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Application of artificial intelligence methodologies to chronic wound care and management: A scoping review

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Abstract

Significance: As the number of hard-to-heal wound cases rises with the aging of the population and the spread of chronic diseases, healthcare professionals struggle to provide safe and effective care to all their patients simultaneously. This study aimed to provide an in-depth overview of the relevant methodologies of artificial intelligence (AI) and their potential implementation to support these growing needs of wound care and management.

Recent advances: MEDLINE, Compendex, Scopus, Web of Science and IEEE databases, were all searched for new AI methods or novel uses of existing AI methods for diagnosis or management of hard-to-heal wounds. We only included English peer-reviewed original articles, conference proceedings, published patent applications or granted patents (not older than 2010) where the performance of the utilized AI algorithms were reported. Based on these criteria, a total of 75 studies were eligible for inclusion. These varied by the type of the utilized AI methodology, the wound type, the medical record/database configuration and the research goal.

Critical issues: AI methodologies appear to have a strong positive impact and prospect in the wound care and management arena. Another important development which emerged from the findings is AI-based remote consultation systems utilizing smartphones and tablets for data collection and connectivity.

Future directions: The implementation of machine learning algorithms in the diagnosis and managements of hard-to-heal wounds is a promising approach for improving the wound care delivered to hospitalized patients, while allowing healthcare professionals to manage their working time more efficiently.

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Scope and Significance

Chronic wounds are costly and labor-consuming due to their non-healing nature; may lead to prolong hospitalization and additional treatments; often decrease health-related quality of life and are associated with a risk of fatal infections and high mortality [1]. An uprising and highly promising scientific approach for improving wound care and management for patients with chronic wounds is the development and clinical implementation of artificial intelligence (AI) technologies. AI-based methodologies and algorithms might provide clinical decision-support in wound diagnosis, prognosis and management, and even contribute to the prevention of chronic wounds.

1.0 Translational Relevance

Though there is a vast potential for AI to improve the safety, clinical effectiveness, cos-effectiveness, accessibility and quality of wound care, the field is still in its early days [2]. The current COVID circumstances, acting as a catalyst for computer-aided and tele-wound care, are expected to boost both technological development and implementation prospects [3]. Accordingly, guidance concerning the most effective and promising ML methods and approaches in wound care is needed in the field, to support this expected technological progress. For example, it is unclear which types of wounds are currently the best candidates for effective application of AI-powered wound care and among those, which specific ML algorithms would show the highest effectiveness. Likewise, mapping of ML algorithms to diagnosis, prognosis, treatment or prevention applications is needed defined per each such application.

2.0 Clinical Relevance

In this scoping review, we explored the relevant scientific and medical literature to-date, to answer the above fundamental questions and in particular, to investigate how ML is currently being used in academic wound care research as well as in clinical practice. In addition, we identified important knowledge gaps in the development and implementation of AI in wound care, which should be helpful in directing future research efforts and progressing the field further.

3.0 Background

3.1 Chronic wounds

Chronic wounds, such as pressure ulcers/injuries, venous leg ulcers and diabetic foot ulcers are defined as wounds that fail to progress through an orderly and timely reparation often due to a stall in the inflammatory phase of healing [4]. Other wounds, which are traumatic in origin, such as burns and surgical wounds, may become infected and shift to chronicity. As all wound types have the potential to become hard-to-heal, and there is no clear consensus concerning the time duration of a wound that defines chronicity, chronic wounds are typically classified by combining their etiological cause, clinical diagnosis and treatment protocol [5–7]. As the number of patients with chronic wounds consistently increases with the global aging of populations and the spread of chronic diseases such as diabetes and obesity (and more recently, under the influence of the COVID pandemic), health care professionals face the growing challenge of providing safe and effective care to all their patients simultaneously [8].

3.2 Implementation of AI methodologies in wound care and management

An uprising and highly promising scientific approach for improving wound care and management for patients with chronic wounds is the development and clinical implementation of artificial intelligence (AI) technologies [9]. The use of AI in healthcare involves machine learning (ML) algorithms and software that mimic human cognition and action in the analysis, presentation, comprehension and interpretation of complex medical and health care data.

Pressure ulcers/injuries, for example, appear to be very good candidates for effective application of AI-powered wound care, both in risk assessment and in early diagnosis aspects. With regards to risk assessment, Xu and colleagues (2022) recently (and post the April 2021 cutoff date of search for this scoping review) published a retrospective cohort study where they had developed a risk assessment tool that analyzed the electronic health records (EHRs) of 618 patients in an intensive care unit (ICU), through a machine learning (ML) algorithm comprising logistic regression and a random forest classifier with a cross-validation technique [10]. They concluded that their ML algorithm can successfully substitute the traditional Braden risk assessment process in the ICU setting, by automatically monitoring and processing the EHRs. In the context of early detection, Lustig et al. (2022) reported (likewise, after April 2021) an ML algorithm that was trained using a database comprising six consecutive daily sub-epidermal moisture (SEM) measurements recorded from 173 patients in acute and post-acute care settings, which demonstrated strong predictive power in forecasting heel deep tissue injury events the next day, based on the weighed trend of the acquired day-to-day SEM data [11]. Indeed, Raju et al. (2015) suggested earlier that prediction of pressure ulcers can be performed more effectively by utilizing data science, and more specifically, data mining modeling, to support and augment the Braden risk assessments conducted by nurses, and it appears that this approach is successfully maturing now, as demonstrated in the aforementioned articles [12].

Accordingly, AI-powered wound care is potentially able to reduce the workload on specialists, increase the accessibility to specific relevant medical expertise and expand the potential of remote (tele-) wound treatment or management. Specifically, using a variety of textual and image data, collected from either new or already-available medical records and imaging modalities (as relevant to the affected body area), AI-based methodologies and algorithms may be able to provide clinical decision-support in wound diagnosis, prognosis and management, and even contribute to the prevention of chronic wounds.

4.0 Discussion

To explore the breadth and depth of integration of AI methodologies and technologies in wounds diagnosis and management in the past decade and to identify gaps between AI technological capacities and clinical implementation, a scoping review was conducted, following the framework of Arksey and O'Mally [13]. This framework describes five subsequent stages: (1) identifying the research question; (2) identifying the relevant studies; (3) study selection; (4) charting the data; and (5) collating, summarizing, and reporting the results.

4.1 Research question and key concepts

The research question that was determined to guide the present literature review process was: How does AI contribute to the diagnosis and management of chronic and acute wounds? Reported AI methodologies were defined as machine learning algorithms that aim to mimic or substitute human expertise in order to replace, assist or perform wound care tasks more efficiently. Such wound care tasks may include prevention and treatment interventions, identifying risk factors and mitigating them, patients risk assessments, wound detection and classification and monitoring of healing processes [14].

4.2 Identifying relevant studies

Five electronic databases were scanned to identify relevant studies: MEDLINE (using the PubMed interface), Compendex, Scopus, Web of Science and IEEE. The search strategy was designed to capture the intersection of the two extensive fields of AI and wound care (i.e. both diagnosis and management). For this purpose, we systematically searched the aforementioned databases for studies that included at least one of the following key terms: artificial intelligence (including the commonly used abbreviation AI), deep learning, machine learning, convolutional neural network (including the abbreviation CNN) and deep network; and at least one of the following key terms related to wounds: pressure ulcer*, pressure injury (or pressure injuries), chronic wound*, surgical wound*, burn wound*, diabetic foot ulcer*, acute wound* (asterisks indicate that plural forms were also considered).

4.3 Study selection

Eligibility criteria were established based on the research question and a pilot search through the preliminary search results. Studies describing a novel AI method or a novel use of an AI method for acute/chronic wound diagnosis or management, published in English, were considered for inclusion. Only articles that specifically reported an evaluation of the AI algorithm performances were considered for inclusion.

In order to focus on the more advanced and novel AI methods which are the most relevant to the contemporary computer hardware and software power, we established a new rate of appearance (ROA) criterion, which has been applied in our present search procedure. We specifically aimed to identify the year of publication in which the ROA of papers in the AI field has turned into exponential growth. The year of reaching this point of exponential growth in the number of published AI papers was defined as the year where the ROA (i.e., the derivative) of the number of publications with respect to time became proportional to the number of AI papers itself. To calculate the ROA in practice, we developed and used a Python (Python Software Foundation, Delaware, United States) computer code which performed curve fitting to the plot of the number of AI publications as function of time. We applied the algorithm to the datasets obtained from the AI key term search, for each of the five electronic databases and found that the year in which the ROA became exponential was 2010. Accordingly, we decided to include AI studies published on 2010 and onwards.

We considered peer-reviewed original research articles, conference proceedings, published patent applications and published (granted) patents. Identified items for which the full text was unavailable were excluded. In the first step, we screened the titles and abstracts of all the retrieved records for eligibility, using the online freeware software system Rayyan [15]. We then performed an in-depth review of the full text of the remaining records to ensure compliance with the above-listed eligibility criteria.

4.4 Charting the data

A data charting form was designed to provide interpretation, comparisons and synthesis of the findings from the included studies. The final form included the following information: Reference of publication, country where the study was performed, aim of the study, the wound types that were considered in the study, setting of the study and the sample considered, the study design, the main AI methodologies considered in the study, the study process, the main and relevant study outcomes, and the limitations stated in the study.

4.5 Collating, summarizing, and reporting the findings

Due to the explorative nature of the present scoping review and the relatively high divergence of the findings, the results were presented in a narrative way, with no attempt to assess the quality of the studies or to determine the robustness and generalization of the findings [13].

4.6 Literature review

The literature search, performed in April 2021, yielded a total of 448 records. The full texts of 154 studies were retrieved to assess eligibility. This assessment resulted in the exclusion of 76 studies which did not describe any AI approach or a novel use of an AI approach for acute/chronic wound diagnosis or management, or that considered wound types that were out of scope for this study. Such wound types were intra-abdominal surgical wounds and colorectal surgical infections. In addition, we excluded reports describing algorithms developed for identification of skin cancers or were trained using skin cancer image databases. A chart table presenting an overview of the characteristics of the assessed studies and the main findings is available in the Appendix.

Most of the included studies (*n* = 59) were focused on development of AI algorithms and evaluation of their performances by means of simulations, using datasets that were collected by clinicians in hospital settings, or from online available databases [1,16,25–34,17,35–44,18,45–54,19,55–64,20,65–74,21–24]. Of the remaining studies, four papers combined a retrospective cohort study for data acquisition, followed by algorithm development and simulations [75–78]. Two studies included a prospective cohort study that was used to first develop a predictive AI algorithm and then simulate and evaluate the performances of the developed algorithm [79,80]. Four studies were experimental studies where in-vivo and ex-vivo porcine models were used for wound evaluation and analysis [81–84]. Three studies aimed to examine an automated approach of in-bed lying posture recognition and prediction using sensor measurements fed into an ML model, as a way of preventing pressure ulcers/injuries [85,86,87]. In another study, an algorithm was developed based on an individual case report [88]. One record was a published patent application [89], another article aimed to develop a novel ML algorithm to predict formation of heel deep tissue injury based on a dataset of change in the sub-epidermal moisture (SEM) measurements [90], and the last study was exploratory work to predict the prevalence of pressure ulcers/injuries based on risk factors extracted from clinical records [91].

We note that no relevant publications specifically concerning venous leg ulcers (VLUs) addressed by means of ML, existed at the time of conclusion of our literature survey (April 2021). However, as the number of patients suffering from this problem is so considerable, we performed an additional search focusing on this particular topic later on, and on June 2021, the first and currently the only such article was published online, by Chan et al. (2022) who investigated intra- and inter-rater reliability of a commercial ML-based handheld 3-dimensional infrared wound imaging system (WoundAide [WA], manufactured by Konica Minolta Inc., Tokyo, Japan) with respect to VLU length, width and area measurements (in 52 patients) by trained nurses [92]. Chan et al. (2022) reported high intra-rater reliability of the WA imaging system for observations of the same wound and independence of the specific WA device that was used for the purpose (of 3 devices utilized in their study) [92]. They further reported excellent agreement between measurements made manually by nurses and those made by the WA systems, which led them to recommend the WA imaging system as a useful clinical adjunct in the documentation of VLUs. [92]

The distribution of the number of published studies per year (from 2010 onwards) is depicted in Figure 2. The data in this figure demonstrates an overall growing interest in implementation of AI in wound care over the last decade. This becomes more feasible with the technological progress (in computer hardware and software including cloud computing) and also, due to improvements in the AI field as a whole. Generally, the aim of the studies that were identified in the present literature search has been to help physicians in wound diagnoses and support clinical decision-making processes regarding treatments and preventative interventions, by means of efficient and systematic algorithms. In most of the included studies, supervised machine learning (ML) techniques were used for different tasks such as wound type classification, tissue type segmentation and classification, detection of infections, or classification of the wound severity. The data were labelled by physicians specialized in wound care and then considered as 'ground truth' for the training and evaluation of the learning algorithms. The metrics that were used to evaluate the algorithm performances varied across the reported studies and included primarily accuracy, sensitivity and specificity, F-score, receiver operating curve (ROC), area under the curve (AUC) and the dice similarity coefficient (DSC). Therefore, it is not feasible to directly compare the different records but it appears that from 2015 and going forward, the methodology that was found to provide superior performances over classical ML and computer vision techniques has been deep learning (DL), which is also commonly referred to as a deep neural network (DNN) [1,16,30,32–38,43,44,18,46–49,51,58,60,63,66,67,19,72,74,75,80,82,85,86,88,89,22,23,25–28]. The classic ML classifiers - support vector machine (SVM), logistic regression (LR) and random forest (RF) - have also been used widely [17,20,50,52–56,59,61,62,64,21,65,68–71,73,76–79,28,80–83,87,88,91,29,31,39,40,45,48] (All mentioned ML and technical terms and their definitions can be found in Table 1).

In 54 studies, the datasets consisted of images of wounds and healthy skin, collected using digital cameras, smartphone/tablet cameras and advanced imaging techniques such as Raman spectroscopy (RS), optical coherence tomography (OCT), ultrasound, infrared thermography, near-infrared thermography and spatial frequency domain imaging (SFDI). In other 20 studies, the datasets consisted of quantitative and categorical information collected from clinical notes and electronic health records (EHRs). The above data were acquired mostly in hospital conditions (by clinicians), and less frequently, under laboratory conditions. In three additional studies, the datasets were consisted of experimental measurements obtained from pressure, force or accelerometer sensors. The studied image dataset sizes ranged between 23 and 2400 images. The clinical records or EHR dataset sizes ranged between 149 and 765,564 patient records. The sensor measurement-based datasets consisted of data from 12 to 22 individuals. The main limitation of most of the relevant studies was the small or limited dataset sizes which affected the robustness, generalization, accuracy and likely the overall performances of the AI algorithms.

4.7 Clinical visual assessment of wounds supported by artificial intelligence

In order to examine a chronic wound (CW), the development of infection in an acute wound, or the progress or healing process of wounds in general, physicians and nurses perform frequent clinical visual assessments (VAs). In this regard, 62 of the studies identified in this scoping review aimed to develop computer-aided tools that may assist clinicians in the VA process and to allow objective, rapid and systematic wound assessments. Two main tasks that ML algorithms appeared to perform efficiently were classification and segmentation. In classification tasks, the AI algorithms acquire a wound image as an input and distinguish between pre-defined sets of classes e.g., class I and class II. In segmentation tasks, AI algorithms also obtain an image as an input but classify each pixel therein to labels such as granulation versus necrotic tissues. It then becomes possible to present regions of the classified tissues per their specific labels or superimpose those with a picture of the entire wound. In the literature reviewed here, these abilities were used together or separately to support VAs.

Specifically, 30 of the reviewed studies were aimed to assist in recognition of wound tissues and distinguish those from healthy skin by means of binary classifications, which determine whether an image (analyzed in a classification task) or a pixel of an image (in a segmentation task) represent healthy skin or wound tissues. Those studies are summarized in Table 2.

In each of these studies, dozens to hundreds of images were acquired using digital cameras or smartphones in healthcare facilities [8, 10–12, 14, 15, 20–22, 24, 25, 28–30, 34, 35, 38, 41, 48, 49, 64, 66, 70, 82] or through infra-red, RS and OCT techniques [1,69,82], hyperspectral and multispectral imaging [83,88] or extracted from available online databases [32,44]. The images were first labelled by expert physicians, manually or using software to establish a ground truth and then preprocessed and fed into the developed algorithms for training and evaluation of the algorithm performances. In several studies, classic ML classifiers such as SVM [29,39,48,61,76,82,88], logistic regression (LR) [76,82], multilayer perceptron (MLP) [22,25], radial basis function (RBF) kernel [22], random forest (RF) [69,82] and k-nearest neighbors (KNN) [83] were employed to perform the classification of healthy versus wound tissues. For example, Song et al. (2012) used 92 diabetic foot ulcer (DFU) digital color images, labelled by experts to identify the wound region; these images were then split into a training set of 78 images and a test set of 14 images [22]. Song and colleagues compared the performances of the MLP method and RBF method in the task of wound area segmentation and found that the RBF was more accurate for this task (85.7% accuracy by RBF versus 71.4% by MLP) and required a shorter training period (1.7 seconds by RBF versus 12.6 seconds by MLP).

Chen et al. (2018) studied a dataset of 131 surgical wound images acquired using different smartphones/tablets and labelled by clinical experts [45]. They developed an algorithm for wound detection and assessment based on classic ML techniques and found that the combined KNN and RF classifiers achieved the highest accuracy (90%). Other studies developed algorithms based on DNNs, after comparing the algorithm performances with the basic ML methods. It was shown that DNNs generally achieve better results than the basic ML methods [39]. For example, Sevik et al. (2019) developed an algorithm for distinguishing between skin and burn areas on burn images taken by technicians in emergency services [23]. They used 105 images acquired in hospital conditions and compared the segmentation and classification tasks performed using traditional computer vision and ML techniques, with those of a more advanced DL technique having a multi-class pixelwise segmentation architecture (commonly known as the 'SegNet') [93]. Sevik and colleagues found that the fully-automated DL system had a greater F-score relative to the classic techniques and was therefore superior to most of the existing methods in the area of tissue health (i.e., healthy skin versus burn) classification. Specifically, the F-score of the DL architecture was 0.85 whereas the F-score of the best classic architecture was 0.742.

Of note is that shallow models (where there are less layers in the neural network structure) typically exhibit poorer performances with respect to all the relevant metrics that are commonly used for assessment of the algorithm performances (i.e., sensitivity and specificity, AUC etc.) [94]. For example, as mentioned earlier in this Section, Song et al. (2012) compared two ANN methods, MLP and RBF (which contain only one hidden layer), for automatic segmentation and identification of wound regions based on colored images of diabetic foot ulcers [22]. The MLP and RBF models, which are considered shallow, gained 71.5% and 85.7% accuracy scores for the segmentation task, respectively. The DFU_QUTNet, however, which was suggested later by Alzubaidi et al. (2019), for the same task of classifying diabetic foot ulcer images, and that consisted of 58 layers for this purpose obtained precision, recall and F-score of 94.2%, 92.6% and 93.4% respectively [34], i.e., substantially better than the 'shallow' architecture. These results demonstrate the superior performance of deep models over shallow ones, where typically, more depth of the neural network structure augments its accuracy.

Fifteen of the studies aimed to provide efficient software tools to distinguish between the different types of tissues within a CW and to correctly classify them. Summary of those studies can be found in Table 3. These algorithms may enable to automatically identify necrotic tissues, granulation tissue, slough and healing tissues. For example, Garcia-Zapirain et al. (2018) have used a database of 193 images to develop a system for automatic segmentation and detection of tissues in a pressure ulcer/injury [30]. Their algorithm consisted of two main steps using a 3D convolutional neural network (CNN) model (a CNN model applied on a 3-dimentional dataset, such as a series of 2D images taken through time or space [95]). In the first step, the 3D CNN model was used to distinguish the external pressure ulcer/injury boundaries using the preprocessed images as an input. In the second step, a deeper 3D CNN model was designed to segment the internal boundaries of the necrotic, granulation and slough tissues from the background. They compared the performances of their algorithm to two traditional computer vision segmentation techniques, the Fuzzy C-Means (FCM) and the Linear Combination of Discrete Gaussians (LCDG) and found that their approach has reached the highest AUC for classification of all the three aforementioned tissue types. Specifically, the average AUC of their algorithm was 95% while the other two tested computer vision techniques reached substantially lower AUC values of 69% and 77%. Accordingly, their layered CNN approach contributed another tier (together with the other aforementioned studies) to the role of AI in VAs.

Veredas et al. (2010) designed a computational system by integrating neural networks and Bayesian classifiers for automatic tissue-type identification and classification in wound images [25]. The latter computational system consisted of wound region segmentation and categorical tissue classification, which performed successfully by designing specific heuristics based on the wound topology. Veredas and colleagues demonstrated high global classification accuracy rates of their system, with average sensitivity, specificity and accuracy scores of 78.7%, 94.7% and 91.5%, respectively.

Another potential capability that AI methodologies may provide for supporting a VA process is in identifying the type of the wound that is under assessment, objectively and automatically. Kavitha et al. (2017) proposed a method to perform an automatic, binary classification between pressure ulcers/injuries and leg ulcers [20]. They suggested a pipeline process for the wound image analysis that included preprocessing of the digital wound images (e.g., color correction, noise removal and color homogenization), segmentation, feature extraction and finally, classification of the CW type. Using 59 wound images, they trained and evaluated their algorithm. They found that the accuracy of their classification process was 83.1% using the MLP classifier.

Similarly, Abubakar et al. (2020) suggested a tool for discriminating pressure ulcers/injuries from burn wounds [28]. They used a database of 29 pressure ulcer/injury images and 31 burn images and developed an algorithm that consisted of a 3D CNN for feature extraction, followed by application of an SVM classifier. They reported impressive accuracy of 99.9% in the task of classifying pressure ulcers/injuries versus burns.

Lustig et al. (2022) aimed to develop an AI-powered classification algorithm to diagnose and predict the formation of heel deep tissue injuries (DTIs), based on a daily-collected database of Sub-epidermal moisture (SEM) measurements [11]. SEM data, which is an established biophysical marker of pressure ulcer formation, was collected in this article using a commercial SEM scanner (Bruin Biometrics LLC, Los Angeles CA, USA). Classification algorithm was developed to identify patients who eventually developed heel DTI among patients who did not, using SEM measurements. Furthermore, prediction algorithm was designed to predict whether a heel DTI will occur. The classification algorithm gained 79% accuracy and 90% sensitivity, where the prediction algorithm gained an average accuracy of 77% and average sensitivity of 80%. These results point out the potential clinical utility of SEM measurements, integrated with AI methodologies, to early detect DTIs and PUs/PIs.

Assessment of the wound severity and depth and identifying the presence of infection and ischemia is also possible using AI methodologies, as reported in 22 of the presently identified studies. Those studies are summarized in Tables 2 and 4, where Table 2 includes studies aimed to obtain quantitative information and measurements concerning the wound size, and Table 4 includes studies which their goal was to detect and assess wound infection and/or ischemia.

4.8 Predicting the formation and progress of wounds based on electronic health records

The practice of acquiring and regularly updating EHRs, clinical background notes, records of examination results, physician assessments, medical procedures and clinical notes in general, generates large (textual and numerical) databases of patient and population conditions. Traditionally, physicians and nurses have used manual scoring tools to identify patients at risk of developing wounds. The currently available AI methods can support this process and provide considerably more rapid and objective risk assessments, by computationally analyzing the large amounts of accumulated data in EHRs. Predictive models which are based on generalizable features (such as data from EHRs) can provide more in-depth information about the risk of patients to develop a new wound and/or the likelihood of an existing wound to deteriorate, which in turn, facilitates informed clinical decision-making concerning preventative or treatment interventions [77]. That being said, in practice, the nature of EHR data is highly diverse across different wound care settings due to differences in data input (i.e., institution-specific workflows and conventions), and the EHR software designs themselves. Accordingly, there are practical and implementation challenges in extracting pertinent features from EHRs in a generalizable way, since for different care settings and facilities, these features exist in different schemes and across structured and unstructured data, and variables are subject to missingness and inaccuracies in input or extraction data [96–98]. For example, NLP systems optimized for notes from one system may not perform similarly for another system, and therefore, in such language-related aspects, non-textual, i.e., image data of wound photographs may perhaps be more generalizable as an input data source than EHRs, despite the images being taken by various devices and users.

Nine of the studies that were identified in this scoping review aimed to develop predictive models for wound formation and evolution based on categorical and quantitative information that has been collected from clinical notes and EHRs (Table 5). For example, Alderden et al. (2018) collected data from EHRs of 6376 patients hospitalized in a surgical ICU and selected a set of predictors as variable inputs to their prediction model [40]. The input variables included the body mass index (BMI), body core temperature, severity of the illness and more; these were fed into a RF model to predict the development of pressure ulcers/injuries. Their algorithm obtained an AUC of 0.79.

In another recent study published by Goodwin et al. (2020), the aim was to develop a generalizable model capable of leveraging clinical notes to predict healthcare-associated diseases 24 to 96 hours in advance and specifically, the onset of hospital-acquired pressure ulcers/injuries [75]. They developed a recurrent additive network for temporal risk prediction (CANTRIP), based on natural language processing (NLP) methodologies, using 35218 clinical reports of patient cases. This CANTRIP algorithm, operating on text alone, obtained AUC of 74%–87% and specificity of 77%–85% which is promising.

Chun et al. (2021) aimed to establish a model that predicts 7-day clinical outcomes in children with a pressure ulcer/injury [78]. They included 152 patients with a category-I pressure ulcer/injury or a suspected deep tissue injury and divided this cohort into two groups, namely, those who demonstrated healing versus children who presented delayed healing. The patients were followed for 7 days and their pressure ulcers/injuries were analyzed by their characteristics, demographics, treatment, clinical situation, vital signs and blood test results. Using the collected data, a prediction model was constructed by RF (including a so called 'eXtreme Gradient Boosting' ML approach). The best prediction model, trained and tested using RF with 10 variables, achieved an accuracy, sensitivity, specificity, and AUC of 0.82, 0.80, 0.84, and 0.89, respectively. The most influential variables, in order of importance, were the serum creatinine level, the red blood cell count and the hematocrit reading. This model, which is unique in being specific to the pediatric population, may allow to improve the quality of care and clinical outcomes in children with pressure ulcers/injuries.

4.9 Predicting the formation and evolution of wounds based on a dynamic evaluation of wound characteristics and relevant physiological measures

Chronic and acute wounds both change over time. Changes in peri-wound skin and the appearance of the wound bed, together with physiological measures such as the skin and wound tissue temperatures, the exudate production, its contents and biophysical and biochemical properties may indicate healthy healing or, alert that the wound is shifting into infection, chronicity or both. By using AI methodologies, it may be possible to predict the potential path of progression of a wound (towards either healthy healing or chronicity) in advance, using data of temporal and dynamic measures, and to clinically intervene accordingly. In fourteen of the studies included in this review (summarizes in Table 6), the authors have developed predictive models based on dynamic wound characteristics and physiological measurements.

Martínez-Jiménez et al. (2018), for example, aimed to determine if temperature differences between a burn region and a healthy skin of a patient, assessed by infrared thermography, could be used to predict the treatment modality of spontaneous healing by re-epithelization, or skin grafting, or amputations [79]. In the algorithm development step, they recorded the temperature differences between the burns and healthy skin tissues of patients during the first three days after injury and then, categorized the patients according to one of the three aforementioned treatment modalities. A prediction model, based on the above burn-skin temperature differences, was developed using a recursive partitioning RF ML algorithm. They found that their algorithm correctly predicted into which treatment category a certain patient would eventually fall, with 85.4% accuracy.

The use of AI algorithms such as the above may contribute to predicting the severity of the injury and the clinical outcome and will, therefore, guide clinical decision-making and optimize institutional healthcare resources. In particular, use of adequate AI algorithms as adjunct to clinical judgment has the potential to prevent or at least mitigate potentially devastating consequences of inadequate treatment procedures.

Kim et al. (2020) built a ML model to predict the healing of diabetic foot ulcers, using both EHRs and an image database [54]. In their research, both hand-crafted color texture features and deep learning-based features were extracted from the wound images. For prediction, SVM and random forest models were trained, and the results showed that models built from hand-crafted imaging features alone outperformed models built with clinical or deep-learning features alone. These results suggested that the use of only hand-crafted image features and raw clinical attributes, which provide more intuitive insights to both clinicians and patients, can yield adequate wound healing predictions. Other articles described models developed based on dynamic image databases, to automatically predict the wound severity [99], infection [76,80], evolution [50,71,78] or care decisions [65].

Another approach for preventing the formation and progression of pressure ulcers/injuries associated with prolonged bed stays is to detect the body position and evaluate whether a monitored patient has remained in a certain posture for a long period of time. As mentioned in three articles included in this scoping review, prolonged bed rests without repositioning may lead to pressure ulcers/injuries [85,86], [87]; accordingly, developing a model that automatically detects movement in bed can be used for scheduling postural changes for patients, which contributes to effectively using nursing labor and time.

For example, Matar et al. (2020) suggested an autonomous method for classifying four in-bed lying postures using data from textile-made pressure sensors embedded under the bed sheet [86]. Data collected from twelve adult subjects were implemented in a supervised artificial neural network model for the in-bed posture classification. The classification model reached high prediction scores, with accuracy of 0.97 and a Cohen's Kappa coefficient (a measure of inter-rater reliability) of 0.972. Apart from preventing pressure ulcers/injuries associated with prolonged stays in bed, an autonomous method of in-bed posture monitoring such as the above can also be used in several other medical fields where in-bed posture identification is much needed, such as in sleep studies and post-surgical (recovery from anesthesia) procedures.

4.10 Smartphone and tablet use in wound diagnosis and management

The outbreak of the coronavirus 2019 disease (COVID-19) has brought the topic of telemedicine into a sharp focus. In the context of pressure ulcers/injuries, the need for tele-healthcare is often associated with limited access to elderly care facilities, in view of the risk of COVID-19 infection to the facilities, and the increased susceptibility of elderly residents in long-term care settings to both pressure ulcers/injuries and COVID-19. Bioengineering contributions in this regard may focus on ML algorithms that provide AI consultation systems to expert healthcare professionals, through smartphone/tablet application software. This can lead to development of big databases of nursing home resident data that will reveal the extrinsic and intrinsic factors affecting the risk of pressure ulcers/injuries or the likelihood of their healing in these individuals for particular settings or institutes (including under the effects of COVID-19). The availability of such AI-based consultation tools may also have an overall positive effect on the standard of care that aged-care residents are receiving as a collective, as well as individually (e.g., if specific measures are taken to mitigate the injury risk).

The data collected by AI systems through smartphones/tablets may include EHRs, VAs, additional physiological measures that indicate susceptibility or early signs of a forming pressure ulcer/injury such as changes in subepidermal moisture, infrared thermography or ultrasound measurements and any relevant risk factors, including ones that can be mitigated by adequate interventions. Based on data mining and ML algorithms employing the collected big data, AI systems can then offer clinicians the specific measures that have been proven to be successful in other similar cases. Such AI systems may further incorporate all the published recommendations in the 2019 International Guideline for Pressure Ulcer/Injury Prevention and Treatment [100]. Hence, effectively, in the future, AI systems will facilitate machine-based, real-time consultation, as adjunct to the expert clinical judgment and experience, which will be the most advanced and up-to-date comprehensive synthesis of all the available and contemporary medical knowledge regarding pressure ulcer/injury prevention and treatment, including in individuals affected by COVID-19. All of that will be available at the click of a button, and will be delivered instantaneously to the cellular devices that healthcare professionals typically use in their daily work already.

In fact, from a hardware and software technology perspective, smartphones and tablets are already mature for implementation of AI systems. Their design features include powerful processors, multiple high-resolution cameras and communication capabilities,

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particularly including wireless connection to cloud computing. Therefore, smartphones and tablets are very likely to play a major role in the growing impact of AI in wound diagnosis and management as they facilitate image and textual data collection, potential integration of physiological sensors, fast data analysis supported by cloud computing and friendly user interfaces. In particular, acquiring image data using smartphone cameras does not require special proficiencies and therefore, can be done by healthcare professionals during their routine care of patients (many clinicians regularly document the wound healing of their patients using smartphones already). Acquiring such visual data in real-life scenarios, under hospital conditions and by unprofessional photographers also provides realistic settings and data for the AI algorithms to cope with, which is a challenge. Eight of the presently identified studies reported that wound images were acquired using smartphone cameras, and summarizes in Table 7.

Shenoy et al. (2019) have implemented their wound image classification network called ‘Deepwound’ on a mobile application that can assist physicians and patients in postoperative wound surveillance [33]. They collected 1335 diverse smartphone wound images containing nine different wound types and conditions, ranged from open wounds with infections to closed wounds with sutures. They then generated a model called 'Deepwound', a combination of three separate models that are based on the VGG-16 CNN architecture after modifications. The mobile application presented in their article, called "Theia", is a suggested way to deliver the 'Deepwound' model to patients and care providers, by classifying every image that a user acquires into one of nine possible categories (wound types). The 'Deepwound' model performances were evaluated through parameters of accuracy, sensitivity, specificity and F-score. Wounds closed by tape strips obtained the best combined accuracy, sensitivity, AUC and F-score of 0.97, 0.82, 0.95 and 0.85 respectively, whereas the drainage classification achieved the best sensitivity score of 0.98. The Shenoy et al. (2019) approach further facilitates remote monitoring of patients, ease of communication with the medical team and early identification of wound infections. Their mobile application can also generate comprehensive medical reports that can be used for the purpose of billing insurers, thus saving the cost of a clinician time.

Another interesting approach is described in Chen et al. (2018) study, which proposed a surgical wound assessment system for self-care, based on an image database acquired by smartphone cameras [45]. This system enabled patients to capture their surgical wound by using mobile devices and upload these images for further analysis of wound segmentation, skin and wound area detection, and wound assessment (state and symptoms). The Chen and colleagues approach achieved an accuracy rate of 90% for wound state assessment and 91% for symptom assessment, using a KNN classifier. The case studies examined in this paper showed that the suggested system could detect and assess multiple symptoms of surgical wounds, and the results further demonstrated that this system may support healthcare professionals in obtaining robust surgical wound assessments, which in turn improves cost-effective usage of medical resources.

4.11 Feasible implementation of AI solutions for wound care delivery and management

Many studies included in this review show promising results regarding wound management and care and have the potential to improve wound care delivered to patients who suffer from chronic wounds by using AI methodologies. However, it appears that many of those studies mainly presented ML models which are still far from being available for implementation in real-life due to various reasons, such as ML models that did not consider the backend processes required for implementation, or in the absence of sufficient details concerning the software and/or hardware for the implementation (e.g., where it was unclear if a mobile phone or a tablet can run the algorithm and provide the desired outputs). Table 8 lists studies describing solutions that we view as feasibly possible for future implementation in clinical practice. Studies describing an achievable goal using approachable methods for data acquisition and easy-to-use systems that can potentially be practiced by healthcare providers and clinicians in healthcare facilities “as is”, were considered as possible for actual implementation in medical settings, and thereby, included in the aforementioned Table 8. Most of the reviewed studies that met the above-mentioned criteria suggested end-to-end automatic systems in which data acquisition, data processing and final results can all be obtained and can be integrated by software updates to existing electronics in the hardware systems or devices that are already in use by healthcare professionals during their daily routine of clinical practice. For example, Lustig et al. (2022) recently demonstrated the feasibility of such potential integration by developing an ML algorithm for early detection of heel deep tissue injuries, based on data collected by the commercial SEM Scanner (Bruin Biometrics LLC, Los Angeles, CA, USA); the SEM Scanner is a medical device which is currently being used clinically, on a daily basis, by care providers in many healthcare facilities worldwide [11].

Zahia and colleagues (2020), for example, described an end-to-end non-intrusive system which automatically retrieves quantitative information of a pressure injury, such as the depth, area, volume and major and minor axes of the wound under observation, using a 2D image and a 3D mesh of the wound [58]. The 2D wound image was obtained by means of a tablet camera, and the 3D wound mesh was acquired through an easy-to-use structure sensor mounted on the tablet. Convolutional neural network (CNN) algorithms were then used to automatically detect and segment the wound area from the 2D image, then the segmentation results were combined with the 3D wound mesh, and the quantitative information associated with the wound was automatically computed. During their research, Zahia et al. showed that caregivers could capture the 2D images and the 3D meshes efficiently, and the acquisition time ranged from 1 to 2 minutes in total, which is clinically feasible. This system appears to be approachable and easy-to-use by healthcare providers using a simple tablet and a mounted sensor, in addition to the short time it takes to collect the relevant data which enables the clinicians to manage their time with their patients more effectively.

Nonetheless, real-life implementation of AI technologies in health care is still subjected to many obstacles. One of the main barriers is the absence of regulations concerning the safety and efficacy of AI systems in the medical field. Related to that are growing concerns regarding data privacy and cyber-security. Furthermore, the medical environment is currently not compatible to automated data exchange and for continuous supply and update of the data for further development and improvement of AI systems [101]. However, we believe that following the substantial growth in medical research regarding integration of AI methodologies in wound care and management, feasible implementation of AI technologies in the wound care field would become available in the near future.

4.12 Types of data modalities for diagnosis, detection and prediction of chronic wounds.

Many data types, i.e., clinical notes, image datasets, electronic health records (EHRs) and experimental measurements, were used for model construction in the studies included in this review. Those data types were used for different tasks, such as wound/tissue type classification, prediction and diagnosis.

Fourteen of the reviewed articles suggested a predictive model for wound prognosis or for providing automated advice concerning the required treatment, or for calculating the likelihood of healing. For these purposes, a variety of data types and modalities were used, including EHRs, image datasets, spatial/temporal dynamic data or a combination of several modalities, to build more reliable databases for the model construction. A notably good predictive model demonstrating promising results is the one recently presented by Song et al. (2021), who aimed to develop an ML model to predict pressure injury development, using phenotypes derived from nurse-entered direct patient assessment data [73]. For the construction of this model, more than 180,000 clinical records were collected from five different US hospitals, forming a relatively large input dataset. For the prediction purpose, several ML models were developed, where Random Forest (RF) performed the best of all models, achieving an AUC of 0.92-0.94.

Image datasets, EHRs and experimental results were the data modalities used in 34 reviewed studies aimed to obtain wound assessment and diagnosis. Image datasets were mostly used for this goal, and images were obtained by means of different hardware types, as mentioned above (e.g., digital cameras, mobile phones and infrared thermography). Liu et al. (2018), for example, developed a deep neural network called WoundSeg to locate and segment chronic wounds automatically in images [18]. The WoundSeg algorithm included a computationally efficient wound segmentation based on a MobileNets model (a CNN containing depth-wise separable convolutions, to build a light-weight deep neural network [102]), as well as data augmentation and post-processing. The Liu et al. model showed promising results of 98.18% accuracy and 93.31% precision, which are considered to position this model as an alternative approach for replacing the traditional empirical and manual wound area measurements.

As for the classification task, 28 reviewed articles aimed to classify wound etiologies, wound tissue types, healthy and infected skin and wound severity stages. Those articles mostly used image datasets collected by digital cameras, while few studies used experimental results or EHRs. Most classifiers obtained relatively good results (>90% accuracy scores), which emphasizes the promising contribution of using AI methodologies in the wound care and management arena.

5.0 Summary

This scoping review focused on the existing and potential contributions of AI-based methodologies and AI-powered technologies in wound care and management. We reviewed articles that reported AI methodologies aimed at supporting both the diagnosis and monitoring of the healing process. After a systematic scanning of electronic databases, a total of 75 studies that were published from January 2010 to April 2021 were included in this work. We documented and classified the findings according to the main study goal, the clinical setting and the patient population and sample that were considered, as well as the design, main AI methodology, primary outcomes and limitations. Taken together, the results are definite and reveal a strong positive impact and prospect of novel AI methodologies in the wound care arena. It was specifically shown that implementation of computerized machine learning algorithms in the diagnosis of acute and chronic wounds has the potential to improve the wound care delivered to hospitalized patients and aged-care residents, particularly by enabling clinicians, healthcare professionals and nurses to allocate their time more efficiently.

Machine learning models based on imaging data are considered to be relatively narrow in terms of the task type the ML algorithm is trained to perform. That said, focusing on implementation of ML in chronic wound care and management, the tasks are relatively coherent and invariable, and can be categorized as classification or prediction tasks. Classification of chronic wounds by means of ML typically requires an imaging model for detection of the wound and its etiology and/or segmentation of the wound and the tissues within (as discussed in Section 5.7). As for prediction tasks, ML models can be taught to predict the potential path of progression of a wound (i.e., towards healing, or stagnation and chronicity, as described in Sections 5.8 and 5.9). Given the successful performance of ML in these aspects as presented in this scoping review, we expect that the above tasks can be supported by ML, first perhaps as adjunct to clinical judgement and then as a robo-advisor where wound care specialty is not immediately available or accessible.

Most of the studies reviewed here were focused on the development and evaluation of AI algorithms for classification and segmentation of the wound area, based on databases of wound images [1,16,27–36,18,37–39,42–48,19,51,55,57,60,61,63,65–67,69,20,74,76,79,81–84,88,89,21–24,26]. Machine learning classifiers that emerged as popular for wound classification were SVM [20,21,55,57,61,62,64,71,73,76,81,82,28,88,29,31,39,48,52–54], logistic regression [17,56,87,59,64,68,70,73,76,77,82] and random forest [20,40,79,82,45,55,64,69,70,73,77,78]. The performances of each classifier were typically evaluated by statistical measures such as sensitivity, specificity, accuracy and the F-score. Several studies used AI methodologies for supporting visual skin or wound assessments [1,17,32–36,38,39,43–45,18,47,51–53,55,58,59,61,63,64,20,65,68,70,74,78,83,88,91,22,23,26,27,30,31], for discrimination between different wound types such as pressure ulcers/injuries versus leg ulcers or burns [16,19,21,25,28,37,48,57], or for classification of the wound severity, depth and the presence and stage of infection [24,29,81,82,84,89,42,46,49,60,66,67,69,72]. Other studies used AI methodologies for risk assessments, i.e., to predict the probability of a certain patient to develop a chronic wound, based on their clinical records or images acquired at different time points [40,50,80,54,56,71,73,75–77,79]. Only two studies suggested NLP methodologies for wound identification based on electronic health records in combination with pathophysiological markers that are specific to the wound etiology, an approach that appears to be promising for prevention and early detection of wounds [64,75].

Another innovative approach for AI-powered wound care is through telemedicine and tele-healthcare, using smartphones/tablets for collecting skin or wound images and possibly other (patho-)physiological measures, which become the inputs for the AI-based system [16,29,33–35,45,54,58]. This appears to be a promising approach for AI-based remote consultation. In such remote consultation, the AI algorithm provides immediate automated advice to the local healthcare professional (as a ‘robo-advisor’), but the medical information can also be transferred via cloud computing to a remote human expert who can further guide the local clinician (with the AI system serving as an adjunct to the clinical judgements of both). The prospect of such AI systems relies on the fact that everyone is now experienced in using mobile apps and in acquiring image data by means of their personal smartphones, hence, no specific expertise or training are needed (in fact, numerous wound care clinicians use their cell phone cameras for documenting the healing of the wounds that they treat, as part of their daily routine). Integration of AI-powered wound care algorithms with cloud computing using smartphones as a platform hardware is therefore a practical and promising way forward.

We believe that telemedicine and tele-healthcare are an innovative approach which is likely to be wildly used and adopted in would care facilities in the near future. As mentioned above, many wound care clinicians already use their smartphones/tablets for wound documentation on a daily basis, hence, we expect that the use of smartphones/tablets for other purposes, such as remote consultation and image collection, would be naturally and easily implemented by practicing clinicians. As for the other novel approaches mentioned in this review, such as predicting the formation and progress of wounds or supporting the clinical visual assessment of wounds using AI technology, we believe that due to the advanced integration of AI methodologies in the wound care arena, they will soon become accessible among clinicians and healthcare professionals by computerized algorithms implemented in handheld diagnostic devices or bedside terminals.

One limitation of this scoping review that is noteworthy is that only peer-reviewed journal articles published in the English language were included, whereas conference abstracts or patents and patent applications were not considered eligible. While we might have missed some of the knowledge in the frontier areas of AI in wound care, we felt that the peer-review filter was necessary as a basic quality measure for filtering the reported work. Second, we did not consider issues of clinical implementation of AI methodologies in this review work but rather, have focused on the technology aspects and the pre-clinical evaluation of algorithms and software codes. The topic of implementation of AI in clinical practice is in its early days and would require a separate meta-analysis which we plan to conduct in the near future. Another notable limitation is that out of the reports that used EHR dataset for the model construction, some EHRs included data collected methodologically during several years, whereas others captured clinical information sporadically, or without specifying the frequency or time period during which the clinical data were recorded, likely contributing to variability and compromising the power of the corresponding AI/ML algorithms, as good as they may be.

Our scoping review of studies about AI-based technologies for wound care and management showed predominantly studies that presented novel techniques and encouraging accuracy results for wound identification and prevention. We believe that the methodologic issues highlighted in our work (such as utilization of smartphones/tablets for remote consultation, and NLP methodologies for wound identification based on electronic health records) can potentially improve wound care delivery and might optimize clinicians and healthcare professionals working time.

6.0 Take-home messages

- There appears to be a strong positive impact of, and prospect for novel AI methodologies in the wound care arena
- The implementation of computerized machine learning algorithms in the diagnosis of acute and chronic wounds has the potential to improve the wound care delivered to hospitalized patients as well as to enable clinicians to allocate their time more efficiently
- Telemedicine and tele-healthcare are innovative and promising approaches for AI-based remote consultation, to provide immediate and automated advice to local healthcare professionals
- Integration of AI-powered wound care algorithms with cloud computing, using smartphones or tablets as a platform hardware, is a practical and promising way forward.

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List of abbreviations

Area under the curve	AUC
Artificial intelligence	AI
Associative hierarchical random field	AHRF
Burn wound	BW
Chronic wounds	CW
Convolutional neural network	CNN
Decision tree	DT
Deep learning	DL
Deep neural network	DNN
Diabetic foot ulcer	DFU
Dice similarity coefficient	DSC
Electronic health record	EHR
Hospital acquired pressure injury	HAPI
K-nearest neighbors	KNN
Linear discriminant analysis	LDA
Machine learning	ML
Minimum distance	MD
Multi-layer perceptron	MLP
Naive Bayes	NB
Natural language processing	NLP
Neural network	NN

Optical coherence tomography	OCT
Percentage area distance	PAD
Pressure ulcer	PU
Raman Spectroscopy	RS
Random forest	RF
Rate of appearance	ROA
Receiver operating curve	ROC
Red green blue	RGB
Region of interest	ROI
Sub-Epidermal Moisture	SEM
Spatial frequency domain imaging	SFDI
Spectral angle mapper	SAM
Spectral information divergence	SID
Support vector machine	SVM
Surgical site infection	SSI

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Table 1: Glossary of key technical terms in the field of artificial intelligence (AI) and machine learning (ML), and related image processing techniques relevant to wound care research and technology development.

Term	Definition
Area under the curve (AUC)	The area under the receiver operating curve [88]
Cohen's Kappa coefficient	An expression of the amount of agreement in excess of that which would be expected by random chance [98]
Convolutional neural network (CNN)	A neural network in which the same operation is performed on different parts of the image. This forces the extracted features in different parts of the image to be computed by the same functions [96]
Deep learning (DL)	A way of extracting higher-level features from the input values by representations that are expressed in terms of other, simpler representations. This method enables the computer to build complex concepts out of simpler concepts [90]
Deep neural network (DNN)	A neural network with more than two layers, using complex mathematical modeling to process data[91]
Dice similarity coefficient (DSC)	Also referred as the "association index", a statistic that indicates the level of association between two given groups compared to the extent of the association between them that is expected merely by chance [89]

Term	Definition
F1-score	A statistic which relies on the associated precision and recall of the prediction model [99]
K-nearest neighbors (KNN)	An on-parametric algorithm used for segmentation and classification. In this method, a new point is classified by its k closest points in the training sample [96]
Logistic regression (LR)	An ML model for binary classification. Logit transformation is used to obtain a probability of 0 or 1 (such as true/false, or positive/negative). A sigmoid function is most commonly used for the logit transformation [93]
Multi-layered perceptron (MLP)	A mathematical function mapping a set of input values to output values [90]
Natural language processing (NLP)	A subfield of linguistics and computer science that utilizes artificial intelligence to process, organize, and extract embedded information from texts [97]
Optical coherence tomography (OCT)	Noninvasive cross-sectional imaging in biological systems, using low-coherence interferometry to produce a two-dimensional image of optical scattering from internal tissue microstructures [95]

Term	Definition
Raman spectroscopy (RS)	A spectroscopy technique that measures vibrations and rotational energies to analyze intermolecular functional groups and corresponding molecular structures. This method can provide the rapid molecular characterization of tissues *in vivo* or *in vitro* [94]
Random forest (RF)	A combination of tree predictors such that each tree depends on a set of randomly sampled vectors [89]
Receiver operating curve (ROC)	A plot that depicts the trade-off between the sensitivity and specificity across a series of cut-offs points when the diagnostic test is continuous or on an ordinal scale [87]
Spatial frequency domain imaging (SFDI)	A non-contact imaging method for measuring the absorption and reduced scattering coefficients of biological tissues on a pixel-by-pixel basis[95]
Support vector machine (SVM)	A supervised ML algorithm that sorts data into two categories, by segregating the two classes in the best possible way (by a hyperplane or a line) [92]
VGG	A deep convolutional neural network of 16-19 convolutional and fully-connected layers, with small convolution filters (3×3) and large depth. This architecture is most commonly used for

Term	Definition
	computer vision [100]

Table 2: Overview of the characteristics of studies that aimed to develop a clinical visual assessment of wounds using AI methodologies for wound segmentation and/or identification or for obtaining quantitative information about the wound

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Liu et al., 2018 [34]	To develop a DNN that locate and segment wound areas automatically	950 images	Data augmentation and CNN	Wound assessment	• WoundSeg reached 98.18 % accuracy, highest from all other evaluated approaches (from both classical image analysis and DL fields) • WoundSeg can be considered a	

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Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					promising approach to replace empirical and imprecise manual measurement for wound areas which can benefit both patients and clinicians.	
Kavitha et al., 2017 [56]	To develop an efficient approach for CW	59 wound images from Medetec database	MLP, SVM, RF and NB	Wound assessment	Binary classification results showed highest accuracy	• Small sample size • More advanced ML classifiers

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	assessment using wound photographs				for MLP (83.0508 %)	should be considered
Song et al.,2012 [68]	To propose a method for image segmentation and identification of DFU wound images using ML approach	92 wound digital color images	MLP and the Radial Basis Function (RBF)	Wound assessment	MLP is less accurate and takes more time to train relative to the RBF.	Small sample size
Badea et al., 2016 [66]	To develop a discrimination tool between healthy and burn wounds using CNN	611 images in hospital conditions	Binary classification task (skin/burn) using CNN	Wound assessment	The proposed approach achieves an overall performance comparable to the	• Very coarse marking of burn area by specialist • The classifier is not

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	that will support burn surgeons in their clinical decision making				literature-reported average performance of a specialist surgeon	optimized and no special calibration was applied to image data; they report overfitting of the model
Sevik et al., 2019 [69]	To create a system that can distinguish skin and burn areas on burn images taken by technicians in emergency services	105 images in hospital conditions	Semantic segmentation using SegNet architecture (DL)	Wound assessment	• SegNet architecture trained with the 64 × 64 pixel-sized blocks sampled from the training datasets managed to	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					obtain an F-score of 0.805 • SegNet architecture is superior to most of the existing methods in healthy versus burned skin classification	
Gamage et al., 2019 [70]	To propose CNN architecture for classification of severity	2400 images collected in diabetic clinic	1) Fine tuning of pre-trained CNN models 2) Feature extraction based on CNN models	Classification	• Fine-tuning approach gave low accuracy and required	Small sample size with low quality

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	stage of DFU				more computational time • Pre-trained CNN models for feature extraction that fed into classifiers gave higher accuracy	
Veredas et al., 2010 [63]	To design a computational approach for tissue recognition in pressure ulcer/injur	113 color photographs of took by clinicians	Hybrid approach based on four-stage-cascade binary classification system consisting of Bayesian	Wound assessment	Their binary cascade approach gives high global performance rates (average sensitivity	Manual segmentation and classification of pressure ulcer/injury tissues is an inaccurate procedure, which yields

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	y images		committee machines composed of MLP		=78.7%, specificity = 94.7%, and accuracy = 91.5%) and shows the highest average sensitivity score (=86.3%) when detecting necrotic tissue in the wound	high inter- and intra-observer variability
Wang et al., 2019 [14]	To propose a wound detection system to determine the boundarie	Images of moulage wounds placed on an artificial foot and	Associative hierarchical random field (AHRF) framework to wound area determinati	Wound assessment	Compared to other conditional random field based ML strategies, their new	• Small sample size of real wounds • Computationally expensive • DL is likely

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	s of foot ulcers	images of real DFTs in hospital conditions	on task		method provides a determination accuracy with the best global performance rates (specificity: >95% and sensitivity: >77%.)	to outperform AHRF when many wound images is available
Jiao et al., 2019 [15]	To propose a novel method employing a state-of-the-art DL technique to segment BW in	1150 burn images collected in hospital conditions	Object detection and segmentation using a Mask R-CNN	Wound assessment	• The R101FA [87] backbone network gains the highest accuracy 84.51% in 150 pictures	Small sample size

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	images				• The R101FA backbone network gains the best segmentation effect in superficial, superficial thickness, and deep partial thickness • The R101A backbone network gains the best	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					segmentation effect in full-thickness burn • Contributes to the calculation of total body surface area burned compared to traditional methods	
Abubakar et al., 2020 [16]	To investigate if the use of an ML approach	• 29 pressure ulcer/injury images	Pre-trained CNN for features extraction followed by a SVM	Wound assessment	Accuracy of up to 99.9% obtained	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	that can aid in accurately discriminating between burns and pressure ulcers/injuries	obtained via search on the internet • 31 burn images acquired in hospital conditions	classification algorithm			
Zhang et al., 2018 [20]	To propose CW image generator for more accurate wound segmentation and recognition	450 images from the dataset built in article [Liu et al., 2018 [34]].	Image generator based on DCGANs [88]	Wound assessment	Addition of newly generated CW images to the training set lead to higher segmentation accuracy	Basic discriminator network

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Application of artificial intelligence methodologies to chronic wound care and management: A scoping review (DOI: 10.1089/wound.2021.0144)

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Rangaraju et al., 2019 [78]	• To assess the combined power of Raman spectroscopy (RS) and optical coherence tomography (OCT) modalities to classify burn wounds • To implement a ML algorithm to classify	RS and OCT images of burns	Supervised ML with logistic regression, SVM and RF classifiers	Wound assessment	The results obtained using ML-based classifiers show value in combining RS-OCT (average AUC-ROC=0.94), although RS (average AUC-ROC=0.93) by itself provides highly accurate classification results compared to OCT alone	• Ex-vivo study • Weak nature of inelastic Raman scattering makes it a point-and-shoot method

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	BW degree/type depending on collective features acquired and or derived from RS and OCT data				(average AUC-ROC=0.83)	
Garcia-Zapirain et al., 2018 [18]	To develop an automatic segmentation system to detect and segment pressure ulcer/injury RGB-colored	• 36 RGB colored images captured by digital camera in hospital and nursing homes conditio	3D CNN for ROI extraction followed by another 3D CNN for tissue segmentation	Wound assessment	• The classification accuracy and robustness were evaluated using DSC, PAD, ROC curve	• Small sample size • 2D wound assessment; the depth of the pressure ulcer/injury is not considered

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	images	ns • 157 images from Medetec database			and AUC • The obtained preliminary DSC of 92%, PAD of 13%, and AUC of 95% are promising	
Shenoy et al., 2019 [21]	To develop a new ML based approach using CNNs to analyze an image of a wound and document its wellness	1,335 smartphone wound images acquired in hospital conditions	CNN - adjusted VGG-16, pre-trained using ImageNet	Wound assessment	Model achieves ROC, AUC scores, sensitivity, specificity, and F1 scores superior to prior work in this area	Dataset size is small and imbalanced

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Alzubaidi et al., 2019 [22]	To propose a novel CNN model for automated classification of DFU	754 images acquired in hospital conditions using smartphones	CNN	Classification	The proposed DFU_QUT Net network outperformed the state-of-the-art CNN networks by achieving the F1-score of 94.5%.	
Goyal et al., 2018 [24]	To propose a novel CNN model for automated classification of DFU	• 292 image of patients DFU and 105 images of healthy skin acquire	CNN	Classification	Using 10-fold cross validation, DFUNet achieved an AUC score of 0.961	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
		d in hospital conditions using digital camera • Another test case captured by a smartphone camera included 20 abnormal skin patches and 32 normal skin patches				
Cui et al., 2019 [25]	To propose a DL based method	445 images	Wound segmentation using CNN	Wound assessment	U-Net architecture is more computati	Small sample size

Reference	**Aim**	**Setting and sample**	**AI methodology**	**Model type**	**Outcome**	**Limitations**
	for accurate segmentation of wound regions				onally efficient and accurate for segmentation than patch-based CNN	
Goyal et al., 2017 [27]	To develop DL approaches to train various fully convolutional networks (FCNs) that can automatically detect and segment the DFU	600 images of DFU and 105 healthy foot images acquired using a digital camera in hospital conditions	FCN trained by transfer learning to automatically segment the ulcer and surrounding skin	Wound assessment	The proposed two-tier transfer learning FCN models achieve a DSC of 0.794 (±0.104) for ulcer region, 0.851 (±0.148) for surroundi	Small sample size

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	and surrounding skin area with a high degree of accuracy				ng skin region, and 0.899 (±0.072) for the combination of both regions	
Calin et al., 2020 [84]	To identify a suitable classification method that could differentiate as accurately as possible between normal and pathological biological tissues in a	• Hyperspectral images acquired from patient with DFU • Training set of 9904 pixels for each classifier. Rest of the pixels were used for	Four supervised ML classifiers were compared: minimum distance technique (MD), spectral angle mapper (SAM), spectral information divergence (SID) and	Wound assessment	• SVM approach has outperformed the MD, SAM, and SID approaches • The overall accuracy and Kappa coefficient for SVM were	Only one case examined and low number of training pixels (mainly in the area strictly related to the ulcer)

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	hyperspectral image with applications to the diabetic foot	testing	SVM		95.54% and 0.9404, whereas for the other three approaches (MD, SAM, and SID) these statistical parameters were 69.43%/ 0.6031, 79.77%/ 0.7349 and 72.41%/ 0.6464, respectively	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Kamath et al., 2018 [28]	To develop a system for mobile wound capture using mobile devices such as smartphones	120 wound images taken from German Celciphlaxis Registry	Wound tissue segmentation using RF and SVM classifiers	Wound assessment	• RF classifier was found to produce superior results • Necrotic, sloughy, and granular tissues are classified with 89%, 39%, and 44% similarity (ratio of correctly classified pixels to the total number of masked	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					pixels in the ground truth image), respectively, using RF classifier • The trained classifier performs fast enough to be implemented on the mobile device	
Squiers et al., 2016 [79]	To compare different common ML algorithms	Multispectral imaging data of BW acquired	8 different ML algorithms including: K-nearest neighbors	Wound assessment	LDA had the highest test accuracy (70.5%)	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	and determine which is capable of classifying burn-injured tissue with the highest accuracy	from animal model	(KNN), DT, linear discriminant analysis (LDA) and variations of these			
Goyal et al., 2019 [32]	• To design DL methods for real-time DFU localization • To evaluate the performance of the models	1775 images with acquired in hospital conditions using digital camera	R-CNN using two-tier transfer learning	Wound assessment	The model achieved a mean average precision of 91.8%, the speed of 48 ms for inferencing a single image and with a model size of 57.2	

Reference	**Aim**	**Setting and sample**	**AI methodology**	**Model type**	**Outcome**	**Limitations**
	on edge device hardware				MB	
Chen et al., 2018 [35]	To propose a surgical wound assessment system for self-care	131 wound images acquired using different smartphones	KNN and RF	Wound assessment	More than 90% state assessment results are correct and more than 91% symptom assessment results consistent with the actual diagnosis	• Some symptoms are identified incorrectly due to similarity • Training data is not generalized enough
Elmogy et al., 2018 [45]	To develop an automatic segmentation system to detect and	193 wound RGB images	CNN	Wound assessment	The system achieved an average AUC equal to 95%, DSC	Small sample size

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	segment pressure ulcer/injury RGB-colored images				equals to 92%, and PAD equals to 10%	
Wang et al., 2021 [1]	• To present CNN which employs in the PI thermal image classification at first time • To attain an elementary and reliable CNN model with a small PI image	Train dataset - 82 PI infrared thermal images and 82 normal infrared thermal images, Test dataset - 82 infrared thermal images of 1 day before PI	CNN	Wound assessment and classification	The system achieved competitive capability in the train and test datasets, and comparing with the SVM and RF, the CNN model performs better showing higher	small sample size

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	dataset				AUC, sensitivity, specificity and accuracy scores	
Haque et al., 2021 [39]	• To depict an intelligent DSPN severity classifier using Adaptive Neuro Fuzzy Inference System (ANFIS) using both MNSI variables and EMG	MNSI dataset of 1,375 patients from 29 different medical centers (total of 10180 samples after removing blank entries) and a second MNSI dataset including	Adaptive Neuro Fuzzy Inference System (ANFIS)	Wound assessment	• The ANFIS model showed better performance in comparison to different ML models • Extracted EMG features were used in the proposed DSPN classifie	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	features	132 cases			r, and it exhibits promising performance in DSPN severity stratification	
Wang et al., 2020 [41]	To propose a novel convolutional framework based on MobileNetV2 and connected component labelling to segment wound regions	1,109 foot ulcer images taken from 889 patients during multiple clinical visits. The raw images were taken by Canon SX 620 HS digital	convolutional neural network (CNN), MobileNetV2 which was adopted to segment the wound from the images	Wound assessment	• This method has demonstrated its effectiveness and mobility in the field of image segmentation due to its fully convolutional	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	from natural images	camera and iPad Pro under uncontrolled illumination conditions, with various backgrounds			architecture consisting of depth-wise separable convolutional layers • This method is efficient and lightweight and could be applied to mobile devices with less memory and limited	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					computational power	
Padierna et al., 2020 [42]	To present a non-invasive methodology of PAD characterization	Infrared Thermography (IRT) from two groups of Mexican participants, one includes twenty-three diabetic patients, and the control group has twenty non-diabetic	SVM	Wound assessment	The average performance of the classification model reached 92.64% of accuracy, 91.80% of sensitivity, and specificity of 93.59%	Foot positions that make the measurements by the infrared camera difficult
Nguyen et al., 2020	To explore machine learning classifiers to	205 wound images	Decision Tree, SVM, Multi-layer Perceptron, Random	Classification	SVM classifier achieved F-score of 0.766 with	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
[46]	generate actionable wound care decisions about four chronic wound types		Forest, XGBoost		only visual features, XGBoost achieved 81% accuracy using visual and textual features	
Abubakar et al., 2020 [48]	To classify skin burn images and other skin injuries using transfer learning concept	300 burn images and 250 bruised and pressure ulcer wound images, which then pre-processed creating	Deep neural networks for feature extraction followed by a SVM classification algorithm	Classification	Accuracy of approximately 99.9%	
Bouallal et al.,	To suggest a user-friendly	394 thermal images	U-Net	Wound assessment	• The multimodal	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
2020 [54]	and mobile protocol (acquisition, transfer and processing) for thermal images of the plantar foot	and their corresponding RGB images of 122 type II diabetic patients, the images have a resolution of 160×120 pixels and the spectral range of the thermal sensors is 8−14µm			approach performs better than the method based only on the thermal image • The average temperature of the plantar surface of the foot is higher in the medium-risk	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					group than in the low-risk group	
Shi et al., 2020 [55]	Aims to investigate the effectiveness of integrating natural language processing (NLP) outputs with structured EHR data to build machine learning models for SSI identification using	Clinical records of 5,795 patients, among which 291 patients were labeled as SSI positive	Logistic regression, support vector machines (SVM), and random forest (RF) integrated with NLP	Wound assessment	RF model reached 0.58 sensitivity, 0.97 specificity, 0.54 PPV, 0.98 NPV, and 0.52 F-0.5 score	The current NLP system does not discriminate the infection status at the time of surgery or later in the postoperative course

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	real-world clinical data					
Chauhan et al., 2020 [58]	To develop a new labeled dataset of burn images and to propose a novel deep learning based approach for burn severity assessment	Burn-images (BI) dataset of 432 images was prepared by using semi-automated scripts on the Google search engine, with the average resolution of 754×823 pixels.	Convolutional Neural Network (CNN)	Wound assessment	ResNet50 pipeline achieved accuracy of 91.53%, precision of 0.881, recall of 0.866 and F1-score of 0.873	Limited image dataset

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
		Poor quality and duplicate images were excluded. Additional 63 burn images, average resolution of 1254×836 pixels, were procured form iStock for model evaluation				
Khan et al., 2020 [59]	To segment burn wounds and classificati	450 images of all the three levels of burn	Deep Convolutional Neural Network (DCNN)	Wound assessment and classification	The proposed method provided the best results of	The proposed technique does not deal with poor quality

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	on of burn depths into 1st, 2nd and 3rd degrees respectively, using Deep Convolutional Neural Network (DCNN)	depths			the classification of burnt skin that is recorded 79.4%	images of burnt skin and it supports only JPEG and PNG image formats
Ladios-Martin et al., 2020 [60]	To build a model to detect pressure injury risk in intensive care unit patients and to put the model into productio	6694 adult patients who admitted to the ICU during their hospital stay from January 1, 2016, through	Logistic regression (LR)	Wound assessment	The model had sensitivity of 0.90, specificity of 0.74, and area under the curve of 0.89 during the initial test. The model	• Some reported risk factors could not be included in the model because of excessive missing

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	n in a real environment	September 30, 2018.			performed well 1 year later in a real environment	values or inability to extract the data from the EMR • It is not possible to ensure that all PIs that developed during the period of the study were accounted for • It is not possible to clearly see how each variable affects the risk of PI developm

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
						ent • PI prevention interventions provided by nurses were not considered in this study • The usefulness of the model to other hospitals in unknown, since the model is dependent on the data that feed it

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Vered as et al., 2010 [13]	To design a computational approach for tissue recognition in pressure ulcer/injury images	113 color photographs of took by clinicians	Hybrid approach based on four-stage-cascade binary classification system consisting of Bayesian committee machines composed of MLP	Wound assessment	Their binary cascade approach gives high global performance rates (average sensitivity =78.7 %, specificity = 94.7%, and accuracy = 91.5%) and shows the highest average sensitivity score (=86.3%) when detecting necrotic tissue in the wound	Manual segmentation and classification of pressure ulcer/injury tissues is an inaccurate procedure, which yields high inter- and intra-observer variability

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Rowland et al., 2019 [77]	To examine the ability of a cubic SVM classification model to predict burn wound severity using calibrated reflectance data from multiple wavelengths and spatial frequencies obtained via	• The data from imaging studies carried out in a porcine model • 160 regions (40 from each class) from one pig used as training set and from the second pig for testing set	SVM classifier	Wound assessment	• The model based on images obtained at all wavelengths and spatial frequencies predicted burn severity at 24 h with 92.5% accuracy • The model composed of all values relative to unburned skin was 94.4% accurate • The model that employed only planar illumination was 88.8%	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	spatial frequency domain imaging (SFDI)				accurate • The addition of calibrated reflectance data collected with spatial modulation adds predictive power to a classification model for burns	
Wannous et al., 2010 [19]	To develop an innovative tool for assessing CWs that combines color analysis and dimensional	Several hundreds of color images have been taken by different digital cameras under uncontrolled illuminati	SVM classifier	Wound assessment	Real tissue areas can be computed by retro-projection of identified regions on the 3D model	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	measurement of injured tissues in a user-friendly system	on hospital conditions				
ROSS et al., 2019 [85]	To provide improved methods and systems for accurately assessing BW depth.	• A database comprising data of nodes and edges of historical burn wound of known depth • Nodes and edges of the examine	CNN	Wound assessment	• Accurate burn depth measurement • Distinguishing between second- and third-degree burns, and thereby allowing improved treatment decisions to be made	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
		d burn wound from ultrasound imaging video				
Cirillo et al., 2019 [36]	To develop cost effective, faster, and objective methods for assessing burn depth so that the utilization of these methods is not limited to specialized burn clinics	23 burn images taken using tissue viability imaging digital camera	Deep CNN with ResNet-101 architecture	Wound assessment	The ResNet-101 CNN was able to classify four types of burn depth in few seconds with an average accuracy of 91% and specificity of 94%	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Wang et al., 2020 [80]	To propose a BdasNet model which combines near-infrared hyperspectral imaging (NIHSI) technology and the CNN-transfer method to accurately assess the cross-domain full-field burn depth	Porcine model of graded burn wounds, by one Bama Miniature Pig which was used throughout the study. The burn wounds were placed on both sides of the pig's abdomen. Each side is received 9 burns, including superficial	BdasNet model which combines NIHSI technology and the CNN-transfer method	Wound assessment	The BdasNet model realized an excellent classification accuracy. The experiments demonstrated that the full-field burn classification system has the potential to be applied for burn diagnosis	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
		thickness burns to full thickness burns. The images were taken by an NIHSI system which combines projections of broad-band near infrared light with multispectral imaging				

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Zahia et al., 2020 [49]	To propose an end-to-end system which automatically retrieves quantitative information of the pressure injury using solely a 2D image and a 3D mesh of the wound	210 photographs of pressure injuries acquired using a cell-phone camera	CNNs for automatically detect and segment the wound, Mask-RCNN for segmentation of the pressure injury	Wound assessment	Mean sensitivity score of 0.85 and mean precision score of 0.87	
Silva et al., 2020 [52]	To propose a model for automatic measurem	105 pressure ulcer images from a	SVM classifier for superpixel	Wound assessment	Average accuracy of 96%, sensitivity of 94%, specificity of	Variety in shape and color observed in the

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	ent of the area affected by pressure ulcers in digital images	public data set	classification, GrabCut for segmentation		97% and precision of 94%	acquired images
Wu et al., 2021 [61]	to propose an adaptive network algorithm with reduced computational complexity to classify clinical burn thermal images and to detect	10 types of near-infrared spectrum signals with burn time of 5 s, 10 s, 20 s, 30 s, 40 s, 60 s, 80 s, 100 s, 120 s, and 140 s which were collected by spectral imaging system.	CAGA-SVR, Random Forest	Wound assessment	the accuracy of the model constructed in this paper is above 80% in the classification of clinical burn images	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	burn depth					

Table 3: Overview of the characteristics of studies that aimed to develop a clinical visual assessment of wounds using AI methodologies with emphasis on tissue type classification

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Elmogy et al., 2018 [45]	To develop an automatic classification framework to detect and segment various tissues from pressure ulcer/injury RGB images	100 images taken by digital camera in hospital and nursing home conditions), and Medetec wound database	CNN	Classification	The obtained preliminary results have AUC of 96%, PAD of 10%, and DSC of 93%. These experimental results are promising and can lead to an accurate assessment of the pressure ulcer/injury status.	Small sample size

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Godeiro et al.,2018 [12]	• To develop a non-invasive methodology for the segmentation and analysis of CW images. • To investigate algorithms for classifying tissue as necrotic, granulation or slough	30 images acquired in hospital conditions using smartphones	CNN	Wound assessment and classification	• The methodology can be applied in a typical work environment of the health care specialists. • The tissue classification task obtained values of 0.9610 ± 0.0408 of accuracy, 0.9876 ± 0.0230 of specificity, 0.9128 ± 0.0740 of sensitivity	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					and Dice coefficient equivalent to 0.9425 ± 0.0598 for the chosen methodology, the U-Net using reduced color spaces.	
Mukherjee et al.,2014 [67]	To develop a computer assisted tissue classification (granulation, necrotic, and slough)	74 images from Medetec database	Bayesian classification and SVM	Classification	SVM with 3rd order polynomial kernel provided the highest accuracies, that is, 86.94%, 90.47%, and	Small sample size

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	scheme for CW evaluation using medical image processing and statistical ML techniques				75.53%, for classifying granulation, slough, and necrotic tissues, respectively	
Nejati et al., 2018 [26]	To classify all 7 different wound tissue types, based on using a pre-trained DNN as a feature extractor for wound tissue classificati	350 images of CWs, captured in different conditions (illumination, pose, etc.), with different camera devices, with different resolutions	DNN	Classification	• Mean accuracy obtained from classification of 7 wound using AlexNet as pre-trained network is 86.4% • Robust in discrimination of	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	on				similarly looking tissue types and also, where illumination condition changes occur	
Pholberdee et al., 2018 [33]	To improve wounds segmentation accuracy, and study the impact of wound tissue types and color on accuracy	Images from Medetec database	CNN	Wound assessment	• The accuracy of the proposed method was 72%, 40%, and 53% in terms of intersection over union for granulation, necrosis, and	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					slough wound tissue types, respectively • The proposed method outperformed a prior end-to-end approach, even though it is simpler and use less training data	
Zahia et al., 2018 [37]	To present a new approach for automatic tissue	23 wound images	CNN	Classification	• Overall average classification accuracy of	Dark regions in the depth of the wound are misclassifie

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	classification in pressure injuries				92.01%, • Average total weighted DSC of 91.38%, • Average precision per class of 97.31% for granulation tissue, 96.59% for necrotic tissue, and 77.90% for slough tissue	d as necrotic tissue, which is generally very dark in color
Veredas et al., 2015 [38]	To present a computer-vision approach based on	113 images of sacrum and hip Pus acquired from	Classification of tissue type by SVM, RF, and NN	Wound assessment	RF and SVM gave significantly higher accuracies than the	High variability in the results, which rejects any prepondera

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	image processing algorithms and supervised learning techniques to help detect and classify wound tissue types that play an important role in wound diagnosis	patients with homecare assistance using digital camera			NN in both recognition tasks	nce of a particular ML technique over the rest of the models

Table 4: Overview of the characteristics of studies that aimed to develop a clinical visual assessment of wounds using AI methodologies with emphasis on infection detection

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Fletcher et al., 2019 [72]	• To predict infection in Cesarean section wounds • To develop a ML algorithm that can automatically detect infection in a surgical wound, using an image of the wound captured from a mobile device.	• 572 women who underwent Cesarean section births in a hospital, 61 infected wounds • Questionnaire responses, one image of the wound, and the clinical SSI diagnosis provided by a trained	Logistic regression models with L1 and L2 regularization and SVM	Wound assessment and prediction	• Developed algorithms that can predict the presence of an infection in a Cesarean-section wound using questionnaire data and image data, respectively, as evaluated 10-days following	• The two models are independent, the combination of the two should be considered • More advanced ML methods should be considered for both models

		doctor of each patient			surgery • The prediction using image data alone has particularly good performance and was able to match the performance of a trained doctor
Hsu et al., 2019 [17]	To propose an automated way to perform wound segmentation and wound infection assessment after surgical operation	293 wound images collected using smartphones in hospital conditions	SVM-based wound infection interpretation method using segmentation results from previous	Wound assessment	• 87.31% accuracy for anomaly detection • 83.58% accuracy for symptom assessment

			part of the study			
Goyal et al., 2020 [31]	To identify the presence of infection and ischemia in DFU using computer vision techniques	1459 images of DFU acquired in hospital conditions using digital cameras	CNN	Wound assessment	• Their method performed better in the classification of ischemia than infection • The proposed Ensemble CNN DL algorithms performed better for both classification tasks as compared to handcraf	Small size and imbalanced dataset

					ted ML algorithms, with 90% accuracy in ischemia classification and 73% in infection classification	
Wu et al., 2020 [64]	To design an integrated framework to support the diagnosis of wound infection	480 wound photographs were taken from 100 patients	deep convolutional neural networks	Wound assessment	Their model achieved a significantly higher AUC score (83.3%) than other three methods (kernel support vector machines, random forest,gradient	• The study was performed on Asian subjects • Diverse quality of wound photographs, which may cause a potenti

					boosting classifier)	al concern interfering with our algorithm • A "test" set in conjunction with a validation on dataset should be considered
Goyal et al., 2020 [24]	To propose a new dataset and computer vision techniques to identify the presence of infection and ischaemia in DFU	1459 images of patient's foot with DFU over the previous five years at the Lancashire Teaching Hospitals which were	Faster-RCNN for data-augmentation, Superpixel Colour Descriptor as feature descriptor and	Wound assessment	Ensemble CNN method achieved the highest score in all performance measures in both	• This experiment included an imbalanced DFU dataset for both ischaemia and

captured with different cameras	Ensemble Convolutional Neural Network for ischemia and infection recognition	ischaemia and infection classification, gaining 0.903 accuracy, 0.886 sensitivity, 0.902 F-score for infection classification and 0.272 accuracy, 0.709 sensitivity, 0.722 F-score	infection conditions • The dataset was collected with different cameras, which leads to more variability of image characteristics • The debridement of DFU removes important visual indicators of

						infection such as coloured exudate • Non-standardized images
Amin et al., 2020 [51]	To propose a CNN for classification and YOLOv2-DFU for localization of infection/ischemia	Infection and ischemia foot images, including 4935 augmented negative and 4935 positive patches for ischemia data and 2946 normal and 2946 abnormal skin patches for bacterial infection data	CNN for classification, YOLOv2-DFU for localization	Wound assessment and classification	The proposed research methodology has shown much improved results compared to the existing methods in terms of classification and localization	

Table 5: Overview of the characteristics of studies that aimed to predict wounds onset and evolution based on EHRs or image dataset

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Goodwin et al.,2020 [71]	To develop a generalizable model capable of leveraging clinical notes to predict healthcare-associated diseases 24–96 hours in advance	• MIMIC-III critical care database • Clinical notes from 35218 hospital admissions	NLP using reCurrent Additive Network for Temporal Risk Prediction (CANTRIP)	Prediction	• CANTRIP, operating on text alone, obtains 74%–87% AUC and 77%–85% specificity • Baseline shallow models showed lower performance on all metrics, while bidirectional long short-term memory obtained the highest	• System relied only on features extracted from clinical notes • Features only indicated the presence or absence of observations, signs, interventions, etc, meaning that values

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					sensitivity at the cost of significantly lower specificity and precision	reported in the text are not available to the model
Hu et al., 2016 [23]	To accelerate the process of extracting postoperative outcomes from medical charts	EHR of surgical patients with 493 SSI	6 models that are based on Lasso-penalized logistic regression	Wound assessment	Multi-task learning, specifically, the propensity weighted observations method, statistically significantly outperformed the single-task learning approach	• Small sample size, heterogeneity of the outcomes and skewed class distribution • More advanced NLP methods for text analysis exist

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Rowland et al., 2019 [77]	To examine the ability of a cubic SVM classification model to predict burn wound severity using calibrated reflectance data from multiple wavelengths and spatial frequencies obtained via spatial frequency domain imaging (SFDI)	• The data from imaging studies carried out in a porcine model 160 regions (40 from each class) from one pig used as training set and from the second pig for testing set	SVM classifier	Prediction	• The model based on images obtained at all wavelengths and spatial frequencies predicted burn severity at 24 h with 92.5% accuracy • The model composed of all values relative to unburned skin was 94.4% accurate • The model that employed only planar	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					illumination was 88.8% accurate The addition of calibrated reflectance data collected with spatial modulation adds predictive power to a classification model for burns	
Moon et al., 2017 [86]	To explore the factors associated with pressure ulcers/injuries among elderly patients admitted to Korean long-term care	Clinical records data of 765,564 patients	DT	Wound assessment	• The DT displayed 15 subgroups with 8 variables showing 0.804 accuracy, 0.820	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	facilities according to the 2014 Health Insurance Review and Assessment Service National Inpatient Sample (HIRA NIS) using DT analysis				sensitivity, and 0.787 specificity • The most significant primary predictor of pressure ulcers/injuries was length of stay - more than 0.5 day • Data mining methods, such as DT analysis, could identify outcome variables in a big data set with many variables	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Alderden et al., 2018 [29]	To develop a model for predicting development of pressure injuries among surgical critical care patients	Data from EHRs of 6376 patients	RF	Prediction	The ROC for both models was 0.79	Important variables in the EHRs could not be accessed
Ke et al., 2017 [76]	To predict the time to SSI onset using spatial-temporal matrix data	Dynamic wound data collected daily from 860 patients in hospital conditions	Bilinear formulation predicting model	Prediction	The suggested model has lowest mean absolute prediction error relative to other models tested	• It might be possible that different kinds of SSI have different risk factors • Variables that have been found predictive of SSI risk in the

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
						literature were not included in the database
Vered as et al., 2010 [63]	To design different ML approaches to predict the evolution of pressure ulcers/injuries in time	• 69 sacrum and hip pressure ulcers/injuries (category 3 and 4) from patients with homecare assistance, weakly photographed for maximum of 16 weeks using digital camera A total of 743 photographs were obtained	Prediction of change of wound-bed perimeter using different ML classifiers including: SVM, MLP and DT	Prediction	• NNs and DTs gave the best performance results C4.5 algorithm achieved the highest accuracy rate (~ 81%) in the prediction of the granulation/devitalized ratio from a small number of input features	

Refer ence	Aim	Setting and sample	AI method ology	Model type	Outcome	Limitation s
Jung et al., 2016 [73]	To develop a predictive model for delayed wound healing that uses information collected during routine care in outpatient wound care centers	Basic demographic information on 53,354 patients, as well as both quantitative and categorical information on 150,277 wounds recorded weekly in EHR	L1 regulari zed logistic regressi on, RF, and gradien t booste d tree	Predic tion	The model achieved an AUC of 0.842 for the delayed healing outcome and a Brier reliability score of 0.00018	The dataset may not be generalize d enough in the aspect of the type of care settings included in the research. Prospectiv e validation of the suggested model is required for application in other institutions

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
CAI et al., 2021 [40]	To develop an ML-based predictive model for SRPI in patients undergoing car diovascular surgery	149 patients who underwent car diovascular surgery	XGBoost	Prediction	ML model has more accurate discrimination power than the nomogram score, which developed previously	• The data were from a single healthcare institution within a confined geographic region, thus the generalizability of the findings may be limited • The data was not collected prospectively, which may affect the performa

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
						nce of the ML prediction model The severity of all SRPI instances in this study were Stage 1
Kim et al., 2020 [44]	To build a ML model that can predict healing of diabetes-related foot ulcers, using both clinical attributes extracted from electronic health records (EHR) and image features extracted from photographs	Electronic health records (EHR) of 2291 visits for 381 ulcers from 155 patients, including smartphone or tablet photographs of the ulcers taken by the medical staff during each visit	SVM and random forest	Prediction	The predictor demonstrated an AUC of 0.734 when using all features, 0.760–0.794 for hand-crafted imaging features alone and 0.670 for only deep learning features	• Small patient population and dataset • Some of the clinical parameters had to be imputed • There may be slight

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Choi et al., 2020 [47]	To identify risk factors and construct a risk prediction model for oral-mucosal PI development in intubated patients in the intensive care unit	Medical record of 194 patient-days	Backwards stepwise multiple logistic regression, Gaussian Naïve Bayes	Prediction	The upper oral-mucosal PI development model had an accuracy of 79%, F1 score of 88%, precision of 86%, and recall of 91%	inconsistencies in clinical attributes that are manually charted • Small sample size • cross-validation of the risk prediction model with external samples was not performed • Several risk factors were excluded in this study

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Goodwin et al., 2020 [71]	To develop a generalizable model capable of leveraging clinical notes to predict healthcare-associated diseases 24-96 hours in advance	35,218 patients for hospital acquired pressure injury	ReCurrent Additive Network for Temporal Risk Prediction (CANTRIP)	Prediction	CANTRIP obtained AUC of 87%, precision of 42% and F1 score of 53%, significantly higher results compared to manual and rule-based prediction systems	• The system relied only on features extracted from clinical notes • Features only indicated the presence or absence of observations, signs, interventions, etc. • Hypothetical and negated mentions of observations were

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
						excluded
Song et al., 2021 [65]	To develop machine learning-based predictive models, using phenotypes derived from nurse-entered direct patient assessment data	188,512 inpatient clinical records of patients affiliated with 5 hospitals. Patients that were hospitalized 24 hours or longer on a nonspecialty acute and/or intensive care unit were excluded	Logistic regression (LR), support vector machines (SVM), random forest (RF), and neural network (NN)	Prediction	RF model reached AUC = 0.92 for nonhospital acquired pressure injury group and AUC = 0.94 for hospital acquired pressure injury group	• Patient comorbidity, acuity, and pressure injury stage were not considered • Only structured data were used for the study
Mombini et al., 2020 [57]	To design a ML system that can accurately predict wound care decisions based on	2056 unlabeled wound images, including 1695 images from a local wound clinic, 249 from	XGBoost	Prediction	XGBoost algorithm achieved on average an overall performance	• Limited image dataset

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	labeled wound image data	publicly available web sources and 114 from previous study			of F-1 = .782 using labels given by an expert and a novice decision maker	
Chun et al., 2021 [74]	To identify predictors associated with PI progression and establish a model for predicting 7-day outcomes in children with PI	Patient information of 152 patients, comprising 130 and 33 with stage I PI and sDTI, respectively	Random Forest	Prediction	Accuracy, sensitivity, specificity, and area under the curve of 0.82, 0.80, 0.84, and 0.89, respectively. The most contributing variables, in order of importance, included serum creatinine, red blood cell, and	• Difficulty to obtain a detailed description of skin status assessment and other indicators • Small sample of patients with PI • A possibility that there was variability in

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					haematocrit	assessing patients • Since it is a single-centre study, the PI healing outcomes may be correlated with the medical setting, quality of treatment, and nursing care
Mansilla et al., 2020 [53]	To create a decision-support tool that will show the risk of SSI in a patient	2251 health records of patients	SVM, decision tree	Prediction	The best model is the decision tree model with all variables included with an accuracy of 93%, balanced	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					accuracy of 77.8%, precision of 89.5%, recall of 56.7%, F1 score of 69%, ROC AUC of 77.8%, and MCC of 68%	
Schäfer et al., 2021 [62]	to understand the risk factors of developing diabetic foot ulcers or amputation using machine learning approaches and sporadic health-care data sources	data of 246,705 patients with diabetes from the Danish national registry database	logistic regression (LR) Random Forest	Wound assessment	• there is a higher hazard for patients with a lower household income • diabetes patients with cardiovascular disorders, peripheral artery, neuropathy, and chronic renal complication are among	•the data was collected from various national registers, thus the coding may differ across databases •in several cases, complications arwhich

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					populations with a high risk of developing DFU and amputation Although the features that have been used in the study can be used for prediction models (based on the classifier results), they are not sufficient enough for accurate prediction of DFU/amputation	were diagnosed at the same time as DFU were omitted in the analysis • this study focuses on DFU occurrence in general, with no consideration of factors that are specific to first time or recurrent incidents

Table 6: Overview of the characteristics of studies that aimed to develop predicting models based on temporal and dynamic wound characteristics and physiological measurements

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Goodwin et al.,2020 [71]	to develop a generalizable model capable of leveraging clinical notes to predict healthcare-associated diseases 24–96 hours in advance.	• MIMIC-III critical care database clinical notes from 35218 hospital admissions for hospitalized acquired pressure injury	Natural Language Processing (NLP) using Recurrent Additive Network for Temporal Risk Prediction (CANTRIP)	Prediction	• CANTRIP, operating on text alone, obtains 74%–87% area under the curve and 77%–85% specificity • Baseline shallow models showed lower performance on all metrics, while bidi-reactional long short-term memory	• systems relied only on features extracted from clinical notes • features only indicated the presence or absence of observations, signs, interventions, etc., meanin

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					obtained the highest sensitivity at the cost of significantly lower Specificity and Precision	g that values reported in the text, such as "HgB: 7.5," are not available to the model
Fletcher et al., 2019 [72]	• to predict infection in Cesarean section wounds • to develop a machine learning algorithm that can automatically detect infection in a surgical wound, using	572 women who underwent Cesarean section births in a hospital. 61 infected wounds. The entire data set for each patient consisted of questionnaire responses, one image of the	• text-based prediction: logistic regression models with L1 and L2 regularization and Support	Prediction and wound assessment	• developed algorithms that can predict the presence of an infection in a Cesarean-section wound using questionnaire data and image data, respectively,	• the two models are independent. The combination of the two should be considered • more advanc

Refer ence	Aim	Setting and sample	AI method ology	Model type	Outcome	Limitatio ns
	an image of the wound captured from a mobile device.	wound, and the clinical SSI diagnosis provided by a trained doctor	Vector Machin e (SVM) • image-based predicti on: 100 rando mly genera ted splits of the dataset , using the same proced ure as in the questio nnaire-based models		as evaluated 10-days following surgery • The prediction using image data alone has particularly good performanc e and was able to match the performanc e of a trained doctor.	ed ML method s should be conside red for both models

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Rowland et al., 2019 [77]	to examine the ability of a cubic SVM classification model to predict burn wound severity using calibrated reflectance data from multiple wavelengths and spatial frequencies obtained via spatial frequency domain imaging (SFDI)	• The data from imaging studies carried out in a porcine model • 160 regions (40 from each class) from one pig used as training set and from the second pig for testing set	support vector machine (SVM) classifier	Prediction	• The model based on images obtained at all wavelengths and spatial frequencies predicted burn severity at 24 h with 92.5% accuracy • The model composed of all values relative to unburned skin was 94.4% accurate • The model that employed only planar illumination	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					was 88.8% accurate • The addition of calibrated reflectance data collected with spatial modulation adds predictive power to a classification model for burns	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Martínez-Jiménez et al., 2018 [75]	to determine if temperature differences in burns assessed by infrared thermography could be used predict the treatment modality of either healing by re-epithelization, requiring skin grafts, or requiring amputations, and to validate the clinical predication algorithm in an independent cohort	The study conducted in a hospital. Infrared thermographic images of burns were acquired using digital camera. Two independent prospective cohorts were used for this study: a cohort used to develop the prediction algorithm (n=34) and a cohort used to test its performance (n=22).	Random Forest predictor using temperature difference measured between healthy and injured tissue.	Prediction	• Significant differences were found in the ΔT between treatment modality groups • The developed algorithm correctly predicts into which treatment category the patient will fall with 85.35% accuracy • Agreement between predicted and actual treatment for both cohorts was	• only included patients with burns in extremities, cannot be extrapolated to other areas in the body • further studies in different populations and settings may be

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					weighted kappa 90%.	required
Alderden et al., 2018 [29]	To develop a model for predicting development of pressure injuries among surgical critical care patients	Data from electronic health records of 6376 patients	Random forest	Prediction	• the ROC for both models was 0.79	• important variables in the EHRs couldn't be accessed

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Vereda as et al., 2010 [63]	to design different machine learning approaches to predict the evolution of pressure ulcers in time	69 sacrum and hip Pus (stage 3 and 4) from patients with homecare assistance, weakly photographed for maximum of 16 weeks using digital camera. A total of 743 photographs were obtained.	prediction of change of wound-bed perimeter using different ML classifiers including: SVM, MLP, decision tree	Prediction	• Neural networks and decision trees gave the best performance results • C4.5 algorithm achieved the highest accuracy rate (~ 81%) in the prediction of the granulation/ devitalized ratio from a small number of input features	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Ke et al., 2017 [76]	to predict the time to SSI onset using spatial-temporal matrix data	dynamic wound data collected daily from 860 patients in hospital conditions	Bilinear formulation predicting model	Prediction	• suggested model have lowest mean absolute prediction error rlative to other models tested	• it might be possible thar different kinds of SSI have different risk factors • variables that have been found predictive of SSI risk in the literature were not included in the database

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Jung et al., 2016 [73]	to develop a predictive model for delayed wound healing that uses information collected during routine care in outpatient wound care centers.	basic demographic information on 53,354 patients, as well as both quantitative and categorical information on 150,277 wounds recorded in EHR weekly	L1 regularized logistic regression, random forest and gradient boosted tree	Prediction	The model achieved an AOC of 0.842 for the delayed healing outcome and a Brier reliability score of 0.00018	The dataset may not be generalized enough in the aspect of the type of care settings included in the research. Prospective validation of the suggested model is required for application in other

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
						institutions
CAI et al., 2021 [40]	to develop an ML-based predictive model for SRPI in patients undergoing cardiovascular surgery.	149 patients who underwent cardiovascular surgery.	XGBoost	Prediction	ML model presented in this paper has more accurate discrimination power than the nomogram score, which developed previously. Therefore, ML may also be used as a technique along with data mining to improve assessment of risk of the development	The data were from a single healthcare institution within a confined geographic region. Thus, the generalizability of our findings may be limited. Moreover, not

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					of SRPI, in addition to logistic regression.	collecting data prospectively may affect the performance of the ML prediction model developed in this study. The severity of all SRPI instances in this study were Stage 1.

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Kim et al., 2020 [44]	to build a ML model that can predict healing of diabetes-related foot ulcers, using both clinical attributes extracted from electronic health records (EHR) and image features extracted from photographs.	electronic health records (EHR) of 2291 visits for 381 ulcers from 155 patients, including smartphone or tablet photographs of the ulcers taken by the medical staff during each visit.	SVM and random forest	Prediction	The predictor demonstrated an AUC of 0.734 when using all features, 0.760–0.794 for hand-crafted imaging features alone and 0.670 for only deep learning features	small patient population and dataset, some of the clinical parameters had to be imputed and there may be slight inconsistencies in clinical attributes that are manually charted.

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Choi et al., 2020 [47]	to identify risk factors and construct a risk prediction model for oral-mucosal PI development in intubated patients in the intensive care unit.	medical record of 194 patient-days	backwards stepwise multiple logistic regression, Gaussian Naïve Bayes	Prediction	the upper oral-mucosal PI development model had an accuracy of 79%, F1 score of 88%, precision of 86%, and recall of 91%.	Small sample size, cross-validation of the risk prediction model with external samples was not performed and several risk factors were excluded in this study.
Song et al., 2021 [65]	to develop machine learning-based predictive models, using	188,512 inpatient clinical records of patients affiliated with 5	logistic regression (LR), support vector	Prediction	RF model reached AUC = 0.92 for nonhospital	patient comorbidity, acuity, and

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	phenotypes derived from nurse-entered direct patient assessment data.	hospitals. Patients that were hospitalized 24 hours or longer on a nonspecialty acute and/or intensive care unit were excluded.	machines (SVM), random forest (RF), and neural network (NN).		acquired pressure injury group and AUC = 0.94 for hospital acquired pressure injury group	pressure injury stage were not considered, moreover only structured data were used for the study
Mombini et al., 2020 [57]	to design a ML system that can accurately predict wound care decisions based on labeled wound image data	2056 unlabeled wound images, including 1695 images from a local wound clinic, 249 from publicly available web sources and 114 from previous study.	XGBoost	Prediction	XGBoost algorithm achieved on average an overall performance of F-1 = .782 using labels given by an expert and a novice decision	limited image dataset

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					maker.	
Chun et al., 2021[74]	to identify predictors associated with PI progression and establish a model for predicting 7-day outcomes in children with PI	patient information of 152 patients, comprising 130 and 33 with stage I PI and sDTI, respectively.	Random Forest	Prediction and wound assessment	accuracy, sensitivity, specificity, and area under the curve of 0.82, 0.80, 0.84, and 0.89, respectively. The most contributing variables, in order of importance, included serum creatinine, red blood cell, and hematocrit.	• it was difficult to obtain a detailed description of skin status assessment and other indicators • small sample of patients with PI

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
						• it is possible that there was variability in assessing patient • since it is a single-center study, it is possible that the PI healing outcomes may be correlated with the medical

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
						setting, quality of treatment, and nursing care.

Table 7: Overview of the characteristics of studies in which wound images were acquired using smartphone cameras

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Godeiro et al.,2018 [12]	• to develop a noninvasive methodology for the segmentation and analysis of chronic wounds images • to investigate algorithms for classifying tissue as Necrotic, Granulation or Slough.	30 images obtained from diabetic patients from different regions of the body, predominantly feet. Acquired in Hospital hosipatl conditions using smartphones.	convolutional neural network (CNN) for classification of wound tissues.	Wound assessment and classification	• The methodology can be applied in a typical work environment of the health care specialists • The tissue classification task obtained values of 0.9610 ± 0.0408 of accuracy, 0.9876 ± 0.0230 of specificity, 0.9128 ± 0.0740 of sensitivity	

Advances in Wound Care
Application of artificial intelligence methodologies to chronic wound care and management: A scoping review (DOI: 10.1089/wound.2021.0144)

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					and Dice coefficient equivalent to 0.9425 ± 0.0598 for the chosen methodology, the U-Net using reduced color spaces.	
Hsu et al., 2019 [17]	to propose an automated way to perform wound segmentation and wound infection assessment after surgical	293 wound images collected using smartphones in hospital conditions. 159 images in the training set and 134 images in	SVM-based wound infection interpretation method using segmentation results from previous part of the study	Wound assessment	• 87.31% accuracy for anomaly detection • 83.58% accuracy for symptom assessment	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	operation	the testing set.				
Shenoy et al., 2019 [21]	to develop a new machine learning based approach using CNNs to analyze an image of a wound and document its wellness	a dataset of 1,335 smartphone wound images in acquired hospital conditions	CNN - adjusted VGG-16, pre-trained using ImageNet to classify 9 classes of wound features	Wound assessment	model achieves receiver operating curve (ROC), area under curve (AUC) scores, sensitivity, specificity, and F1 scores superior to prior work in this area.	dataset size is small and has imbalance

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Alzubaidi et al., 2019 [22]	to propose a novel CNN model for automated classification of DFU	754 images acquired in hospital conditions using smartphones which then processed to 542 healthy skin patches and 1067 DFU	deep CNN architecture for classification of DFU	Classification	The proposed DFU_QUTNet network outperformed the state-of-the-art CNN networks by achieving the F1-score of 94.5%.	
Goyal et al., 2018 [24]	to propose a novel CNN model for automated classification of DFU	292 image of patients DFU and 105 images of healthy skin acquired in hospital conditions using digital camera. Another	deep CNN architecture for classification of DFU	Classification	Using 10-fold cross validation, DFUNet achieved an AUC score of 0.961.	

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
		test case captured by a smartphone camera included 20 abnormal skin patches and 32 normal skin patches.				
Chen et al., 2018 [35]	to propose a surgical wound assessment system for self-care	131 wound images acquired using different smartphones. Images were labeled by state and symptoms of the wound by medical professiona	algorithm consists of several classification tasks using KNN and Random Forest	Wound assessment	• more than 90% state assessment results are correct and more than 91% symptom assessment results consistent with the actual diagnosis.	• some symptoms are identified incorrectly due to similarity • training data is not generalized enough

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
		ls.				
Kim et al., 2020 [44]	to build a ML model that can predict healing of diabetes-related foot ulcers, using both clinical attributes extracted from electronic health records (EHR) and image features extracted from	electronic health records (EHR) of 2291 visits for 381 ulcers from 155 patients, including smartphone or tablet photographs of the ulcers taken by the medical staff during each visit.	SVM and random forest	Wound assessment	The predictor demonstrated an AUC of 0.734 when using all features, 0.760–0.794 for hand-crafted imaging features alone and 0.670 for only deep learning features	small patient population and dataset, some of the clinical parameters had to be imputed and there may be slight inconsistencies in clinical attributes that are manually charted.

Reference	**Aim**	**Setting and sample**	**AI methodology**	**Model type**	**Outcome**	**Limitations**
	photographs.					
Zahia et al., 2020 [49]	to propose an end-to-end system which automatically retrieves quantitative information of the pressure injury using solely a 2D image and a 3D mesh of the	210 photographs of pressure injuries acquired using a cell-phone camera	CNNs for automatically detect and segment the wound, Mask-RCNN for segmentation of the pressure injury	Wound assessment	mean sensitivity score of 0.85 and mean precision score of 0.87.	

Referen ce	Aim	Setting and sample	AI methodolo gy	Model type	Outcome	Limitations
	wound,					

Table 8: Overview of the characteristics of studies aimed to suggest a feasible route for implementation of artificial intelligence (AI)-powered, or machine learning (ML) technologies in wound care and management in clinical practice.

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
Fletcher et al., 2019 [72]	• to predict infection in Cesarean section wounds • to develop a machine learning algorithm that can automatically detect infection in a surgical wound, using an image of the wound captured from a mobile device.	572 women who underwent Cesarean section births in a hospital. 61 infected wounds. The entire data set for each patient consisted of questionnaire responses, one image of the wound, and the clinical surgical site	text-based prediction: logistic regression models with L1 and L2 regularization and support vector machine (SVM). Image-based prediction: 100 randomly-generated splits of the dataset, using the same	Prediction	• developed algorithms that can predict the presence of an infection in a Cesarean-section wound using questionnaire data and image data, respectively, as evaluated 10-days following	• the two models are independent. The combination of the two should be considered • more advanced ML methods should be considered for both models.

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
		infection (SSI) diagnosis provided by a trained physician.	procedure as in the questionnaire-based models.		surgery. • The prediction using image data alone has particularly good performance and was able to match the performance of a trained physician.	
Shenoy et al., 2019 [21]	to develop a new machine learning based approach using CNNs to analyze an image of	a dataset of 1,335 smartphone wound images in acquired hospital conditions	CNN - adjusted VGG-16, pre-trained using ImageNet to classify 9 classes of wound	Wound assessment	model achieves receiver operating curve (ROC), area under curve (AUC) scores,	dataset size is small and potentially imbalanced.

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	a wound and document its wellness.		features		sensitivity, specificity, and F1 scores superior to prior work in this area.	
Caggiari et al., 2020 [43]	to examine the potential of an automated approach for the detection of a range of static lying postures and corresponding transitions between postures.	training group of 9 healthy participants, test group of 10 healthy participants, where interface pressure measurements were recorded using a full body pressure monitoring system.	Naïve-Bayes, k-Nearest Neighbors and SVM classifiers	Wound assessment	The accuracy in predicting the range of postures from new test data ranged between 82%–100%, 70%–98% and 69%–100% for Naïve-Bayes, k-Nearest Neighbors and Support Vector	The current method would require an improvement in accuracy and validation to account for random postures on specialized mattresses used by patients in both acute and community clinical

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
					Machine classifiers, respectively.	settings where the recommended frequency and magnitude of movements are not strictly followed.
Alinia et al., 2020 [81]	to propose a comprehensive approach for designing a sensor system that uses a single accelerometer along with ML algorithms for in-bed lying	Class-Act dataset from 22 subjects.	Adaptive LSTM network	Wound assessment	The best models in our approach achieve an F1 score that ranges from 95.2% to 97.8%	lack of sufficient data.

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	posture classification.					
Zahia et al., 2020 [49]	to propose an end-to-end system which automatically retrieves quantitative information of the pressure injury using solely a 2D image and a 3D mesh of the wound.	210 photographs of pressure injuries acquired using a cell-phone camera	CNNs for automatically detect and segment the wound, Mask-RCNN for segmentation of the pressure injury	Wound assessment	mean sensitivity score of 0.85 and mean precision score of 0.87.	No important limitations noted.
Matar et al., 2020 [82]	to propose an autonomous method for classifying different	data from 12 healthy adults collected from textile pressure	Feed-Forward Artificial Neural Network (FFANN)	Classification	The model obtained accuracy of 97.9% and Cohen's Kappa	• relatively limited number of subjects (12)

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	HBLP with no sensors or cables attached to the body.	sensors			coefficient of 97.2%. Prone and supine postures were successfully separated in the classification, in contrast to the majority of previous similar works.	• the system has not been tested under special conditions.
Bouallal et al., 2020 [54]	to suggest a user-friendly and mobile protocol (acquisition, transfer and processing) for thermal	394 thermal images and their corresponding RGB images of 122 type II diabetic	U-Net	Wound assessment	• the multimodal approach performs better than the method	No important limitations noted.

Reference	Aim	Setting and sample	AI methodology	Model type	Outcome	Limitations
	images of the plantar foot	patients, the images have a resolution of 160×120 pixels and the spectral range of the thermal sensors is 8−14μm.			based only on the thermal image • the average temperature of the plantar surface of the foot is higher in the medium-risk group than in the low-risk group.	
Wong et al., 2020 [83]	to propose a method to detect a person's orientation in bed using data from	data from single axis load cell of 20 able-bodied individuals.	Logistic Regression and Feed Forward Neural Network	Wound assessment	The Feed Forward Neural Network yielded prediction accuracy of	• the system used in this research assumes the

Referen ce	Aim	Setting and sample	AI methodolo gy	Model type	Outcome	Limitations
	load cells placed under the legs of a hospital grade bed.				94.2%.	patient is lying parallel to the long axis of the bed. • the dataset is relatively small

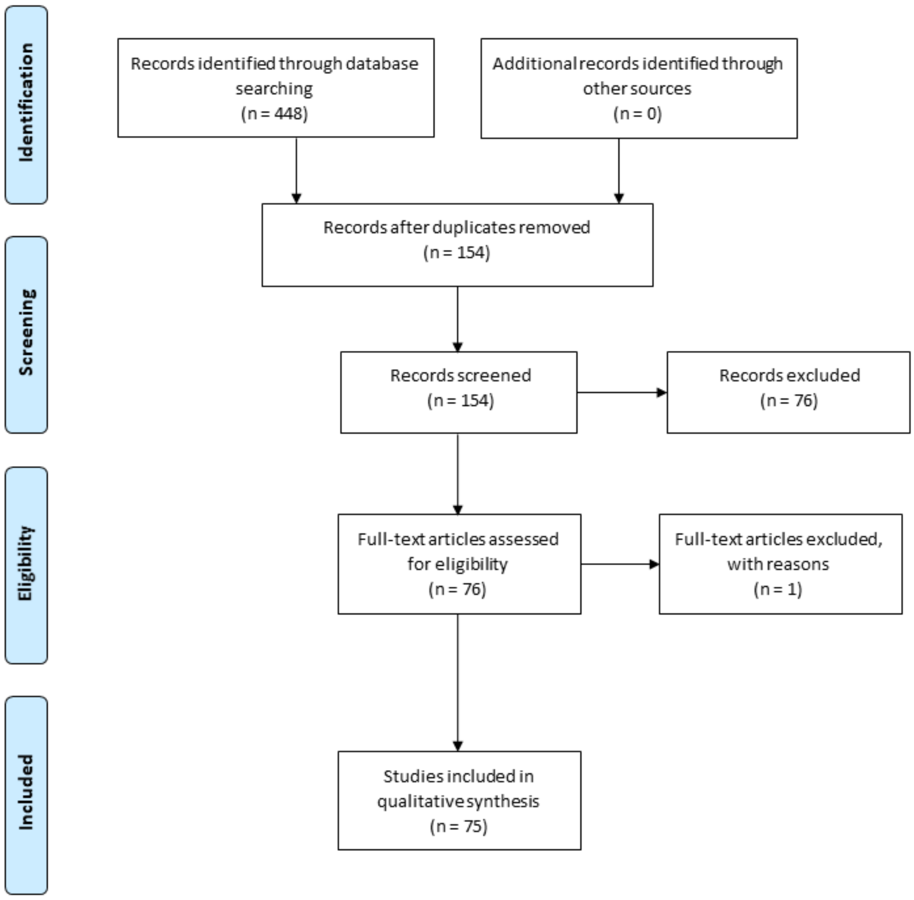

Figure 1

Figure 1: PRISMA flow diagram describing the review decision process, indicating the primary results from the search, removal of duplicate citations, study selection and eligibility check.

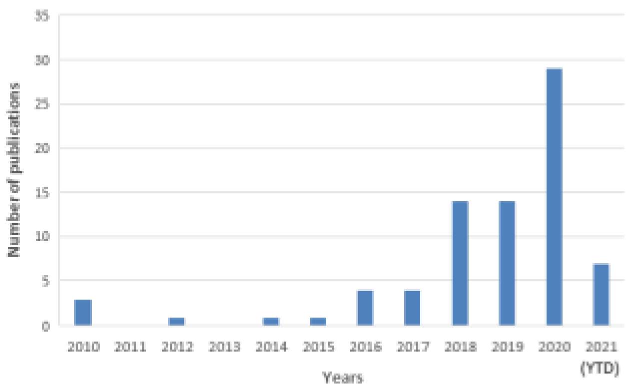

Figure 2

Figure 2: The number of published studies per year from 2010 onwards, out of the included articles.