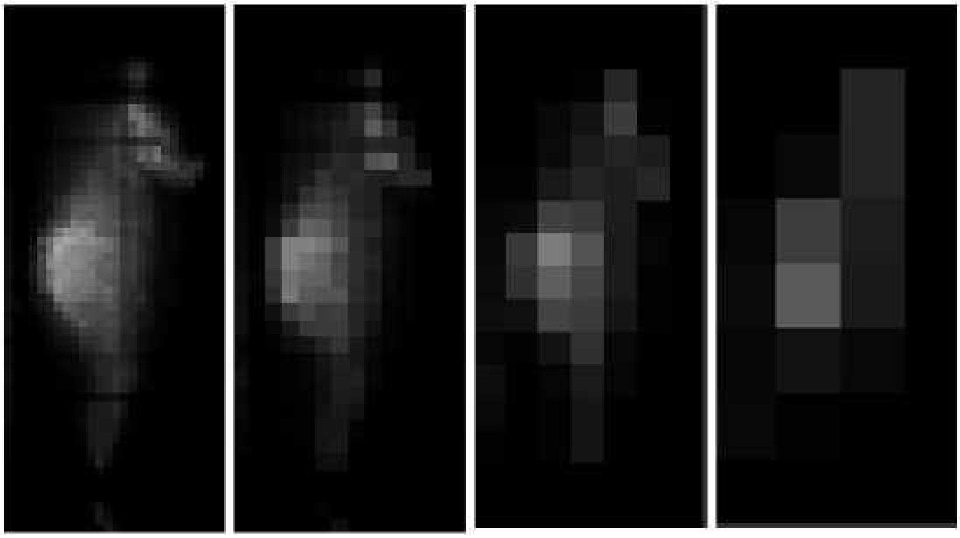


Figure 4. Resulting images from pressure values with different resolutions. From left to right: First 64 × 27 matrix; Second 32 × 14 matrix; Third 16 × 7 matrix; Fourth 8 × 4 matrix.

The first split was performed, and the models were trained using a 32 × 14 matrix, which lowered the number of pressure points from the original 1728 to 448. The results on Tables 7 and 8 were obtained using the exact same techniques as previous experiments regarding the cross-validation technique.

Table 7. Results of 5-fold cross-validation with 4 classes using a reduced (32 × 14) pressure matrix.

Algorithm	*k*-NN	Linear SVM	Decision Tree	Random Forest	MLP
Average Accuracy %	91.34%	91.16%	79.07%	95.29%	95.31%
Standard Deviation	0.0115	0.0252	0.0379	0.0130	0.0185
Average Precision	0.9134	0.9116	0.7907	0.9529	0.9531
Average Recall	0.9134	0.9116	0.7907	0.9529	0.9531
Average F1-score	0.9134	0.9116	0.7907	0.9529	0.9531

Table 8. Results of 5-fold cross-validation with 28 classes using a reduced (32 × 14) pressure matrix.

Algorithm	*k*-NN	Linear SVM	Decision Tree	Random Forest	MLP
Average Accuracy %	43.67%	57.80%	34.52%	61.25%	58.59%
Standard Deviation	0.0169	0.0214	0.0250	0.0152	0.0281
Average Precision	0.4367	0.5780	0.3452	0.6125	0.5859
Average Recall	0.4367	0.5780	0.3452	0.6125	0.5859
Average F1-score	0.4367	0.5780	0.3452	0.6125	0.5859

As the results observed were still above 90% for the 4 posture classifiers and there was no significant change in any of the classifier's accuracies, the matrix was split even further into a 16 × 7 matrix, which reduced the number of pressure points to 112. The results obtained using this data are displayed in Tables 9 and 10.

Table 9. Results of 5-fold cross-validation with 4 classes using a reduced (16 × 7) pressure matrix.

Algorithm	*k*-NN	Linear SVM	Decision Tree	Random Forest	MLP
Average Accuracy %	87.90%	88.91%	75.94%	94.23%	94.59%
Standard Deviation	0.0188	0.0168	0.0322	0.0124	0.0178
Average Precision	0.8790	0.8891	0.7594	0.9423	0.9459
Average Recall	0.8790	0.8891	0.7594	0.9423	0.9459
Average F1-score	0.8790	0.8891	0.7594	0.9423	0.9459

Table 10. Results of 5-fold cross-validation with 28 classes using a reduced (16 × 7) pressure matrix.

Algorithm	*k*-NN	Linear SVM	Decision Tree	Random Forest	MLP
Average Accuracy %	38.87%	53.85%	32.37%	55.76%	53.86%
Standard Deviation	0.0336	0.0230	0.0135	0.0348	0.0238
Average Precision	0.3887	0.5385	0.3237	0.5576	0.5386
Average Recall	0.3887	0.5385	0.3237	0.5576	0.5386
Average F1-score	0.3887	0.5385	0.3237	0.5576	0.5386

The overall accuracy decreases considerably at this point for most algorithms, but some still show high accuracies for the 4 posture classifier. Considering this, the matrix was further reduced to a low of 8 × 4 to assess how a minimum amount of pressure points would affect the accuracy of the algorithms in the 4-posture classification experiment. Results are presented in Table 11. As the accuracies for the 28 posture classifiers are already dropping under 40% in most of the algorithms, this was the stopping point for the 28-posture classification experiments.

Table 11. Results of 5-fold cross-validation with 4 classes using a reduced (8 × 4) pressure matrix.

Algorithm	*k*-NN	Linear SVM	Decision Tree	Random Forest	MLP
Average Accuracy %	68.93%	77.97%	66.44%	83.03%	81.62%
Standard Deviation	0.0273	0.0132	0.0441	0.0148	0.218
Average Precision	0.6893	0.7797	0.6644	0.8303	0.8162
Average Recall	0.6893	0.7797	0.6644	0.8303	0.8162
Average F1-score	0.6893	0.7797	0.6644	0.8303	0.8162

Although the resulting accuracies for the 4-posture models were still relatively high in some cases (up to 83%), the accuracy at this point was much lower, and for this reason, the 16 × 7 matrix was thought to be the best stopping point for the matrix resolution reduction experiment, considering 112 (16 × 7) as the minimal amount of pressure points for a sufficiently accurate classification method. Furthermore, reducing the resolution any more would significantly alter the matrix shape and the manner of reducing the resolution. Nontheless, a final confusion matrix was generated to assess how the classifications were distributed on the lowest resolution experiment. Figure 5 shows the confusion matrix of MLP classification with 4 classes trained using reduced 8 × 4 matrix.

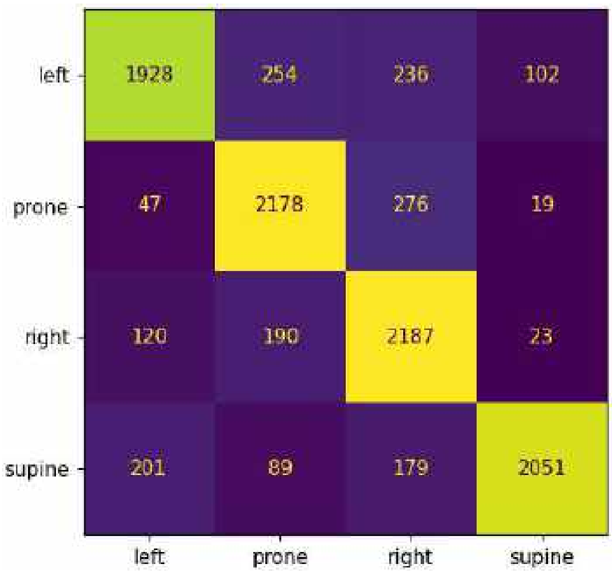


Figure 5. Confusion matrix of MLP classification with 4 classes trained using reduced 8 × 4 matrix.

Some of the related works presented an alternative to the classification in which they considered only 3 postures, combining the supine and prone positions because of their similarity regarding the pressure information. However, even in the lowest resolution considered in this experiment, there does not seem to be a high number of misclassified samples in that regard.

5. Discussion and Final Remarks

The field of posture classification has been studied in various manners, and mostly considers 4 postures as classes for classification. The experiments in this study show that ML algorithms—namely k-NN, SVM, decision tree, random forest, and neural networks (MLP)—can achieve high accuracy with the best-performing classifier, achieving 99% accuracy for 4-posture classification and a lower accuracy considering the finer-grained 28-posture classification alternative presented (up to 68%). These accuracy values are in line with the values identified in the systematic review [5], which analyzed pressure-based posture classification algorithms. When considering only the four main postures, the eight works analyzed in this review presented accuracies between 87.9% and 99.7%. Only two of them have an accuracy value higher than the value obtained in this work. However, comparisons between these studies could be misleading because results were obtained under different conditions, namely the resolution of the pressure sensor matrix and number of samples in the dataset. The 28-posture classification models were also noted for how their incorrect classifications were distributed, as they are still mostly found within the parent posture, which means that even for a wrongful classification when considering the 28 postures, there is a high chance that the parent posture is accurate.

The PoPu dataset plays a crucial role in achieving high accuracies in this study, and it includes a 64 × 27 pressure map along with participant characteristics. This study also includes experimentation regarding the data used in model training.

First, the additional participant characteristics were removed from the dataset training and results show that the additional parameters are not very important for the classification as the results remained relatively alike the first experiment. Secondly, after analyzing the initial results and noticing that the misclassified postures were mostly contained within one of the seven variations within the main positions, an experiment was conducted in which the models were input the main position to assess how it would influence the outcome of the algorithm, which did not alter the results for the most part, excluding the models using random forest, which had an average 10% increase. Thirdly, the dataset's pressure map's resolution was reduced to verify its impact on the accuracy, and although there is a decline, even the lowest tested resolution of 8 × 4 (from the original 64 × 27) achieved respectable accuracy for the 4-posture models, with a highest accuracy of ~85% in both random forest and MLP despite these results. Since the 28-posture models did not achieve such a positive outcome, the 16 × 7 resolution shows the most promise since it achieved an accuracy quite similar to that obtained from using the original resolution with a small decrease. The 28-posture classification experiments show that finer granularity classification needs the additional resolution, as the accuracies for the 16 × 7 resolution showed a significant decrease, with most models nearing 50% accuracy.

The purpose of lowering the resolution of the pressure maps is to understand if a lower number of sensors would still allow for an accurate posture classification even in finer-grained classification approaches, and the results of the experiments seem to confirm that lower resolutions are able to maintain high accuracies for a reduced number of classes only. The higher resolution allows for a more accurate fine-grained classification, but for applications that do not require such granularity, a lower resolution would suffice. With the need for a high resolution out of the picture, a smaller number of sensors can be used for pressure sensor sheets, which would not only result in more inexpensive sensor sheets but—with the reduction of the data being passed as input—the algorithms would provide classifications with ease, allowing for solutions in the field to have machine learning solutions without high computation requirements.

To better understand how the usage of this paper's findings would affect healthcare applications, a similar study with classification done in real-time would be the logical next step, as it would help further validate the models trained for the purpose of this study.

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6. Publication 5: Integrated System for Pressure Ulcers Monitoring and Prevention

6.1. Publication Summary

This publication introduces a system that is centered around patients suffering from pressure ulcers. The system aims to make use of pressure data gathered from sensor sheets and aid caretakers by giving them necessary information when it comes to the monitoring and prevention of pressure ulcers.

The system includes a management portal (web) and a mobile app which allow the user (caretaker) to save patient information, not only regarding their characteristics but also different metrics that can be used to measure not only the likeliness of the pressure ulcer condition worsening but also track any current pressure ulcers.

The pressure data is fed to the system and generates alerts whenever it seems appropriate based on input from medical professionals. These alerts include prolonged pressure in certain body areas, friction detection, among others.

The study concludes the usage of such a system should result in not only a better treatment for the patients but also a minimization of the workload on healthcare professionals.

6.2. Full Publication

Integrated System for Pressure Ulcers Monitoring and Prevention

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Abstract. Pressure ulcers are a critical issue for patients and healthcare professionals, requiring their frequent monitoring, with a consequent impact on healthcare costs. This problem has been gaining attention and approaches have been proposed, using sensor-based systems, to facilitate this monitoring and help health caregivers to achieve greater effectiveness in the treatment of this type of ulcer. In this paper, the architecture, and the prototype of a new system for pressure ulcer monitoring and prevention are presented. It considers information related to both intrinsic and extrinsic predisposing factors and it addresses the components of data acquisition, data analysis, and production of complementary support to well-informed clinical decision-making. The system includes a pressure ulcer management portal and a mobile application, that allows caregivers to manage clinical information about pressure ulcers of the patients and uses data acquired from a pressure sensor sheet under the mattress to provide useful information for monitoring the patients. Considering the situation of each patient, the system will produce indicators/alerts to healthcare professionals, simultaneously improving pressure-ulcer patient care quality and safety and minimizing the burnout in healthcare professionals.

Keywords: E-Health, Pressure Ulcers Prevention, Sensor-Based Systems, Smart Healthcare.

1 Introduction

Quality of healthcare is an important goal for patients, healthcare professionals, and the healthcare system. However, close monitoring is often still essential to implement specific prevention measures and ensure patients' quality of life. It is a healthcare intensive task and many technological approaches have been proposed to help both improve the outcome for patients and alleviate the burnout risk of healthcare professionals.

Particularly, in patients at risk of developing Pressure Ulcers (PU), or patients with PU, intrinsic data about the patient (e.g., limited mobility, poor nutrition, comorbidities, aging skin) [1][2][3][4] and/or extrinsic data (e.g., pressure from hard surfaces, shearing from involuntary muscle movements, excessive moisture) are very important to provide the healthcare provider with additional information which can facilitate the definition of appropriate monitoring schedule and treatment. Thus, close monitoring is essential to ensure their quality of life and that their condition does not become more serious. The improvement of these services can be supported by systems that can monitor the status of patients in real-time and provide information for acting according to individual diagnoses. These solutions help in monitoring and treatment, generating alerts and recommendations that are relevant to support healthcare professionals' decisions/actions, reducing their burden, contributing to an improvement in the patient's quality of life, and a decrease in health service costs [5]. In this sense, the use of IoT technologies associated with ML technologies creates new opportunities to develop a large range of solutions.

In this paper, we present a system, denominated SensoMatt, for pressure ulcer prevention cantered around body pressure data acquired from a sensor sheet placed under the bedridden patient. The system produces indicators/alerts to healthcare professionals, simultaneously minimizing the burnout in healthcare professionals and improving pressure-ulcer patient care quality and safety.

The remainder of this paper will be as follows. Section 2 presents the goal and main requirements of this proposal. Section 3 provides an overview of related works. Section 4 provides an overview of the proposed solution, including the proposed architecture technologies and main functionalities. Finally, Section 5 presents the conclusion and directions for future work.

2 Goal and Requirements

The main goal of this project is to conceptualize, model, and develop a system that could be suitable for supporting healthcare professionals' decisions when taking care of pressure ulcer patients. The research and development are focused on the establishment of indicators based on two ways of acquiring data: a sensor sheet (placed in the bed of the patients) and data observed and inserted by healthcare professionals. Data will be stored resulting in intelligence reports and alarms for healthcare professionals for preventing and lowering the risk of pressure wounds developing further, so that actions can be adjusted according to the generated alarms.

Based on the demands and needs for this specific target of application, for this system the functional requirements that were identified are:

- The system should allow registering of users and editing of their personal data;
- The system should allow the creation and validation of indicators KPI (Key Performance Indicators);
- The system should allow the building of dashboards with direct and/or parameterized consultation, with the option to produce reports and the respective consultation;
- The system should generate alerts and allow users to consult them.

The non-functional requirements are:

- Portability - Limitations regarding hardware and software on which the system will be implemented and on the ease of migration;
- Security – blocking unauthorized access;
- Usability – Ease and accessibility in using the system.

The developed functionalities are displayed in the use case diagram of Fig.1:

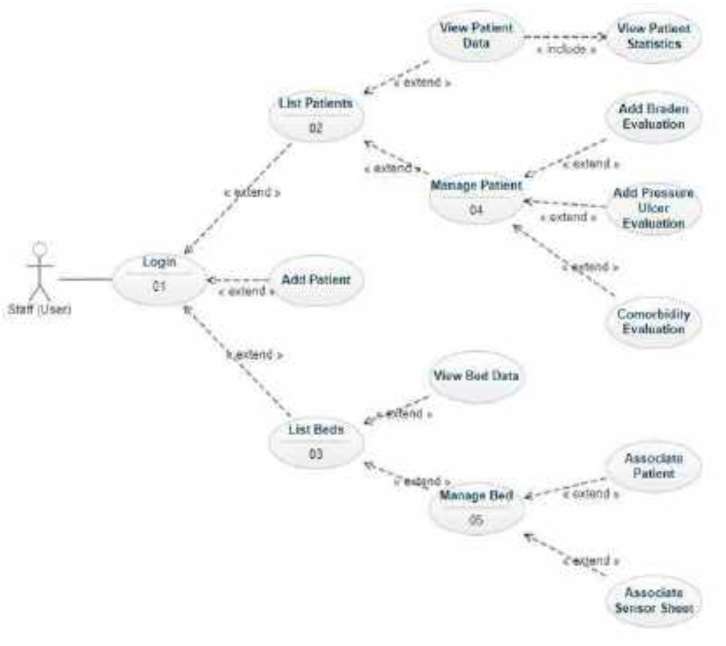

Fig. 1. Use Case Diagram.

The staff role represents every user with access to the platform, this access must be given by the system administrator. The Staff User is required to login information to have access to the platform, once entered, the staff user will be redirected to whichever page they were trying to access. The system should allow the Staff User to see a list of patients. The patient list view can be searched for patient information (name, age, birthdate). It should also allow the Staff User to create new patients in the system or select a specific patient from the list and manage his medical record. The patient's clinical information should include information on risk factors for pressure ulcers (intrinsic and extrinsic) as well as other relevant Inputs for pressure injury predictive algorithms. This includes providing information about the actions that are taken on that patient's condition but also information about the patient's condition and pressure ulcers. Staff Users should be able to monitor and visualize the patient’s condition at each moment, as well as analyse statistics about the patient's pressure map in the most critical parts of the patient, over time. Whenever necessary, the user must be allowed to enter information about any actions he has taken that change the patient's conditions. Finally, the system should allow the staff user to see a list of beds. The beds list view can be searched by location or bed identification. It should also allow the staff user to insert new beds in the system or select a specific bed from the list and manage its features and status. It must also be allowed to assign a patient with a bed. The implementation of these requirements will be described in section IV.

3 Related Work

In the last decades, there have been several research works to propose technical approaches to gather sensorial information deemed useful for pressure ulcer prevention. The fundamental goal of these approaches is to acquire the information needed to classify the lying position of the patient using some sort of pressure sensor usually placed below the patient's sheets (e.g., [6] [7]). Furthermore, other different approaches based or complemented by several types of inertial sensors [8][9][10], video images [11][12], and others [13], also get satisfactory results. The fact that pressure sensors do not need to be attached to the patient is relatively flexible in the information they provide, are easily installed, and can be used successfully with different algorithms for lying position classification, seems to have increased, over the years, of the number of approaches based on this type of sensor. The information acquired from the sensors is processed in varying ways according to the sensor type. Mostly it included simple processing steps of the numerical raw data obtained from the sensors, but, mainly in the case of the pressure sensors, some effort is made by various authors to obtain higher-level features from the original data matrix (e.g., [6] [7]).

The algorithms can be used in pressure ulcer prevention approaches in the following three stages:

- preprocessing of data: In this stage, the processing is usually relatively simple, but in some works, more sophisticated algorithms were used (e.g. [14]).
- lying position classification: this is a very important factor for pressure ulcer prevention, and it can be implemented using many combinations of different sensors and algorithms. Some form of pressure sensor matrix is possible, and it is the most common sensor used. Regarding the classification algorithms, neural networks (including deep networks) (e.g. [8][15][6][7]), support vector machines [9][13], principal component analysis [13], and tree or rule-based systems [8] [16] are some of the usual approaches. Neural network-based approaches are the most popular, followed by support vector machines.
- decision towards ulcer prevention: considering, as input, data about the lying position and other sources (patient history, etc.) generate outputs to help caregivers to decide what actions to apply to the patient.

However, most research works stop at lying position classification. The ones that go forward tend to contribute to pressure ulcer prevention in the following ways:

i. Monitoring [15][16][17][14]– data gathered from the sensors can be analysed by caregivers. This can include pressure maps or other values (e.g., time since the last change in position, physiological data, etc.). These values can be displayed, usually in graphical form or using mobile apps.

ii. Notifications [15][9][16][17][10][11][14][18][19] – Raising of alarms when the patient is resting in the same position for longer than a specified amount of time. This reduces the risk of the patient resting for extended periods in the same position (the most common cause of pressure ulcers) and can save the caregiver's time if the patient changes position spontaneously. Other alarms can be raised if the patient moves too much - when restlessness is a risk - or gets up from bed (maybe falling).

iii. Personalization e.g. [9][14] – allow that data to be visualized as is relevant for that particular patient. Information regarding the patient's medical history can be inputted into the application, to be displayed or used in some decision-making processes.

iv. Actuation [16][17] – these are not common and tend to be very expensive. As an example, a few beds have pressure actuators that can control pressure in specific areas. Some of these actuators can be controlled remotely by caregivers.

v. Prediction [20] – offer some kind of prediction of pressure ulcer occurrence based on diverse sources of information, both sensor-based and obtained in other ways, such as patient history or physiological data.

Good results can be achieved in lying position detection using a variety of techniques. However, these results are yet rarely tested in real conditions and are measured in some form of a simulated environment. Several approaches raise alarms that are helpful to the caregivers and health professionals, namely as a warning system for the position changing cycle and as an alarm for dangerous situations such as restlessness or getting up of bed (or falling). So, there are several successful approaches to the lying position detection problem with clear practical implications, yet there are less successful cases of approaches able to use this information in conjunction with other data sources to effectively predict pressure ulcer development risk.

4 A System for Pressure Ulcers Monitoring and Prevention

In the context of what was mentioned in the previous section, the architecture and prototype of a new approach that is being developed to fill some of the identified gaps, and contribute to a more complete decision support system, are presented below. This system is also based on data from a pressure map, constructed from the acquisition of values using a pressure sensor sheet, and personalized data from the respective patient being monitored.

4.1 Architecture and Technologies

This section contains information regarding the overall implemented architecture of the system, split into two sections, one for the sensor sheet data and one for the clinical data.

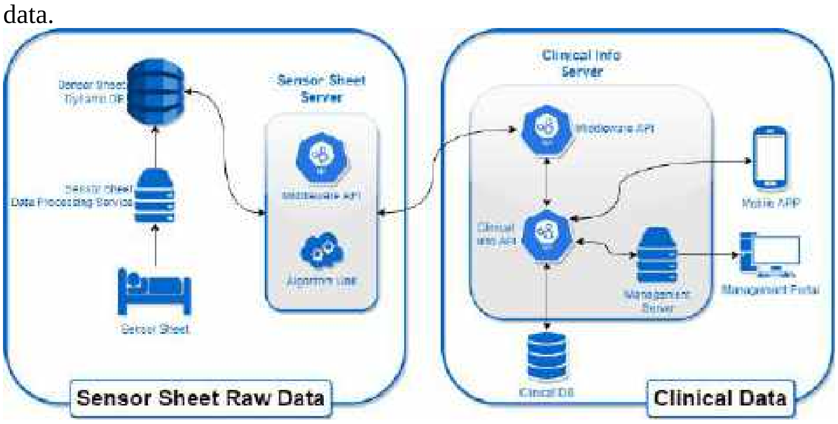

Fig. 2. Architecture Diagram.

The sensor sheet data section portrays the system capable of extracting data from the sensor sheet and, using artificial intelligence algorithms, the creation of alarms to be used by the applications used by the staff. The clinical data section is the section responsible for clinical data that will also be used in the algorithms, according to each patient's physical and medical characteristics the algorithm will have different outcomes.

The architecture on the left side of the Fig. 2 contains the sensor sheet, which gathers the data of the bedded patient, a data processing service that receives the data from the sensor sheet and cleans it so only the required data is stored in a database. The two other elements on the sensor sheet raw data section are responsible for passing the raw data through the algorithm unit so that body positions and body parts that are under pressure can be identified. This information can be translated into alarms to be used in the management portal and application. Alarms will be transmitted through an API that ensures communication between the different sections.

The right side of the diagram contains the architecture for the clinical data section of the architecture which accounts for the data acquired through the usage of both the management portal and the mobile application, the database (Clinical DB) is where the information regarding the patients, beds, and users is stored, this can be accessed through the backend, encapsulated inside a server where the clinical info API is responsible for managing data on the database, this API is the communication bridge between the management server/mobile application and the clinical database, the server also contains the Middleware API responsible for communicating with the left section of the architecture for the algorithmic processes regarding the patient's health condition. The front end of the architecture is hosted on a React server for the management portal which can be accessed from any browser with internet access.

4.2 Prototype

Most healthcare systems already have an application to facilitate patient data management, mostly generalized so they can have as much information as possible. For the SensoMatt system, there was a simplistic approach in which only the data considered relevant to pressure wounds (intrinsic/extrinsic factors) is managed. This way the responsible medical staff can view and edit information related to this subject more quickly and easily.

Fig. 3. Left: Sensor sheet in the bed. Right: Sensor sheet.

A pressure sensor sheet under the mattress provides useful information about the patient's body parts under pressure. Placing the pressure sensors underneath the mattress is a less intrusive solution for the patient. This way there are no changes in temperature or friction, it does however pose a challenge when trying to accurately measure the pressure and identify the patient's body position when lying down. The sensor sheet layout shown in Fig. 3 (left), presents the 3 corresponding intervening factors for its functioning. First the bed mattress, for an all-around solution the sensor sheet should be put below the mattress and be able to correctly measure the pressure distribution despite the differences in mattresses. Secondly, the sensor sheet measures patient movement and pressure and sends the measured data to the Sensor Sheet Data Processing service. Thirdly, the data obtained by the sensor sheet is registered, which allows producing a pressure distribution map of the body and identifying the posture of the bedridden patient, using Artificial Intelligence algorithms. Based on this information, it is possible to identify the parts of the body which are under pressure, and this information is used to predict the risk of pressure ulcers. The sensor sheet is presented in Fig. 3 (right). In its current version, it contains an array of 4 × 10 sensors, and a sheet sensor with a higher number of sensors is being developed.

The information is later processed using technologies such as cloud computing, mobile computing, and artificial intelligence to provide patients and clinical staff with personalized technology for the early detection and prevention of pressure ulcers.

Considering each patient's situation, together with the clinical information, the system will produce indicators/alerts to healthcare professionals, simultaneously improving the quality and safety of pressure ulcer patient care and minimizing the burnout on healthcare professionals. In the prototype's current stage, alerts are based on rules that consider the patient's existing ulcers, the patient's body position and for how long the same position is kept. The platform includes a web portal and a mobile application for managing information on pressure ulcers using information obtained by the sensor sheet. The management portal was designed to convene a faster way of evaluating the patient's state concerning pressure ulcers, the patient is added into the system with the filling of a simple form that includes some medical parameters like height and weight as well as some other possibly related health issues. The patient can then be associated with a bed in the system and be monitored by a sensor sheet when available. After admission, the medical staff can perform multiple evaluations, be it relevant medical information like comorbidities or Braden[1] scale evaluations that measure the risk of pressure ulcers or evaluate the patient's afflicting pressure ulcers so they can be recorded and monitored throughout the bedding period.

In Fig. 4 there is a portion of the pressure ulcer evaluation screen in which the clinical staff can evaluate the state of the patient's ulcers, in here the staff can select a body part from a body image mapped with the multiple body parts, after selecting a body part they are prompted to input the wound's width, depth, and pressure ulcer stage, this can be done for multiple body parts and once the user is finished they can complete the evaluation by clicking the "Evaluation Complete" button.

[1] https://www.bradenscale.com/

Fig. 4. Left: Pressure Ulcer Evaluation Screen. Right: Braden evaluation table.

The evaluations are then stored and can be viewed in a table, displaying all the previous evaluations along with the parameters for each body part's ulcer, for easier assessment of the evolution of the patient's wounds each body part can be selected from the table so the staff can view a graphical representation of it.

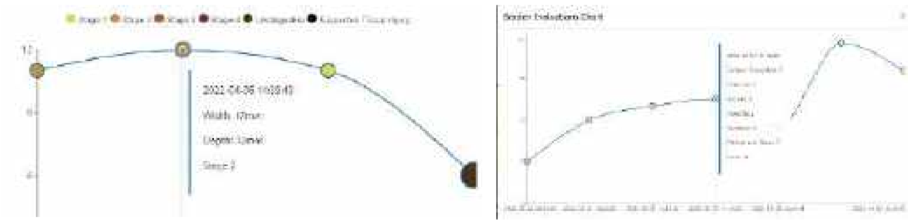

Fig. 5. Left: Pressure Ulcer graphical representation. Right: Braden evaluation chart.

Fig. 5 shows the graphical representation of a simulated pressure ulcer and its evolution over 4 different evaluations, each dot represents an ulcer, the Y-axis represents the depth of the wound, the size of the dot represents the width, and the colour represents the corresponding stage. The dots can also be hovered for a more detailed report on the evaluation of a certain ulcer at a certain time. Apart from this graphical representation the system also has a graphical representation for the Braden scale evaluations and all other data collected from the medical staff interactions with the platform.

The mobile app has a more simplistic approach to the functions included in the platform considering screen size and other conditioning factors. As such the main goal of the app is for healthcare professionals to have remote access to the patient's information and most importantly getting the same alerts the platform gets but in the shape of notifications for quicker access.

5 Conclusion and Future Work

In this paper, a system has been presented to support caregivers of patients with pressure ulcers. The architecture and the prototype of the new system for pressure ulcer monitoring and prevention were presented in their present state. This system is based on pressure data collection, using a pressure sensor sheet, and lying position determination. An information system to explore the acquired data, including back-office storage of relevant information and a mobile application for healthcare professionals are still under development, with specific care being taken to ensure that privacy, security, and other specific regulations in the healthcare field are fully met. Considering the situation of each patient, the system will produce indicators/alerts to healthcare professionals, simultaneously improving pressure-ulcer patient care quality and safety and minimizing the burnout in healthcare professionals. Work is also being done with healthcare professional partners to adjust different aspects of the prototype system, that will influence the requirements for the mobile application being developed, the definition of the data that is both useful to store in the information system, and the several aspects of the visualization, alarm, and predictive components that these professionals consider more helpful in managing patients with pressure ulcers.

Thus, future work will evolve in two directions. On the one hand, a sensor sheet is being developed with a greater number of sensors to obtain more accurate pressure map images. It will also be necessary to obtain pressure map images from a larger sample of patients. These will be important to train the body position detection algorithms and thus improve their accuracy. On the other hand, predictive algorithms will be studied and implemented to make recommendations to health professionals. The results will be compared with other similar works and evaluated by potential users.

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7. Conclusions

7.1. Final Remarks

The work in this dissertation has led to a comprehensive exploration of posture classification solutions, resulting in the five different publications presented in this document. Each of the publications has a unique contribution to the end goal, being a solution for monitoring bedded or lying people using posture classification methods. Although the studies are not presented in chronological order, all of the information gathered from the research work put into them has culminated in a more succinct document with solid, grounded information.

From the research work included in the first publication [3], a set of indicators was withdrawn that lead to an understanding of not only the datasets that were already present in the literature but also the standard procedures elaborated throughout the development of a pressure map dataset. Using this output, it was possible to develop a dataset that not only is in a standard format but solves issues that were observed within this publication.

The second publication [1] exposes the whole process behind the development of the PoPu dataset, from the data gathering setup to the structure of the data included in the dataset, having a previous knowledge on the different existing datasets in the literature lead to considerations regarding some of the issues found earlier, namely the additional participant characteristics collected, and the distribution of the participants within these characteristics.

The following publication [4], alike the first one, intends to study the literature to find the best and most common applications in the field of posture classification, specifically works using pressure data. The main takeaways from this publication are that the solutions included in the review mostly struggle at achieving high accuracies when attempting to classify a high number of postures, and that for higher accuracies, the most important factor is the quality of the pressure data itself, although there is no indication as to the importance of a high resolution pressure map.

The subsequent publication [5] explores the usage of the PoPu dataset for posture classification and contains various ML experiences by training and validating models employing algorithms selected from the previous study. The experiments show that using the PoPu dataset for training yields very high accuracies (up to 99%) when classifying postures and quite lower accuracies when considering fine-grained 28 posture classification (up to 68%). Additional experiments were conducted to test if classifying the main posture before attempting fine-grained classification, but no significant changes were noted, and removing additional participant characteristics (weight, height and sex) which also did not alter the accuracies noticeably, therefore proving once more that the most influencing factor to accurate posture classification is the pressure data itself.

Perhaps the most interesting experiment came by lowering the resolution of the pressure maps to determine whether the accuracy of the classification methods would maintain their results, and it seems that is the case, since when reducing the pressure maps from a 64x27 resolution down to a 16x7 resolution the accuracy remained quite high, up to 95% for the 4 posture classification experiment and up to 56% for the 28 posture experiment. This experiment may result in future applications that are less expensive as the number of sensors required for an accurate classifier are much lower than the number of sensors in the sensor sheet used for gathering the data in the PoPu dataset.

The last publication included in this study [2] demonstrates a potential application of a posture classification centered system in the healthcare field, namely pressure ulcer monitoring and prevention. The system includes various functions such as patient data storage and access, graphical representation of the patients' states, among others. Regarding the usage of posture classification, the platform herein demonstrated suggests the generation of alerts whenever an issue is detected with the patient, be it prolonged pressure or friction detection in certain body areas which lead to the pressure ulcer conditions worsening or by alerting the healthcare professionals of a fall if there is no pressure data at the time.

This system or any other that makes use of pressure classification technologies will most certainly aid healthcare professionals and ease their burden when dealing with such delicate conditions as pressure ulcers.

In its entirety, this dissertation presents a full solution, all the way from the development of a dataset that is used to train the models capable of posture classification which in turn can be used in healthcare applications to not only bolster patient care but also to alleviate the schedules of medical professionals. The contents of the publications are also helpful for future researchers who intend to create new posture classification solutions, or platforms centered around bedridden people's condition.

7.2. Future Work

By analyzing the literature, this work was able to find common issues and come up with possible solutions to existing problems, however, there is always room for improvement.

Regarding the PoPu dataset, since it contains 3 different layers from which one of them is used and portrayed in this document, the remaining 2 layers remain untested. Both layers should yield interesting results, especially the layer containing data gathered using sensors beneath the mattress as at the time the literature regarding lying people pressure datasets was analyzed there was no solution found using sensors beneath a mattress. The remaining layer contains body segmentation data, which can also be used for classification algorithms and should lead to a more accurate description of which body parts are currently under pressure, which is a great tool for healthcare professionals.

Regarding the experiments done in posture classification, testing whether or not the results of the resolution reduction experiments would remain the same with real data gathered using sensor sheets with a lower number of sensors could have an interesting outcome and perhaps comparing the two, not only in terms of classification accuracy but also regarding the hardware that was used would show that this sort of application can be reproduced without the need of very expensive materials.

Lastly, using the posture classification models included in this study in real time in combination with the platform demonstrated here as well, would accurately depict how useful this sort of system would actually be in a real-world environment.

This suggestion would fully integrate the system by having a middleware service responsible for processing the output from the trained classification models and generating useful information for the platform in the shape of time of pressure on body areas, real time previews of the patient's position and alert generation.

This could be done by clinical trials or testing with participants in a manner similar to the procedures used in the data gathering process for the development of the PoPu dataset.

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