Smart Wound Monitoring and Healing Assessment System with Deep Learning Methods

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Abstract

This review describes a Deep Learning Smart Wound Monitoring (DL-SWM) system, focusing on the healing process of both acute and chronic skin wounds. Recognizing the impact of various factors such as environment, patient characteristics, and wound features on the healing timeline, the review emphasizes the need for more efficient wound monitoring methods. The proposed DL-SWM integrates biosensors, a microcontroller, and a fuzzy inference system to assess critical wound indicators, primarily focusing on hydration levels. The hardware design incorporates an Arduino-based biometric sensor device, while the fuzzy inference system predicts the impact of biomarkers on wound hydration. The review study also explores the segmentation of wounds using a Convolutional Neural Network (CNN) called MobileNetV2, providing detailed insights into the wound healing stages. In the literature review, various advancements in wound monitoring technologies, such as hydrogels, clinical decision-making systems, and wearable biological sensors, are discussed. The proposed DL-SWM is compared with existing methods through simulation analysis, demonstrating superior efficiency, accuracy, and lower error rates. The study concludes with the potential prospects of DL-SWM in revolutionizing wound monitoring and treatment, offering a more convenient and effective approach for healthcare practitioners and improving patient outcomes.

Keywords: Wound Monitoring, Healing System, Biosensor Technology, Deep Learning, Fuzzy Inference System

Significance | Wound features impact healing; indicators like temperature, oxygen levels, and moisture influence the process. DL-SWM offers effective at-home wound monitoring with biosensors.

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1. Introduction

Both minor and chronic skin wounds undergo a process of healing over time. The healing length varies for acute and persistent wounds Falanga et al. (2022). Minor injuries often have a shorter healing period; persistent wounds generally require a longer length to heal fully. It is essential to note that this is a common occurrence Adnan et al. (2023). Even a little skin injury needs an extended period to recover due to factors such as the surrounding environment, individual age, nutritional intake, and medication usage Cui et al. (2022). In addition to these factors, the local characteristics of a wound can also influence the healing process. The features of a wound include its location, the internal and external surroundings around the wound, the kind of wound, the density of the wound, the degree of hydration, the body temperatures, the oxygenation stage, and the presence of infection. Conventional wound treatment necessitates frequent visits to a healthcare facility Mirhaj et al. (2022). The advancement of science in the present period requires the development of more convenient and effective methods for monitoring wounds. This involves the utilization of sensors, gadgets, analytic elements, and patient involvement at the patient's site, compared to relying solely

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on clinical-based wound surveillance Wang et al. (2022).

The wound ecosystem can be described as what is outside around the wound region and the underlying surroundings beneath the area of injury Peterson et al. (2021). The skin wound ecosystem is classified into two primary categories: the exterior environment and the inside ecology Short et al. (2022). The external setting refers to the surroundings beyond the wound region, whereas the internal setting refers to the surroundings underneath the wound area. Any alteration in the outside world indirectly impacts the interior environment of a wound. The outside world encompasses ambient temperature, humidity, air condition, atmospheric pressure, dust particulates, and gases like oxygen and carbon dioxide Wang et al. (2014). The internal setting refers to parameters such as body temperatures, moisture content of the skin level, body breathing, and the presence of infections. These interior elements have an impact on the process of wound repair Qi et al. (2022).

Severe and chronic nonhealing injuries impose a significant strain on healthcare systems, impacting millions of individuals globally. Medicare cost forecasts for all injuries in the United States are projected to range from \$29.2 billion to \$98.4 billion. Unlike acute injuries, chronic injuries do not follow a predictable and rapid progression through the healing processes Kumar et al. (2023). As a result, they require hospitalization and further care, leading to billions of dollars in added costs for medical facilities each year. The need for more proficient wound care practitioners in urban and rural medical facilities increases the availability and excellence of healthcare services for millions of Americans Cicceri et al. (2020). Precise assessment of the wound area is crucial for evaluating and treating persistent wounds, as it allows for monitoring the progress of wound recovery and planning future treatments Jeong et al. (2023). The manual measuring could be more timely and precise, leading to potential adverse patient effects. Segmenting wounds from photographs is a widely used method to address these issues since it not only automates the measuring of the wound region but also facilitates the input of information into an electronic health record to improve the treatment of patients Khalil et al. (2019).

To monitor the progress of wound recovery, it is essential to assess the features of the wound, particularly the most critical biological indicators. These parameters must be analyzed to ensure the internal setting maintains favorable values, enhancing healing. The current study presents a novel method for quantifying significant indicators utilizing a biosensor integrated with an microcontroller Chen et al. (2018). The research assessed the impact of these indicators on hydration levels through a fuzzy inference system Phiri et al. (2021). The suggested approach can be utilized to provide recommendations for promoting the healing of wounds.

The subsequent sections are arranged in the provided fashion: Section 2 pertains to the literature survey and its corresponding outcomes. The suggested Deep Learning Smart Wound Monitoring (DL-SWM) is an advanced system that monitors wounds and analyzes the healing process using deep learning technology. Section 4 contains a detailed discussion of the software analysis and its outcomes. The conclusion and prospects of the proposed DL-SWM are discussed in section 5.

2. Literature review and analysis

Information technology is crucial in answering the daily challenges encountered in several sectors. Several researchers have suggested healthcare applications for tracking and handling various disorders to support the medical field. This section will specifically address healthcare programs, emphasizing multiple skin illnesses and their corresponding remedies Farahani et al. (2021).

This study utilizes a versatile hydrogel as the dressing for the wound for intelligent wound tracking Wang et al. (2022). The hydrogel possesses antibacterial, hemostatic, and adhesive characteristics, successfully facilitating wound healing. It enables real-time monitoring of wound position, such as pH levels. The entire procedure of intelligent wound monitoring primarily consists of three components: wound identification, continuous status tracking, and tailored wound treatment.

The research introduced a paradigm that utilizes a clinical decision-making system to assess the wound microenvironment's internal and exterior aspects Sattar et al. (2022). The structure has many operational modules that will cooperate to determine the wound environment. The research has developed a detailed plan and outline for the structure and execution of all these components. The platform uses the Internet of Things and deep learning methods to collect and evaluate information efficiently.

This research aims to create a system that uses DeepLabV3+SE to identify the borders of wounds Kumar et al. (2023). The system will measure the dimensions and surface area of the injuries, as well as analyze their shape using a series of morphological procedures and related component evaluation components. The research contributes to the self-learning procedure by using a physician's comments to upgrade the DeepLabV3+SE modeling over time.

An innovative device is shown, which is a small, cordless, and battery-free injury monitoring. This device accurately analyzes lactate levels in real-time and can be easily attached to dressings for a perfect fit on the wound site Garland et al. (2023). Lactate is chosen because of its diverse function in commencing the healing process. Predictors can be enhanced by developing computational models incorporating various wound factors, such as pro-inflammatory and physiological indicators.

The research has created an innovative machine-learning system that can identify heel deep tissue damage at an early stage Lustig et al. (2022). The system was trained to utilize a database that included six successive daily readings of sub-epidermal wetness of 173 individuals treated in acute and post-acute care settings. The system demonstrated high predictive accuracy in anticipating heel deep tissue damage occurrences occurring the following day, with an overall sensitivity of 77% and precision of 80%.

The research introduces Detect-and-Segment (DS), a deep learning method that generates wound segmentation maps with strong generalization capability Scebba et al. (2022). The process involved using specialized deep neural networks to identify the location of the wound accurately, separate the wound from any distracting elements in the backdrop, and generate a map that clearly outlines the boundaries of the wound. Using the DS allowed for the development of segmentation algorithms with a much-reduced amount of training data, resulting in a segmentation accuracy that was not negatively affected.

This work aims to fill the academic gap in the application of machine learning to identify wounds caused by Peripheral Artery Disease (PAD) Huang et al. (2023). The primary goal is to introduce an innovative approach for automatically segmenting and detecting wounds using the Mask Recursive Convolutional Neural Network (R-CNN) architecture. The study used a database consisting of 3329 clinical injury photos, encompassing wounds in individuals with PAD as well as those resulting from general trauma. The Mask R-CNN structure is utilized to identify and distinguish wounds.

The research has examined and emphasized recent progress in wearable biological sensors for thoroughly evaluating wound conditions Wang et al. (2022). This includes a compilation of physical, tiny molecule, macromolecular, and microbiological indicators and ideas for therapeutic systems that are activated when needed. The latest iteration of closed-circuit-wearing injury biological electronics can rapidly and noninvasively identify biomarkers while providing flexible and controlled therapeutic delivery.

3. Proposed Deep Learning Smart Wound Monitoring

Healing wounds is a natural process in the human body that occurs in the distinct and well-regulated stages: hemostasis, inflammation, proliferation, and remodeling. For the successful completion of rehabilitation, all the phases must occur sequentially. Many circumstances can disrupt one or more wound healing stages, leading to inadequate or compromised healing.

3.1 Wound healing process

Several factors can substantially impact a wound's healing process, such as size, kind, setting, moisture, temperature, breathing, necrotic tissue presence, and wound ulceration. The following paragraphs will focus on the significance of a prominent biomarker in the procedure of healing, as seen in Figure 1.

Wound healing consists of the sequential phases, which are outlined below:

- First stage

Hemostasis is the starting point of wound healing that promptly follows the occurrence of the wound. During this phase, blood vessels constrict and reduce blood flow at the point of damage. The body forms blood clots to impede blood flow, halting blood loss.

- Second stage

Inflammation induces vasodilation surrounding the site, facilitating the delivery of vital nutrients and oxygen to promote wound healing. The elevated oxygen content stimulates the macrophage, a white blood cell, to infiltrate the wound, combat infection, oversee the healing procedure, and release growth hormones essential for the repair. The transparent fluid within the injury is known as a macrophage.

- Third stage

The third phase of the healing process is referred to as proliferation. This is the era of growth and reconstruction. During this stage, blood cells facilitate the formation of fresh tissues to replace those harmed. During this stage, the body synthesizes a protein known as collagen, which serves as a scaffold to facilitate the process of tissue healing.

- Fourth stage

Restructuring is the final wound healing phase, during which the inflammatory response is progressively resolved, and the collagen is degraded. Scar tissues replace old or damaged structures. Scar cells lack the same level of strength as regular tissues. It takes significant time, ranging from a few months to nearly a year, to achieve their maximum strength.

Oxygen is necessary for all stages of healing wounds. Acute hypoxia, a lack of oxygen in the blood, promotes wound repair. Chronic hypoxia might hinder the healing process, although inducing oxygen restoration can help improve oxygen delivery to tissues.

3.2 Deep Learning-based Wound Monitoring

This section focuses on the design and operation of the suggested DL-SWM architecture for monitoring the healing of wounds. The system measures wound features and compares them to accepted standards to ensure the progress of wound recovery. The research has presented a DL-SWM method that can evaluate two crucial indicators of wounds to monitor the healing process. This is achieved through assessing the degree of water in the wound.

The DL-SWM approach presented is illustrated in Figure 2. The system has two primary elements:

(1) A detecting system that uses biosensors to detect wound biomarkers.

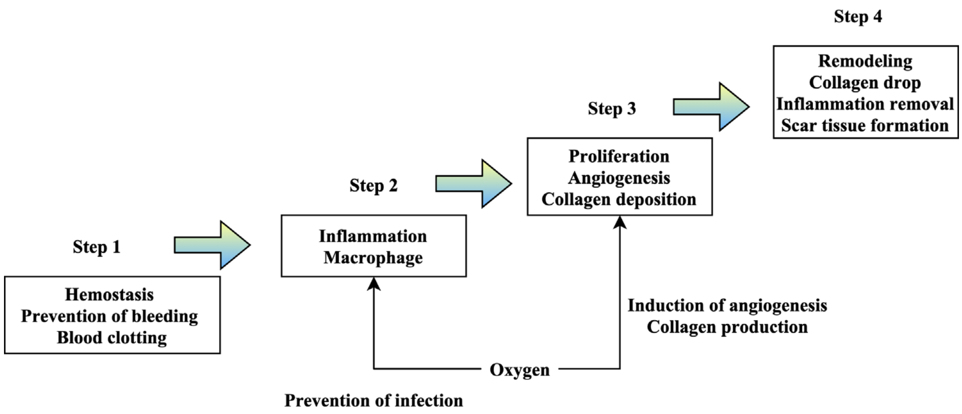

Figure 1. Wound healing procedure

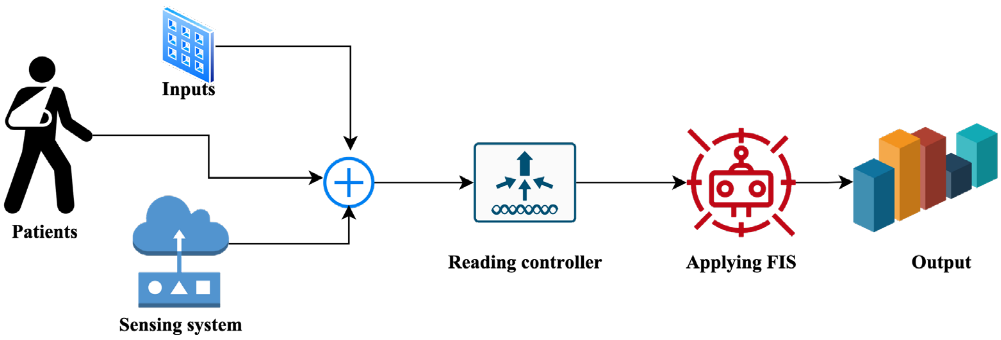

Figure 2. Learning-based Wound Monitoring Process

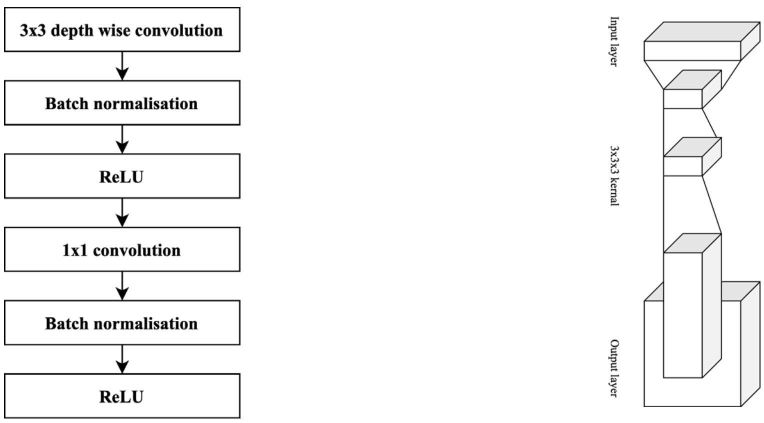

Figure 3. (a) Workflow of the proposed CNN, and (b) Schematic diagram of the 3x3 convolutional level

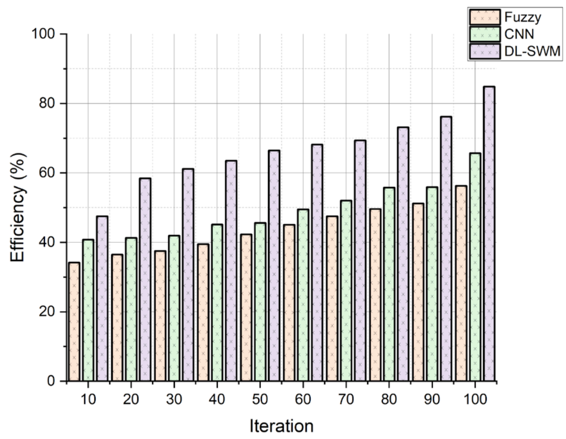

Figure 4. Efficiency analysis for wound monitoring and healing process

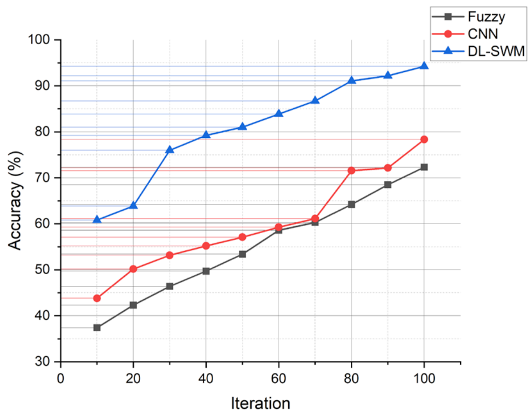

Figure 5. Accuracy analysis for wound monitoring and healing process

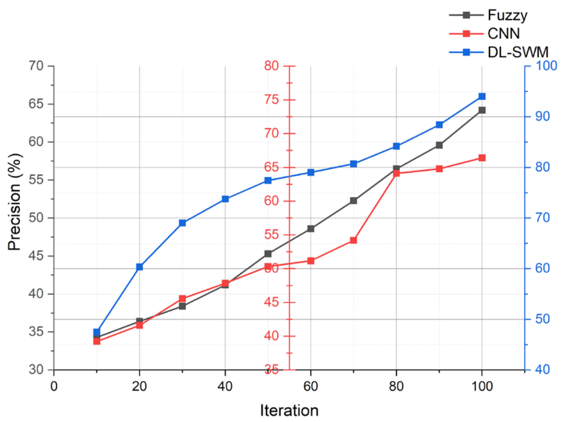

Figure 6. Precision analysis for wound monitoring and healing process

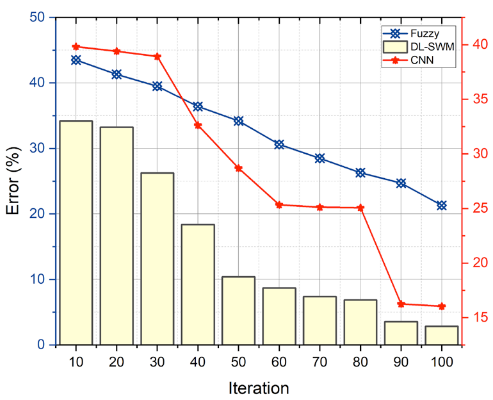

Figure 7. Error analysis for wound monitoring and healing process

(2) A fuzzy inference system that predicts the impact of biomarkers on the hydration of wounds.

The following sequential steps execute the functioning of the suggested DL-SWM system:

(1) Utilizing a biosensor-detecting framework to measure wound biomarkers.

(2) Establishing criteria for biomarker information.

(3) Developing guidelines for the suggested systems.

(4) Creating a fuzzy system that utilizes the defined rules to identify degrees of wound moisture.

3.2.1 Hardware Design

During the initial stage of the suggested structure, the research assessed wound attributes by employing an Arduino-based biometric sensor device. The study selects body heat and blood oxygenation levels when considering wound features. The study developed a circuit based on Raspberry to accurately measure the features of wounds. The study employed a biometric sensor device to measure the features of the wound. This system utilizes an Arduino-based circuit that consists of several elements:

(1) Raspberry microcontroller, (2) Cardiac rate detector component, and (3) LM35 heat detector

3.2.2 Fuzzy Inference System

The research employed an FIS method to determine the amount of wound hydrated. This determination was made by analyzing the body heat and oxygenated stage, which were measured using biosensors. The FIS is founded on the principles of fuzzy logic, enabling machines to emulate human reasoning. These machines possess the capability to process a wide range of options that lie within the binary values of YES and NO. FIS can manage several output opportunities, such as affirmative, definitely affirmative, perhaps affirmative, indeterminate, etc. Fuzzy logic is capable of processing inputs with diverse magnitudes and spans.

A fuzzy set is a collection of components where each element is assigned a grade of membership ranging from 0 to 1.

The system for fuzzy inference is comprised of several elements.

The rule base consists of operational rules for a FUZZY structure, presented in the IF-THEN format. Rules can incorporate many conditions using logical operators such as AND and OR.

Fuzzy rules employ functions of membership to forecast the result. Membership participation is stored in a database.

(a) Decision Making Unit - The fuzzy structure utilizes principles to assign signals to specific processes to facilitate decision-making.

(b) Fuzzy Interface Modules -The fuzzy logic system receives data for input in crisp numbers during fuzzing. These crispy numbers are then transformed into fuzzy numbers.

(c) The Defuzzification Interface Unit converts fuzzy logic outputs into crisp values. The reverse fuzzing method refers to changing from fuzzy to crisp numbers.

3.3 Wound healing assessment using the segmentation process

This section provides a comprehensive explanation of the approach, detailing the structure of the deep learning system used for wound separation. The training of the system incorporates transferable learning and post-processing techniques such as hole filling and elimination of tiny sounds.

3.3.1 Pre-processing

In addition to the clipping and zero-padding methods mentioned in the database generation section, the research applies conventional data enhancement methods to the dataset before inputting it into deep learning. The picture changes include rotations ranging from +25 to -25 certificates, randomized horizontal and vertical flips with a 60% chance, and randomized magnification within 70% of the initial picture region. Random zooming is the sole non-rigid translation employed, as the research hypothesizes that additional non-rigid modifications, such as shearings, do not accurately capture typical changes in wound geometry. The training database will be expanded to include around 4000 photos. The research maintains the verification datasets in their original, unaltered form to produce credible outcomes from the assessment.

3.3.2 Model architecture

The injury is segmented from the photos using a Convolutional Neural Network (CNN) called MobileNetV219. In contrast to traditional CNNs, this network replaces the essential convolutional layering with depth-wise separated functional layers, which consist of a depth-wise convolution component and a point-wise convolutional level. A depth-wise convolutional applies an additive filter to each input route, resulting in lightweight filtration. A point-wise convolution is a convolution procedure with a kernel size of 1×1. It is used to create novel characteristics by linearly combining the input streams. This substitution significantly decreases computational costs compared to conventional convolution levels by nearly a factor of k, wherein k represents the dimension of the convolutional kernels. Depth-wise separable transformations are significantly more economically effective than traditional convolutions, making them well-suited for mobile or embedded programs with limited computer resources. For instance, the portability of MobileNetV2 might be advantageous for medical healthcare professionals and patients as it enables prompt segmentation of injuries and quick measuring of the wound region right after capturing a photo utilizing handheld gadgets such as smartphones and tablets.

The encoding algorithm is constructed by iteratively implementing the depth-separable convolutional block. Every block, seen in Figure 3(a), comprises six levels: a 3 × 3 depth-wise convolutional level, then batch standardization and Recurrent Learning Unit (ReLU) activation, and a 1 × 1 point-wise compression level, followed again by batch normalizing and ReLU. Figure 3(b) shows the schematic diagram of the 3x3 convolutional level. More precisely, the activating function employed was ReLU. The decoding process utilizes a spatial pyramidal pooled module to collect the encoded characteristics at many scales. These characteristics are combined with higher-level characteristics obtained from a pooling stage and a bilinear upward sampling level. Following the combination, the research employs many 3 × 3 transformations to enhance the characteristics, followed by a straightforward bilinear up-sampling by an integer of 4 to get the ultimate result. Every bottleneck phase is augmented with a batch normalization level, and a dropout level is placed just before the output level. MobileNetV2 incorporates a width converter α to accommodate different sizes of input photos. By setting α equal to 1, the research establishes that the algorithm's input picture size is 252 pixels × 252 pixels.

4. Simulation Analysis and Results

The research subjected the suggested biosensor technology and FIS to 500 distinct input scenarios to evaluate their accuracy percentage. The study obtained input information from five patients with varying injury levels who were hydrated using the suggested bio-sensor-based Raspberry circuitry. The research then utilized these input instances to forecast the degree of injury hydrated using the suggested FIS. The study outlines the methodology used by selecting 5 cases from each set of patient information.

4.1 Data Collection

The functionality of the suggested system is evaluated through experiments conducted on a sample of 5 individuals afflicted with skin injuries. The information was gathered at different times utilizing the recommended biosensing equipment. The research obtained 100 samples from every patient at various times and selected five samples from every instance, each taken at distinct times.

4.2 Data Sampling

The research conducted data selection to decrease the quantity of input information. Specifically, the study employed a random sampling approach to choose the input information instances from the information sheets of five distinct individuals. Every patient's dataset consists of 100 examples. The research randomly selected five inputs from every scenario, with every input example having an equal probability of being chosen. Every input example had a 1/100 probability of being included in the selected information.

4.3 Results

Figure 4 displays the efficiency study of wound monitoring and healing process for Fuzzy, CNN, and the suggested DL-SWM. The results of the techniques are examined by systematically changing the iteration size, ranging from 10 to 100, with an increment of 10. As the size of the iteration rises, the efficiency of the suggested DL-SWM likewise increases correspondingly. This is accomplished using an advanced hybrid deep learning technique combining CNN and FIS to enhance processing capabilities. This facilitates the optimization of the medication for the wound and expedites its treatment for prompt recovery.

Figure 5 illustrates the accuracy evaluation of different techniques for wound monitoring and the healing process, including the suggested DL-SWM. As the number of iterations rises, the precision of the procedures likewise increases. The DL-SWM approach performs superior to other methods, exhibiting a 12.5% enhancement compared to the Fuzzy and CNN methods. The suggested DL-SWM, employing a deep learning model, accelerates the process of monitoring wounds and boosts the segmentation and classification of wound health.

The precision analysis of several techniques for wound monitoring and the evaluation of the healing process are depicted in Figure 6. An analysis of the outcomes of the fuzzy, CNN, and suggested DL-SWM algorithms is conducted by adjusting the iteration from 10 to 100 with a step size 10. As the number of iterations grows, the corresponding level of accuracy likewise increases. The DL-SWM system surpasses existing methods by utilizing a deep learning model to monitor and facilitate the healing process of wounds.

Figure 7 displays the error analysis of several techniques used for wound monitoring and assessing the progress of the healing process. The iteration size varies from 10 to 100 with a step size of 10, and the results are evaluated. As the size of the repetition changes, the corresponding inaccuracy in monitoring the wounds decreases. The suggested DL-SWM has the lowest error across all iterations. The suggested DL-SWM surpasses the current approaches in all measures, resulting in enhanced wound monitoring and healing progression.

5. Conclusion and Future Scope

The features of a wound substantially impact the process of its healing. Several indicators influence injury healing, including temperature, blood oxygen saturation straight, and tissue wetness level. These indicators can affect the healing process and demonstrate an association with additional wound features, such as heat and oxygen levels, associated with injury hydration levels and inversely. To provide an effective wound surveillance structure, it is imperative to prioritize examining these indicators. The recent study introduces an innovative method to track wound moisture using biosensors. The Deep Learning Smart Wound Monitoring (DL-SWM) involves using a Raspberry-based circuitry that utilizes biological sensors LM35 and MAX30100 to detect body indicators, namely temperature and oxygen values. Once the indicator levels are detected, the device can estimate the amount of wound hydrated using the suggested FIS. The implemented FIS enhances healing by forecasting injury hydration values. If hydration levels are low, individuals should augment their drink intake to expedite healing. The suggested device functions as a protective barrier for wounds by allowing patients to track the state of their wounds continuously. By utilizing it, patients proactively prevent detrimental wound complications by promptly implementing preventive measures. Thus, the suggested system actively contributes to the medical patients' receiving care in their homes. It is an effective Internet of Things (IoT) tool for the medical sector, similar to other IoT technologies. The suggested DL-SWM approach offers a highly effective method to enhance recovery at the patient's core. In the future, advanced wound-tracking devices should prioritize discovering additional wound features to enable effective tracking centered on the patient's requirements.

Author contribution

A.M.H., A.M., S.S.D. wrote, reviewed and edited the article. All authors read and approved for publication.

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Competing financial interests

The authors have no conflict of interest.

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