Automated Surgical Wound Classification for Intelligent Emergency Care Applications

Original Scientific Paper

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Abstract *– Developing AI-powered solutions for emergency care is critical to improving patient outcomes. This study presents an advanced AI model designed to accurately classify surgical wounds to facilitate prompt and appropriate emergency response. We used two state-of-the-art image classification models, ResNeXt and Vision Transformer (ViT), to evaluate their effectiveness in classifying wound images. These models were selected based on preliminary evaluations of several popular models, and their superior performance metrics justified their final selection. The models were trained on a combined dataset of approximately 1,000 images from the Medetec and AZH(Advancing the Zenith of Healthcare) datasets. To improve classification accuracy, the dataset was preprocessed, including image resizing, flipping, normalization, and augmentation. The ViT model demonstrated superior performance, achieving an accuracy of 92.78%, precision of 94.89%, recall of 91.87%, and an F1 score of 92.44%. These results surpass those of existing studies such as Shenoy et al. (85.1% accuracy), Rostami et al. (68.7% accuracy), and Gao et al. (76.6% accuracy). Our proposed AI system not only accelerates life-saving first aid by providing timely and accurate wound classification but also enhances the skills of emergency responders through continuous learning and real-time feedback. By integrating AI into emergency service protocols, we aim to improve response times and collaboration among medical personnel, ultimately contributing to better patient survival rates.*

Keywords: *surgical, wound, images, classification, emergency care, Intelligent, AI, Assistant*

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1. INTRODUCTION

Wounds are a prevalent medical condition, and the severity and optimal treatment depend on the type of wound. Accurately identifying wound types and administering appropriate first aid in emergencies is critical for ensuring patient survival. However, current research on wound classification has primarily focused on assessing wound healing [1-4] or diagnosing diseases, such as diabetes, ulcers, and cancer [5-8], leaving a significant gap in wound classification for effective emergency response and treatment.

Machine learning and deep learning techniques in medical fields have increased, but wound classification has been neglected. Identifying the type of wound and providing the appropriate treatment quickly and effectively can significantly impact a patient's recovery. Therefore, developing AI-powered wound classification systems that can quickly and precisely assess wounds and recommend the most effective treatment is crucial.

In this study, we employed two wound image classification models: ResNeXt [9] and ViT (Vision Transformer) [10]. ResNeXt secured second place in the ILSVRC 2016 competition and has since been widely adopted for vision applications. ViT, on the other hand, has recently gained significant attention. Most of these foundation models can trace their roots back to the Transformer [11], a large language model developed by Google in 2017 with its source code made publicly available. Scaling up this model, which is specialized in natural language processing, and pre-training it with multimodal data, including text and code, has demonstrated superior performance compared to models trained solely on single-modality data. In visual recognition, reports suggest that ViT outperforms models derived from the widely used CNN family. This study contrasts the wound image classification capabilities of both ResNeXt and ViT.

To achieve the goal of developing an accurate and effective wound classification system, collecting a substantial amount of diverse data is crucial. After the data collection, we preprocess the raw data into a format the model can use. This may include tasks such as image resizing, noise reduction, and image augmentation to increase the variability of the data and improve model performance. We then generate labels based on the wound characteristics to enable the model to classify new images accurately. The optimization process involves training and fine-tuning the model to achieve the highest possible accuracy in wound classification. By employing these steps, we can create a robust and reliable system for automated wound classification that can be applied in various medical settings.

Our study aims to improve public health and medical welfare by developing an AI model for surgical wound classification that utilizes artificial intelligence technology to advise administering first aid based on the immediate and professional judgment of images of patients' wounds that occur in emergencies or daily life. The proposed AI model has the potential to significantly improve the accuracy and number of wound classifications and first aid recommendations, thereby enhancing public health and medical welfare.

Ultimately, we expect our work to contribute to the following:

- Improve public health and medical welfare by developing an AI model for surgical wound classification and an AI Assistant.
- Demonstration of the potential of AI technology to enhance the first aid process.
- Exploration of the potential for developing a virtual reality first aid training system using the proposed wound classification system to improve first aid proficiency through continuous learning.

This paper is structured as follows: Chapter 2 reviews prior research. Chapter 3 explores wound types, emphasizing the significance of first aid and the golden time. Chapter 4 introduces the dataset and preprocessing methods and compares the performance of underlying models. Chapter 5 analyzes the findings, while Chapter 6 illustrates an example of an assistant application utilizing the model. Finally, Chapter 7 discusses the contributions and proposes future research directions.

2. RELATED WORKS

Among existing studies, "Deepwound: Automated Postoperative Wound Assessment and Surgical Site Surveillance through Convolutional Neural Networks" [1] shares many similarities with our research. The study employs CNNs to classify various wound images captured by smartphones into nine categories: Wound (Acc: 82%), Surgical Site Infection (84%), Granulation Tissue (85%), Fibrinous Exudate (83%), Open Wound (83%), Drainage (72%), Steri Strips (97%), Staples (95%), and Sutures (85%). Improving performance is relatively straightforward because the study categorizes wound types with distinct characteristics. However, in our study, one of the nine wound types classified by Deepwound, namely "Surgical Site Infection," is further subdivided into 14 different types. Consequently, the recognition difficulty varies considerably.

Another study titled "Multiclass wound image classification using an ensemble deep CNN-based classifier" [7] conducted two and three-class classification experiments on four types of wound images: venous, diabetic, pressure, and surgical. They employed two classifiers - per-patch and per-image - based on an ensemble DCNN. The results showed a maximum classification accuracy of 96.4% and an average of 94.28% for binary classification. The maximum and average accuracies for the three-class classification problems were 91.9% and 87.7%, respectively. Notably, this study has the potential to expand the scope of wound classification by accurately distinguishing 14 types of surgical wounds. Such distinctions can offer significant contributions to emergency medicine and first aid management.

3. BACKGROUND

In this section, we will discuss the medical classification of wounds and the crucial role of surgery in emergencies. Additionally, we will provide an overview of the current state of image recognition technology and its potential application in wound classification.

3.1. WOUND TYPES

A wound is an injury that causes a break in the skin or other bodily tissue and can be classified as either open or closed based on whether or not the skin's surface is broken [12]. Open wounds, which are the focus of this study, involve broken skin and exposed bodily tissue and can be further categorized based on their cause, shape, and level of contamination. Specifically, this study only considers open wounds that require surgical intervention. Table 1 provides a summary of the different types of open wounds.

Table 1. Open Wound Types

Open Wound Types	Wounds
Penetrating wounds	• Puncture wounds
	• Surgical wounds and incisions
	• Thermal, chemical, or electric burns
	• Bites and stings
	• Gunshot wounds or other high-velocity
Blunt force trauma	• Abrasions
	• Lacerations
	• Skin tears

Minor injuries can be managed using rudimentary first-aid procedures, including cleansing, hemostasis, and disinfection. Nonetheless, some circumstances necessitate hospitalization, such as penetrating wounds, amputations, and serious burns, and wounds with indeterminate extent and depth may impede decision-making. An AI system trained with appropriate data to identify appropriate first aid strategies can facilitate informed decision-making and promote timely wound care, enhancing the healing process and quality of life.

3.2. FIRST AID AND SURGERY

When an accident requires emergency surgery, timely and thorough treatment is crucial to success. In such situations, proper first aid can have an average success rate of 80%, with a success rate of 95% for clean amputations.

Surgical procedures are a form of life insurance that can be used in urgent situations where every minute counts. As is well known, if no action is taken within four minutes of a heart attack, it can mean death. In this way, the life and death of an injured person can depend on the quick and accurate actions of the first responders. Of course, not all diseases and injuries require surgery. Because it's not common to face these situations, most people don't know how to handle emergencies. Therefore, developing an application that recommends surgical procedures through wound image recognition is essential to make it simpler and more accurate to know which surgical procedures are needed for which diseases and wounds.

3.3. IMPORTANCE OF GOLDEN TIME AND HOSPITAL TREATMENT

The "Golden Time" refers to the critical period immediately following an accident when timely medical intervention, such as surgery, can mean the difference between life and death. This period is typically considered to be the first hour after a patient is critically injured. For instance, in the case of an adult who experiences cardiac arrest, surgical intervention within four minutes of the event can restore most of the central nervous system functions that existed before cardiac arrest and greatly reduce the likelihood of permanent disability [13]. Countries like the United Kingdom, the United States, Canada, Australia, and New Zealand place great value on the Golden Hour and have well-organized emergency medical systems that integrate fire and emergency rescue with requests to the police department. When an ambulance is called, fire trucks and police vehicles respond jointly. In Korea, integrating 112 and 119 services highlights the importance of the Golden Time.

A hospital visit is an essential step in receiving medical treatment. Unfortunately, many people tend to downplay their symptoms and avoid seeking medical attention, potentially worsening their condition. Helping individuals understand when to visit a doctor is critical in preventing delayed treatment and serious health consequences. Proper guidance can encourage individuals to seek timely treatment, avoid misjudging the severity of their symptoms, and ultimately receive proper care for their condition.

3.4. WOUND IMAGES ANALYSIS

Recent research suggests that electronic devices such as smartphones can collect wound data, which can aid in situational analysis and decision-making during emergencies [14]. In addition, the field of surgical data science, which employs convolutional neural networks (CNN) and transfer learning models, has been introduced to recognize wound tissue images, making it possible to study wound assessment [15-17]. The recognition of wound images is a prevalent method of digital image processing that involves analyzing the color of the skin surrounding the wound using measurements of saturation, chroma, and intensity [18]. This method digitally processes the image, with color changes occurring step-by-step as the wound changes, allowing for the establishment of a scale for surgical treatment [19]. Developing algorithms for detecting and classifying wound tissue types, which play a crucial role in wound diagnosis, is beneficial to studying AI-powered wound image recognition [20].

Convolutional neural networks have gained significant attention for solving medical tasks and research [1, 7, 15, 18, 21]. CNN-based approaches are considered state-of-the-art for intelligent wound diagnosis and assessment. These networks consist of pixel-to-pixel architectures that use a large set of image data with damaged features and tunable neural network parameters. Many pre-trained models, such as VGGNet [22], ResNet [23], ResNeXt [9], DenseNet [24], EfficientNet [25], and MobileNet [26], and ViT [11] exist. Among these transfer learning models, ResNeXt and ViT are chosen and mainly compared their performance for our application because they are efficient and commonly used across various applications.

Transfer learning has already proven to be a powerful technique in machine learning. It involves taking pre-trained models and fine-tuning them on new tasks or datasets, which saves time and computing resources while achieving better performance. However, there is still room for improvement, and advancements in transfer learning are expected in the future. One area of research is the development of more efficient and effective methods for transferring knowledge between domains. Current transfer learning techniques typically rely on a fixed set of pre-trained models, limiting their ability to adapt to new or emerging tasks. Future advancements may involve the creation of more flexible and adaptable transfer learning frameworks that can better handle domain shifts and enable faster adaptation to new tasks.

4. WOUND CLASSIFICATION MODELING

This section describes our wound classification model, covering the dataset, preprocessing, classification model, training, optimization, and experiments.

4.1. WOUND IMAGE DATASET

Obtaining meaningful data is critical to the success of AI and is a key element of our research. Unfortunately, copyright-free wound images are limited, so we primarily utilized the Medetec dataset [27], a publicly available dataset of 561 wound images of 14 different types.

To improve the classification accuracy in our experiments, we merged images of the same class ("leg ulcer-1", "leg ulcer-2") into one class called "leg ulcer." We excluded other classes whose classification was unclear. This reduced the number of classes from 14 to 11, and only 502 images were used in our experiments. Table 2 shows the class-wise sample count for the 502 images from the Medetec dataset utilized in this study.

Table 2. Configuration per Class for Medetec Dataset with 502 Samples

Labels	Number of Samples
Abdominal	13
Burns	19
Epidermolysis-bullosa	5
Extravasation	20
Foot-ulcers	48
Haemangioma	6
Leg-ulcers	134
Malignant	9
Meningitis	24
Orthopaedic	49
Pressure-ulcer	175

Additionally, we used another public dataset, the AZH (Advancing the Zenith of Healthcare) dataset [8], which includes 538-foot ulcer images of four different wound types: Diabetic, Venous, Pressure, and Surgical. Table 3 summarizes the distribution of samples per class for the 538 images used in this study's AZH dataset.

Table 3. Configuration per Class for AZH Dataset with 538

Labels	Number of Samples
Diabetic	154
Venous	156
Pressure	100
Surgical	128

Sample images of Medetec are presented in Fig. 1. Fig. 2 shows sample images from the AZH Wound and Vascular Center database. Despite using these two datasets, they are still insufficient to achieve high classification accuracy. In this study, we used a combination of the Medetec and AZH datasets, and Fig. 3 shows the composition by class across the datasets used in this study. Fig. 3 shows the organization by class across the datasets used in this study.

Fig. 1. 12 classes of Medetec sample images

Fig. 2. 4 classes of AZH sample images

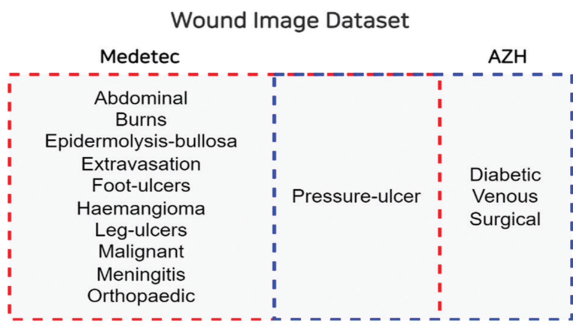

Fig. 3. Class organization of the dataset used in this study (Medetec + AZH)

4.2. WOUND IMAGE CLASSIFICATION PIPELINE

The first step in developing an AI application is to collect good data, which must then be preprocessed to improve performance before being inputted into the main classification model. Fig. 4 provides an overview of the wound image processing pipeline, which will ultimately predict the type of wound.

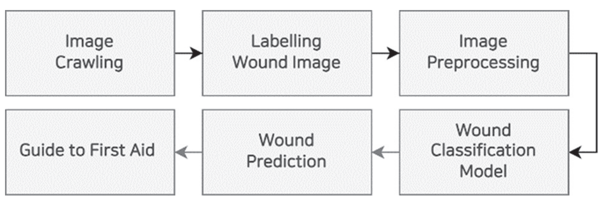

Fig. 4. Wound image classification pipeline

4.3. PREPROCESSING OF WOUND IMAGES

After collecting the wound data, the next step is to preprocess it for optimal performance before feeding it into the main classification model. Based on data analysis, preprocessing techniques can be applied to the training data to improve accuracy. The calibration of medical images is a crucial step in this process. The preprocessed training data is then classified into detailed attributes in a format suitable for the AI model. The Medetec dataset underwent preprocessing with the following steps:

- Resizing the entire image to 224x224
- Randomly flipping train images horizontally
- Randomly flipping train images vertically
- Normalizing all images

Details of the dataset preprocessing are presented in Fig. 5. The collected wound data was normalized into a format suitable for deep learning models for classification. The preprocessing involved dimensionality reduction and color correction of the wound image data. As a result, we were able to augment our dataset by a factor of 4 through data preprocessing.

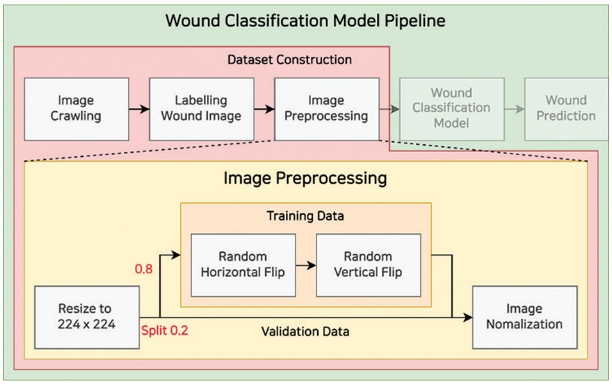

Fig. 5. Wound image preprocessing

4.4. WOUND IMAGE CLASSIFICATION MODELS

The preprocessing and optimization of data are important steps in the wound image classification pipeline. However, the most critical aspect is the classification model, which recognizes wounds and recommends optimal first aid. Deep neural network models are generally effective at extracting features from image data, and the final result label should correspond to one of the types listed in Fig. 3.

Before choosing the optimal classification model, we conducted a preliminary performance evaluation of several popular image classification models on the dataset used in this study. The results are presented in Table 4. For classification, we adopted two image classification models with the highest accuracy: the ResNeXt-101 32x8d architecture from "Aggregated Residual Transformation for Deep Neural Networks" [9] and the ViT architecture as the primary image classification model. In this paper, these two models will be analyzed from various perspectives.

Table 4. Accuracy by Model

Models	Accuracy
MobileNetV3-Large	81.73%
VGG19-BN	84.13%
EfficientNetV2-L	87.98%
ResNet152	87.98%
DenseNet161	88.46%
ResNeXt101-32x8d	90.38%
ViT-B/16	92.78%

4.4.1. ResNeXt

ResNeXt-101 32x8d is a deep convolutional neural network architecture introduced in 2016 by Facebook AI Research (FAIR) researchers as an extension to the ResNet (Residual Network) architecture. The ResNeXt-101 32x8d architecture has 101 layers and a cardinality of 32, which refers to the number of parallel paths within each ResNeXt block. This allows the network to capture diverse features from the input images, making it more effective at image recognition tasks. The "8d" in the name of the architecture refers to the width of the bottleneck layers within each ResNeXt block, designed to reduce the number of parameters in the network and improve its computational efficiency. ResNeXt-101 32x8d has achieved state-of-the-art performance on several image recognition benchmarks, including the ImageNet dataset, which contains over 1 million images across 1,000 categories.

After preprocessing, the wound image data is input to the ResNeXt-101 32x8d model illustrated in Fig. 6. The schematic diagram of the proposed approach is presented in Fig. 7.

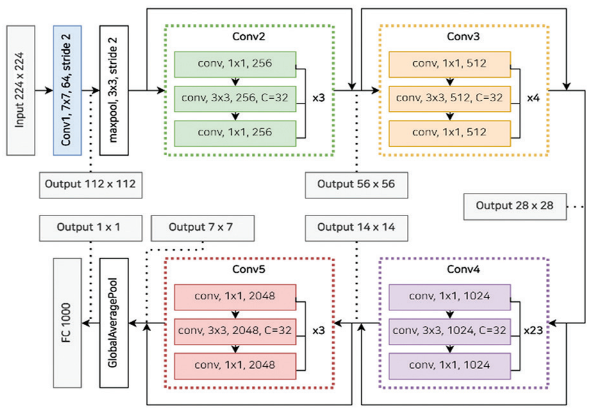

Fig. 6. ResNeXt-101 32x8d model architecture

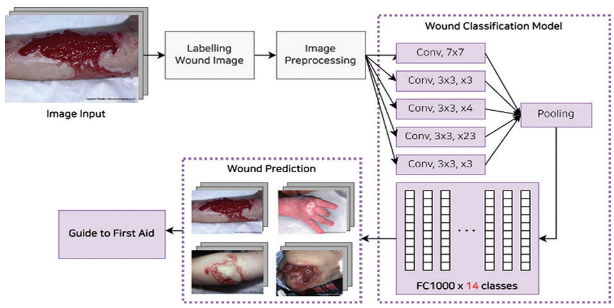

Fig. 7. Schematic diagram of the ResNeXt approach

4.4.2. Vision Transformer (ViT)

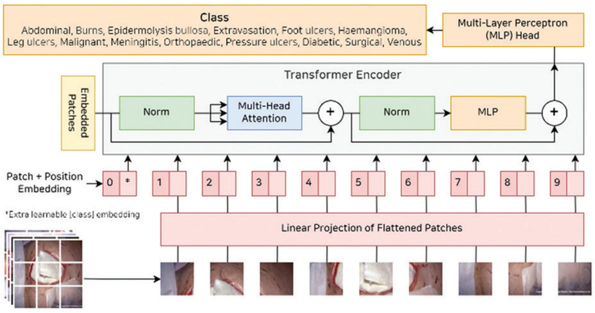

Fig. 8. ViT model architecture

The Vision Transformer (ViT) is a novel approach that adapts the transformer architecture to the domain of image classification. Notably, ViT has demonstrated the ability to surpass the performance of conventional convolutional neural networks (CNN) and their variants while utilizing fewer computational resources. The ViT model architecture was unveiled in a research paper titled "An Image is Worth 16*16 Words: Transformers for Image Recognition at Scale" [11]. The ViT model underwent pre-training on both the ImageNet and ImageNet-21k datasets. The recent success of transformers in NLP has paved the way for their promising performance in image classification tasks. Moreover, several transformer variants like CrossViT [28] and VIP-P [29] have been introduced, each optimized for specific applications. Within the medical realm, the ViT model has even outperformed the DenseNet model in diagnosing COVID-19 [30]. For processing, the ViT model divides an image into patches of 16x16x3. These patches are subsequently flattened and transformed into vectors of size 1x768, culminating in a patch embedding matrix with dimensions of 4x768. This matrix undergoes processing through 12 successive ViTLayers (transformer encoders) carrying location metadata. Each ViTLayer comprises a multi-head self-attention (MSA) block and a multi-layer perceptron (MLP) block.

4.5. WOUND IMAGE CLASSIFICATION MODELS

To achieve optimal wound classification, it is essential to extract key features from wound images for accurate classification. This requires building an AI model that can effectively learn from wound images while preventing overfitting and over-parameterization during training and validation with real data. The optimization process then generates an optimal model that can accurately classify the cause of wounds for new wound image inputs.

During the model-building process, various components of the wound image classification model, such as hyperparameters and parameters, are adjusted and optimized to best fit the training data. Techniques such as removing the influence of similar images and preventing overfitting are applied to optimize the model. Through this process, the wound image classification model is optimized for the training data and wound images and can accurately classify wound types.

We fine-tuned our wound image classification model using the combined dataset of Medetec and AZH and experimented with various hyperparameters to ensure optimal generalization and prevent overfitting. Table 5 displays the optimal hyperparameter values for the ResNeXt and ViT models.

Table 5. Hyperparameters for each model

Hyperparameters & Performance Metrics		ResNeXt101 -32x8d	Vision Transformer(ViT)
Batch size	3-100	37	8
Learning rate	0.01-0.00001	0.0001	0.00003
Epoch	3-500	100	100

5. RESULTS

We used accuracy Eq.1, precision Eq.2, recall Eq.3, and F1 score Eq.4 for performance metrics. Table 6 shows the results for each performance metric based on the optimal hyperparameter values for both the ResNeXt and ViT models. The ViT model achieved an accuracy of 92.78%, with precision, recall, and F1 score values of 93.16%, 89.93%, and 90.79%, respectively. In contrast, the ResNeXt model yielded an accuracy of 90.38%, a precision of 94.61%, a recall of 84.10%, and an F1 score of 87.89%.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} = \frac{2 * TP}{2 * TP + FP + FN} \tag{4}$$

Table 6. Performance for each model

Models	ResNeXt101 -32x8d	Vision Transformer(ViT)
Accuracy	90.38%	92.78%
Precision	94.61%	94.89%
Recall	84.10%	91.87%
F1 score	87.89%	92.44%

Fig. 9 illustrates the evolution of each performance metric over 100 epochs. While ResNeXt exhibits instability across several metrics during its learning phase, the ViT model becomes increasingly stable as it learns. This stability suggests the potential for further improvement. Overall, ViT outperforms and is more consistent than ResNeXt across all metrics.

Fig. 10 and Fig. 11 show the confusion matrix of the predicted results versus the true results of the ResNeXt101-32x8d and ViT models. ViT shows equal or better accuracy for most labels compared to ResNeXt101_32x8d. The labels Malignant, Abdominal, and Burns, which have relatively few sample image data, show a lower accuracy of 50% for both models compared to the other labels. In terms of misclassifications, the two models are similar.

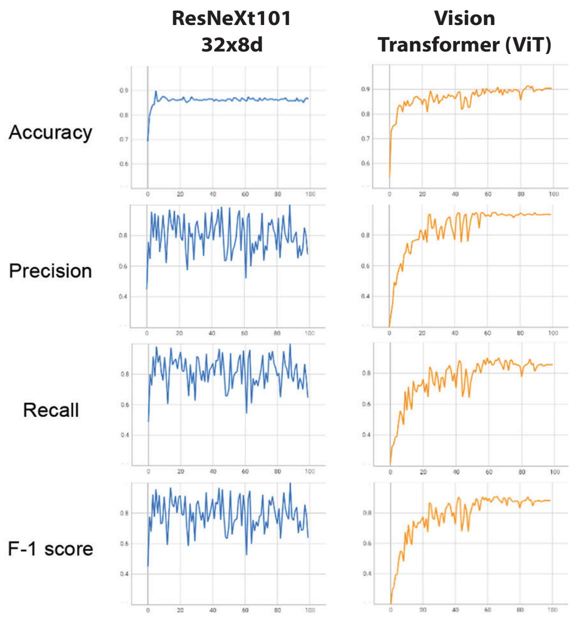

Fig. 9. Accuracy, Precision, Recall, and F1 score

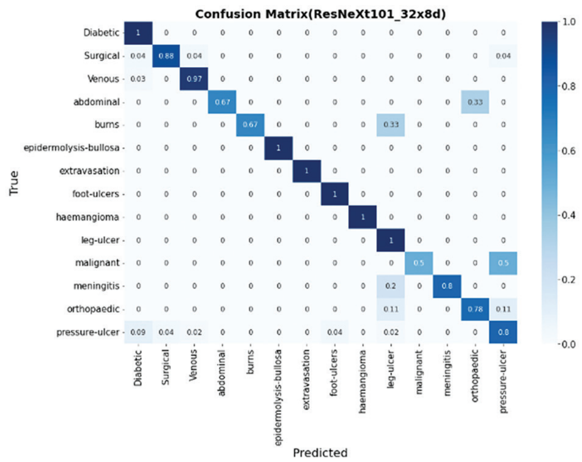

Fig. 10. Confusion Matrix of ResNeXt101-32x8d

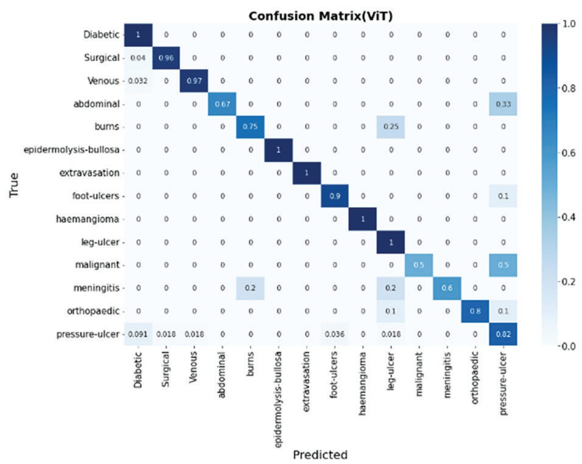

Fig. 11. Confusion Matrix of ViT

A comparison of the accuracy of our study with related studies is shown in Table 7. V. N. Shenoy et al. [1] classified wound types and wound treatment methods using images and showed an average accuracy of 85.1%. B. Rostami et al. [7] used the AZH and Milwaukee Vascular Center datasets, which were also used in this study. The study showed an accuracy of 68.7% for classifying six classes. X. Gao et al. [30] used ViT to classify COVID-19-infected and uninfected individuals and achieved an accuracy of 76.6%. Our proposed model demonstrated a high accuracy of 92.8% in classifying 14 classes, with the best performance in classifying wounds by type.

Table 7. Accuracy versus previous studies

Paper	V. N. Shenoy et al.	B. Rostami et al.	X. Gao et al.	Our Paper
Accuracy	85.1%	68.7%	76.7%	92.8%

6. AI ASSISTANT FOR FIRST AID

There are various criteria for categorizing wounds and their corresponding labels. Wounds can be categorized based on their cause, shape, or presence/absence of infection. For instance, wounds can be classified based on their cause, such as cut, stab, laceration, scab, thermal, and shooting. Based on their shape, wounds can be categorized into linear, plate, and missing wounds. However, these criteria may not be easily understood. Therefore, in this study, wound classification uses commonly used and easily understood terms by the average person.

Table 8. illustrates seven types of wounds for first aid based on common criteria and terminology, along with brief summaries of first-aid treatment options for each type of wound.

Table 8. Seven Types of Wounds and Their Treatment Options

Types	Photos	Definition	First Aid
Contusions		Vascularized wounds caused by physical impact (edema formation, bruising)	Apply cold compresses to reduce swelling before applying warm compresses.
Burns		If the main cause of the wound is a hot object	For first-degree burns, soothe with cold water. For second and third-degree burns, cool the burned area with cold water, wrap it in gauze, and go to the hospital without forcing the blisters to pop.
Abrasions		Wounds in which the epidermis or part of the dermis has been removed (scratches)	Apply an antibiotic ointment along with simple wound cleaning.

Cuts (penetrating)		A deep puncture wound is caused by a long, narrow object such as a nail or awl.	If the foreign body is small, remove it to clean and disinfect the wound. If it is large, do not remove it, and go to the hospital immediately if you suspect profuse bleeding.
Lacerations		A tear in the skin	Wash the wound with running water or saline solution and apply gauze or a bandage to keep it under control.
Incision		Cuts from sharp objects	In addition to simple cleaning, hemostasis is used to stop bleeding.
Amputations		A cut where skin tissue or part of the body has been severed.	Wash the wound with running water or saline, apply gauze or bandages, and apply pressure to control bleeding.

Fig. 12 shows a simple user interface for a prototyped first aid assistant. Here are some scenarios where the public can use First Aid Assistant Scenario:

Fig. 12. Application Example for First Aid Assistant

1. Accident scene: A person gets injured.
2. Utilize the AI assistant app: A bystander launches the AI assistant app on their phone and takes an image of the wound.
3. Provide first aid guidance: The app analyzes the wound image to determine the depth, type, and danger of a wound and provides immediate first aid instructions (e.g., instructions to apply pressure or elevate the wound).
4. Send information to paramedics: The app sends information about the wound and location data to the nearest paramedic.
5. Hospital referral: At the same time, the app sends patient information and the severity of the wound to the emergency room of the nearest hospital.
6. Interaction with specialists: Specialists at the hospital can view wound images directly through the app and send information to paramedics for further action or medication.
7. Patient arrival and first aid: Paramedics arrive at the scene, provide the patient with hands-on first aid based on the first aid guide provided in the app, and transport the patient to the hospital.
8. Hospital arrival: When the patient arrives at the hospital, specialists already know the patient's condition and can respond quickly.

7. CONCLUSION

This paper presents a study on developing an AI-powered first-aid assistant designed to classify surgical wounds and recommend appropriate treatments intelligently. We emphasize the importance of precise wound classification in emergencies and highlight the benefits of utilizing state-of-the-art AI techniques to enhance the first aid process, potentially saving lives.

The surgical wound classification system proposed here forms the core of the AI-powered first aid assistant. This system leverages recent deep-learning models to classify wound images and related data, suggesting the most fitting first-aid treatment based on factors like wound type, skin thickness, tension, and scarring. Such an approach minimizes errors, increases safety, and is time-efficient.

The key findings of this study include:

- Despite being trained on a limited dataset of roughly 1,000 images, the wound image classification using ViT models achieved an accuracy of 92.78%. The precision, recall, and F1 score values were 94.89%, 91.87%, and 92.44%, respectively, underscoring the model's potential for deployment in first-aid scenarios.
- To enhance the wound classification model, acquiring wound images from actual first aid situations is essential, highlighting the need for collaboration with medical institutions to collect such images.
- The proposed AI model can be applied beyond first aid to various medical treatments. A first aid assistant system based on this model can empower individuals with knowledge of effective first aid, potentially saving lives. It can also promote collaborative efforts, transmitting the first aid process to paramedics in real-time and thus shortening response times. The system opens up avenues for remote first aid, collaboration with paramedics, and consolidated treatment that merges diagnosis and prescription within one platform.

In this study, we tried to augment the data with preprocessing due to the small number of images in the original dataset. However, this was limited by lower accuracy for some labels. This suggests that more images of real wounds should be added to the dataset in the future.

Future research will concentrate on enhancing data augmentation techniques to boost the performance of surgical wound classification and ensure meticulous performance evaluation. We also aim to design AI systems for remote first aid, collaboration with paramedics, and real-time integration with specialist diagnostic and prescription platforms.

Another next step for this research is to develop an AI assistant for first aid that incorporates augmented reality (AR) technology. Previously, the research team conducted various haptic virtual simulation studies for medical education and training, such as suture surgery simulation [31-35] and the haptic visual discrimination test (HVDT) [36]. With the growing interest in mixed-reality technology, transitioning these simulations to a mixed-reality environment could enhance their utility. Combining this paper's research with virtual simulations is expected to enable AI surgical assistants to identify wounds in real time, suggest appropriate first-aid strategies, and guide the surgical process. This approach will likely accelerate learning and promote mastery of optimal first-aid techniques.

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