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Prediction of burn wound response to low level laser using artificial intelligence

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***Abstract*---**Background: chronic diseases increased with aging process, chronic wounds also increased, creating a huge load on the health system. Accurate documentation and measurement of wounds healing become critical. More research is required to construct and validate wound predictive measures to guide more accurate treatment plan with better clinical treatment. Artificial intelligence is widely used to help clinician in clinical decisions and save effort and time. A non-parametric supervised learning technique for regression and classification is called a decision tree (DT). The objective is to build a model that, by utilizing basic decision rules deduced from the data features, predicts the value of a target variable. A piecewise constant approximation can be thought of as a tree. Aim: to predict burn wound response to low level laser using artificial intelligence inform of decision tree tool through using the following variables: patients' age, burn wound size ,wound stage and total burned surface area. Methods: fifty patients (male and female) with partial thickness burn wound were recruited from the burn units. There was only one intervention group receiving low level laser for six weeks divided to 18 sessions (three sessions per week). Results: The current study reveals that the tree model has generated specific rules to classify burn wound responses to low-level laser therapy into three clinically relevant categories.

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***Keywords*---**artificial intelligence, burn, decision tree, low level laser, ulcer, wound.

Introduction

Wounds require proper attention and specialized care. First, second, and third degree burns are the different degrees of burn injuries. [5] Burns of the first degree are minor burns that just affect the superficial layer of the skin and don't need any additional care. They do not leave a scar and recover in less than a week. Although the skin is the largest organ in the human body, just 16% of the body's weight comes from it. The epidermis, dermis, and hypodermis are the three skin layers. [6]

It is unlikely to recommend a single treatment approach for all kinds of wounds because different types of wounds differ from one another due to differences in biology, pathophysiology, and structure. [2] The four phases of the wound healing process are homeostasis, inflammation, proliferation, and finally tissue remodeling, these phases and their physiological processes should take place in the right sequence, at the right time, and should last for a specific period of time. [3] The first stage of wound healing is homeostasis where the body responds very quickly to bleeding, three steps occur during homeostasis in rapid sequence. [4]

Damage to biological tissues, such as the skin, organ tissues, and mucous membranes, is referred to as a wound. Various traumas can be the root of this. To prevent the spread of infection, it's crucial to make sure that wounds are properly cleaned and treated.[1] It is also important before applying any kind of treatment to know the type of wound. [2]

Burn wounds typically result from distinct physical and chemical variables, requiring a different approach to care than that taken for other wounds. While total blood loss from other acute wounds causes shock, severe wounds enhance capillary permeability and do so because of the significant loss of plasma. Compared to most other wounds, burn wounds are initially sterile. Despite this, wound infection and septicemia, which are brought on by immunodeficiency, are the leading causes of death in people with severe burns. Deep burns cannot be treated with the same dressings and antibacterial treatments used on traumatic wounds. [7]

Numerous factors, including the injury's complete absence of tissue perfusion, the release of several active media in the arteries, and inflammation, can all have an impact on how deep the burn is. As a result, the burn wound gets deeper. [5] There are numerous reasons why measures of wounds are necessary to determine whether they are improving, worsening, or not changing. [14] Even so, assessment techniques exaggerate or underestimate the size of the wound; they also are helpful in determining how efficiently the wound is healing.

For the purpose of determining the healing rate, reliable but not necessarily accurate measurements of the size of the wound are required[15]One of the most popular ways to calculate wound area is by tracing the borders of the wound (the manual planimetric approach). The wound is covered with sterile acetate paper or a clear film. On acetate paper or translucent film, the margins of the wounds are marked. The paper or film is then adjusted on a piece of paper with a millimetric grid, and the millimetre squares inside the designated region are counted. [16]While High Power Laser Therapy (HPLT) is defined as having an output power greater than 500 mW or 0.5 Watts, Low Power Laser Therapy (LLLT) is defined as having an output power less than 0.5 Watts (class III in the USA) (Class IV lasers in the USA). Due to its higher power density, HPLT cause heat to be produced on the skin's surface (irradiance). LLLT treatments are sometimes referred to as "Cold Lasers" because they don't provide a heating feeling."[12]Low level laser therapy (LLLT), phototherapy, and photobiomodulation all involve the non-thermal irradiation of photons to modulate cellular activity.

LLLT uses coherent (lasers) or Non coherent (filtered lamps, LEDs, or sometimes a combination of both) light sources, such as both. The main medical uses of low level laser treatment include reducing pain and inflammation, improving tissue repair, stimulating neuron and tissue regeneration, and preventing tissue damage in situations where it is likely to occur (LLLT).

Although decision tree algorithms often perform worse than other algorithms, they can be employed in a wide range of application situations. Having said that, data mining and knowledge discovery jobs benefit greatly from the usage of decision trees. [35] Decision trees include a visual representation and Boolean logic that make them simpler to comprehend and use. The decision tree's hierarchical structure also facilitates the identification of the most crucial features, something that other algorithms, such as neural networks, may not always be able to do. [35]

Unlike many other algorithms, decision trees can be used for both regression and classification applications. Additionally, it is immune to underlying correlations between attributes; in the event of a substantial correlation between two variables, the algorithm will select just one feature for splitting. [36]

This study may define the benefits of low level laser in accelerating burn wound healing and also may predict the patient suitable to get benefits from low level laser based on selected variables. This study may help physical therapist to treat burn wound, may help physical therapist as a clinical guidance to select suitable patients for low level laser therapy, save time and get better results with the patients.

Materials and Methods

Fifty patients of both genders were selected from the burn departments in the period from Dec 2020 to January 2021.
The subjects had been chosen under the following criteria:
Fifty patients (male and female) were recruited with:

Inclusive criteria:
- Partial thickness Burn wound depth.
- first and second wound healing stage.

- Age varied from 20-50 years.
- TBSA greater than 15%

Exclusive criteria:
- Third wound healing stage
- Diabetic patients.
- Patients receiving immunosuppressive drugs.
- associated co-morbidities, such as neurological diseases, malnutrition, and other inflammatory and/or infectious diseases.

Procedures of the study:
- Each patient received a verbal explanation regarding the significance of the study's protocols, primary goals, and conceptual approach.
- This study's procedures will fall into two primary categories:

Measurement procedures:

Preparatory phase:
Each subject completed the following actions at this phase:
- Prior to testing, an informed consent form approved by the institutional review board was signed by each participant.
- Before testing started, subjects were made familiar with the tools and protocols.
- Prior to the evaluation process, each patient had an explanation session in accordance with the established standards.
- In order to determine if the patient could participate in the experiment, demographic information on age, sex, height, weight, and general health had been recorded in addition to primary medical history, which had been taken from the patient's medical record.
- The following measurements had been made in standardized settings: The same researcher conducted the measurements.
- The measuring procedures were carried out twice: once prior to the application of therapy (pre-treatment) and once again six weeks following the application of treatment (post-treatment).

Measuring phase
The wound surface area had been measured before and after treatment through the following steps:
- The metric graph sheet was used to measure the surface area of the wound in each subject.
- The clear grid paper was disposed of after being used just once and cleaned with alcohol before use.
- After that, it was positioned above the incision, and a fine pen marker was used to sketch the incision's edge in centimeters.
- The primary investigator manually determined the area of the wound by counting all squares inside the wound border that were entirely filled and then grouping the partially filled squares.

The burn wound had been classified to stage I (inflammatory), and stage II (proliferative) according to stage of healing based on clinical feature and duration of wound.
Total body surface area (TBSA) was measured using Rule of Nine method.
The degree of healing divided to three levels according to percentage of healing Complete healing, moderate healing and mild healing

Therapeutic procedures:
This study was carried out at the AHMED ORABI hospital's inpatient burn unit in Egypt. There were fifty patients (both male and female) in a single intervention group. The study will last six weeks, broken up into eighteen sessions (three meetings a week).

Preparatory phase:
Preparation of the patients: Prior to starting therapy, each patient received information regarding the measurement and treatment protocols.

Application phase:
Low level laser therapy: For six weeks, the chosen burn wound region received three 30-minute sessions of low-level laser therapy. At the wound bed, a red 655 nm light with 150 mW and 2 J/cm2 intensity was applied to the affected area.

Results

Statistical analysis
In the current study, fifty patients were participated and their age ranged from 20 to 50 year. The mean ±SD value of age, TBSA, and initial wound size at pre-USA were 35.60 ±8.05, 27.04 ±5.59, and 10.42 ±6.92, respectively for study population group (Table 1). The number (percentage) distribution stages I and II were 29 (58%), and 21 (42.0%), respectively in study population group (Table 1).

Table 1. Ociodemographic characteristics of the study population

Variables	**Study population (n=80)**		
	Mean ±SD	Minimum	Maximum
Age, year	35.60 ±8.05	20.00	50.00
TBSA	27.04 ±5.59	16.00	42.00
Initial wound size (Pre-USA)	10.42 ±6.92	3.33	33.10
Stages (Stage I : Stage II)	29 (58%): 21 (42.0%)		

Data are expressed as mean ±standard deviation for age, TBSA, and initial wound size

The Correlation between burn wound response to low level laser and tested variables show significant relation with all variables (table 2).

Table 2. Correlation between burn wound response to low level laser and all parameters

Variable		Class
Age	Pearson Correlation	-.104*
	Sig. (2-tailed)	.014
	N	200
TBSA	Pearson Correlation	-.113*
	Sig. (2-tailed)	.011
	N	200
stage	Pearson Correlation	-.196**
	Sig. (2-tailed)	.005
	N	200
Initial WSA	Pearson Correlation	.486**
	Sig. (2-tailed)	.000
	N	200

Data analysis by Decision tree of artificial intelligence

Proposed Decision tree

In the realm of burn wound care, predicting the response to low-level laser therapy (LLLT) is of paramount importance for optimizing treatment strategies. To address this challenge, a decision tree-based approach has been employed, classifying burn wound outcomes into three distinct categories: complete healing, moderate healing improvement, and mild healing improvement. The dataset encompasses four key attributes: Initial Wound Severity Assessment (WSA), Age of the patient, the STAGE of the burn wound, and the Total Body Surface Area (TBSA) affected. The decision tree algorithm analyzes these parameters to construct a predictive model that stratifies burn wound responses based on their anticipated outcomes.

The "Initial WSA" provides a quantitative measure of the severity of the burn wound at its onset, offering insights into the initial extent of tissue damage. Age, as a crucial demographic factor, is incorporated to account for variations in healing mechanisms across different age groups. The "STAGE" attribute captures the temporal progression of the burn, allowing the model to discern the impact of the therapy at various stages of the wound healing process. Finally, the "TBSA" parameter, representing the proportion of the body surface affected, contributes to understanding the overall physiological burden on the patient.

Through the application of a decision tree, the algorithm can effectively navigate the intricate interplay of these attributes, identifying patterns and relationships that influence the burn wound response to low-level laser therapy. This predictive model, capable of categorizing outcomes into complete healing, moderate healing improvement, and mild healing improvement, stands as a valuable tool for clinicians and researchers alike, guiding personalized treatment decisions and advancing our understanding of the nuanced dynamics involved in burn wound healing.

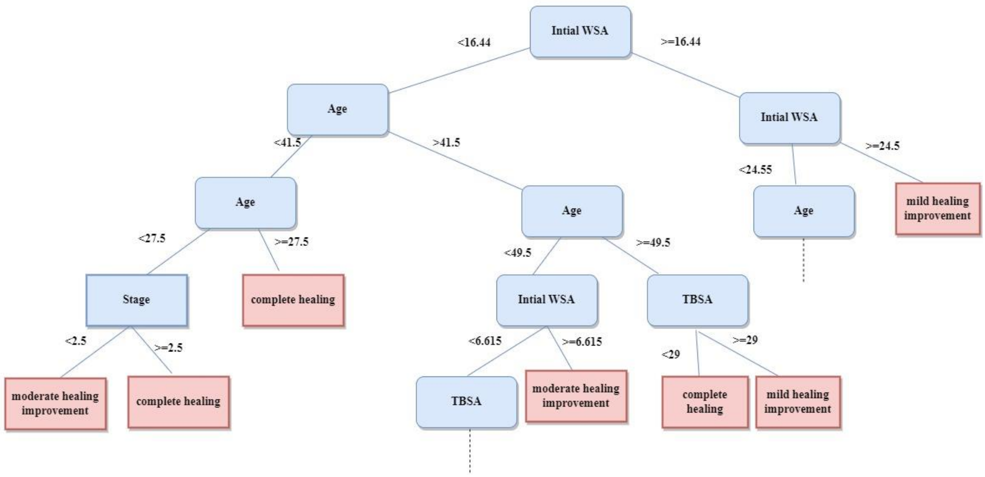

Figure 1. Decision tree

After rigorous training, our decision tree model has generated specific rules to classify burn wound responses to low-level laser therapy into three clinically relevant categories. When the initial Wound Severity Assessment (WSA) is less than 16.44 and the patient's age is 27.5 years or older, the model predicts a favorable outcome of complete healing. On the other hand, when the initial WSA is less than 16.44, the patient's age is less than 27.5 years, and the burn wound is at an early stage (STAGE < 2.5), the model foresees a scenario of moderate healing improvement. Interestingly, if the same conditions of initial WSA and age are met, but the burn wound has progressed to an advanced stage (STAGE > 2.5), the model predicts complete healing. In contrast, if the initial WSA exceeds 24.5, regardless of age or stage, the model suggests a trajectory toward mild healing improvement. These decision rules underscore the intricate interplay of initial wound severity, patient age, and burn stage in shaping the anticipated response to low-level laser therapy, providing valuable insights for personalized treatment strategies in burn wound care. This data-driven approach holds promise for enhancing clinical decision-making and advancing our understanding of tailored interventions for burn patients undergoing laser therapy.

Discussion

The integration of decision tree algorithms into the realms of medical diagnostics and physical therapy represents a significant advancement in personalized healthcare and treatment planning. Decision trees, rooted in machine learning, provide a structured and interpretable framework for analyzing complex datasets, aiding healthcare professionals in making informed decisions based on patient-specific attributes. This innovation holds particular promise in the medical and physical therapy fields, where individualized treatment strategies are paramount for optimizing patient outcomes.

In the medical domain, decision trees have proven invaluable for predicting disease outcomes, identifying risk factors, and guiding treatment selection. Their ability to consider multiple variables, such as patient demographics, medical history, and diagnostic test results, allows for the creation of decision nodes that reflect the nuanced interplay of factors influencing a patient's health. By systematically branching through these decision nodes, healthcare practitioners can arrive at specific predictions or recommendations tailored to the unique characteristics of each patient.

In the field of physical therapy, decision trees play a crucial role in assessing rehabilitation needs, designing targeted exercise regimens, and predicting recovery trajectories. These models take into account diverse factors such as patient age, injury severity, previous rehabilitation outcomes, and adherence to exercise programs. By navigating through the decision tree structure, physical therapists can gain insights into the most effective interventions for promoting recovery and enhancing functional outcomes.

This introduction sets the stage for a comprehensive exploration of decision tree applications in the medical and physical therapy domains. From predicting disease outcomes to tailoring rehabilitation plans, decision trees offer a dynamic and adaptable approach to healthcare decision-making. As we delve into specific examples and case studies, we aim to highlight the transformative potential of decision tree algorithms in optimizing patient care, fostering a new era of personalized and data-driven healthcare interventions

The aim of this research was to determine which patients would benefit most from low-level laser therapy in order to help better medical decisions. According to several studies, low level laser treatment (LLLT) affects a variety of biological processes, including angiogenesis, cell proliferation, differentiation of fibroblasts into myofibroblasts, and collagen formation. [25] Additionally, it has been proven that LLLT accelerates burn healing [26]. A cell type called myofibroblasts is responsible in wound contraction, which is essential for the proper healing of major wounds with significant tissue and cell loss [27]. Due to their extensive positivity for a-SMA (alpha smooth muscle actin), these cell subsets can be recognized by immunohistochemistry because they exhibit a contractile phenotype and have a cytoskeleton rich in actin microfilaments [28]. In that study, LLLT appeared to promote the differentiation of fibroblasts into myofibroblasts. It has been proposed that there may be a correlation between laser-induced up regulation of specific cytokines necessary for myofibroblastic differentiation, such as TGF-b, and the phenomenon, even though the precise mechanism is yet unknown [30]. Previous research has shown that LLLT has the ability to up-regulate the release of cytokines including FGF-a and TGF-b, which are responsible for collagen synthesis and fibroblast proliferation, respectively. [29]

Both the number and density of fibroblasts increase over the course of the experimental periods under research, according to quantitative examination of samples exposed to radiation of various energies [19]. Chiarotto et al. also reported it in second degree burns when they utilised the laser 670nm InGaP, 4.93J/cm2. Silveira et al. hypothesised that the acceleration of fibroblast migration and proliferation caused by this treatment was the cause of the increase in collagen seen in irradiation excising lesions, particularly in 3J/cm2 in rats. Because the improvement in wound healing happened at both stages without a discernible difference, the current study demonstrates that there is no significant relationship between wound stage and wound improvement. Enwemeka CS, ET al. (2004) demonstrate that all stages of tissue repair are significantly improved by LLLT, and that the selection of wavelength and energy density is essential to a successful course of treatment [20].

After rigorous training, our decision tree model has generated specific rules to classify burn wound responses to low-level laser therapy into three clinically relevant categories. When the initial Wound Severity Assessment (WSA) is less than 16.44 and the patient's age is 27.5 years or older, the model predicts a favorable outcome of complete healing. On the other hand, when the initial WSA is less than 16.44, the patient's age is less than 27.5 years, and the burn wound is at an early stage (STAGE < 2.5), the model foresees a scenario of moderate healing improvement. Interestingly, if the same conditions of initial WSA and age are met, but the burn wound has progressed to an advanced stage (STAGE > 2.5), the model predicts complete healing. In contrast, if the initial WSA exceeds 24.5, regardless of age or stage, the model suggests a trajectory toward mild healing improvement. These decision rules underscore the intricate interplay of initial wound severity, patient age, and burn stage in shaping the anticipated response to low-level laser therapy, providing valuable insights for personalized treatment strategies in burn wound care. This data-driven approach holds promise for enhancing clinical decision-making and advancing our understanding of tailored interventions for burn patients undergoing laser therapy.

Conclusion

This research offers the capacity to pre-identify the subset of burn patients most likely to benefit from low-level laser therapy, which could enhance clinical practice decision-making. Future studies are needed to validate the results with other artificial intelligence tools. The current study reveals that the tree model has generated specific rules to classify burn wound responses to low-level laser therapy into three clinically relevant categories. When the initial Wound Severity Assessment (WSA) is less than 16.44 and the patient's age is 27.5 years or older, the model predicts a favorable outcome of complete healing. On the other hand, when the initial WSA is less than 16.44, the patient's age is less than 27.5 years, and the burn wound is at an early stage (STAGE < 2.5), the model foresees a scenario of moderate healing improvement. Interestingly, if the same conditions of initial WSA and age are met, but the burn wound has progressed to an advanced stage (STAGE > 2.5), the model predicts complete healing. In contrast, if the initial WSA exceeds 24.5, regardless of age or stage, the model suggests a trajectory toward mild healing improvement.

Limitations

Extended follow up was not performed.

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