AI Wound Assessment Using Deep Learning

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Abstract

The latest pandemic caused by the coronavirus highlighted the worldwide shortage of medical staff. Nearly one-third of the world's population lacks access to essential health care. This shortage can reach severe levels during war times. Amid the current circumstances in Gaza, the health care system has collapsed and the medical staff are now forced to decide on the patients who have a priority to be treated first. Our research tackles the problem of wound healing prediction time, in general, using a deep-learning-based web application that classifies the wound and its healing time. Since we did not manage to find a dataset labelled with healing time, we obtained the average healing time for each class using online sources. As a result, time prediction in our research is based on wound classification. This application also provides a tool for medics in war zones who can not treat all wounded people at once to get a priority list by uploading the wound images. To classify wounds we collected a dataset from online public sources and used a pre-trained residual neural network deep learning model (ResNet) that achieved an accuracy of 96% on our dataset. To categorize different wounds and produce a priority list, we used a subset of our dataset consisting of wound classes usually encountered in war zones. Such classes are burns, cuts, lacerations, burns, and bruises. Our future work includes working on a way to predict time from the wound image itself rather than using average time.

Keywords: Wound Classification, Wound Healing, Wound Healing Time Prediction, Deep Learning, ResNet, Field medicine, Combat Medicine

1. Introduction

As the global population expands, the demand for medical workers intensifies. However, the number of medical school graduates can not satisfy the need for health services. The World Health Organization reports that one-third of the world's population lacks access to essential medicine. The global shortage of healthcare workers was 20 million in 2013, then it reduced to 15 million in 2020. The expectations are for it to be 10 million in 2030(1). Moreover, some regions, especially those composed of developing countries suffer much more than developed countries. In 2020, there were 12.65 million medical doctors and 29.10 million nurses. The African region had about 330 thousand doctors and about 1.19 million nurses, the Eastern Mediterranean region had 800 thousand doctors and 1.11 million nurses and the Region of the Americas had 2.49 million doctors and 8.27 million Nurses.

Many countries especially in Africa and the south of Asia are still facing health staff shortages and this has resulted in severe disruptions. (2)

The recent years have made it clear that the patient's needs are more than what healthcare systems can provide. This has become evident in the time of the COVID-19 pandemic when healthcare workers were redeployed to assist and the retired were called to help, which affected other healthcare services.

In light of these insights, the need has arisen to find long-term sustainable solutions to make sure that the healthcare systems perform efficiently and will not be overwhelmed in times of crisis.

The progress witnessed in AI technologies offers promising solutions to make the basic medical diagnosis reducing the workload on medical workers, allowing them to focus on critical medical tasks which reduces the overall workforce demand. Furthermore, with development, it can be the first step to designing reliable AI models to do more complex diagnoses.

Looking at the numbers and statistics, it was found that wound care is one of the largest issues that healthcare providers face. In 2014, 17.2 million hospital visits were because of acute wounds, including ambulatory/outpatient and inpatient surgical visits. The global prevalence of chronic wounds is estimated at 1.51 to 2.21 per 1000 population, and these numbers are expected to rise with ageing populations worldwide (3).

The wounds vary from acute with basic care needs to chronic with more high-level care needs necessitating a physician with mid-level experience to determine its type which is more challenging in times of pandemics and wars. During the COVID-19 pandemic, it was challenging for the doctors to give the patients the care they need without risking their lives and patients' lives. And in wars, the number of wounded is so huge that the physicians can't keep up and the hospitals become overwhelmed.

In Gaza, as witnessed recently, the Palestinian Ministry of Health reported a staggering 50,500 wounded individuals in hospitals within just five weeks. This surge has pushed healthcare facilities to operate at more than double their capacity. Doctors have faced overwhelming challenges dealing with many injuries and casualties. Tragically, a significant number of wounded individuals succumbed to their injuries before medical assistance could reach them

In this research, we have developed a deep learning web-based application that can classify the type of wounds and their healing time using the ResNet classifier. The application also comes with a feature that will come in handy in war zones to help medics quickly decide which wounds need more attention and prioritise individuals most in need of urgent care, reducing fatalities.

2. Literature Review

In this review, we're addressing the previous attempts to understand the wound healing process. We shall look into mathematical models of partial differential equations (PDEs) that were used to relate biological and environmental factors that affect the wound healing process.

Since the 80s of the last century, the interest in mathematically modelling the wound healing process has been increasing. We can mainly categorize the mathematical models used into four groups: a mechanical approach, a discrete approach, a multi-scale approach, and a reaction-diffusion approach.

In 1985, McElwain and Balding (4) used a reaction-diffusion approach that Edelstein (5) (6) (7) used to address the growth of fungi and model the dynamics of tumour-induced angiogenesis. The model relied on the blood vessels and capillary tip density. Including both blood vessels and tip density highlights that endothelial cells (ECs) in the tip of a capillary guide the ECs in the vessel. This model claimed that the wound healing process depends on the blood that reaches the wound site. So during the healing process, given that (n) capillary tips move with velocity (v), the rate of increase of blood vessels is given by $(nv).\hat{v}$, where $\hat{v}$ is a unit vector in the direction of v. The model however does not account for vascular loops extension.

In 2002, Gaffney, Pugh, Maini and Arnold (8) introduced their model of cutaneous wound healing angiogenesis. Their model was focused on describing a linear, superficial wound that is significantly longer than its width and depth. They therefore assumed that the wound is one dimensional with assumed reflective symmetry about a plane parallel to the long edges of the wound and equidistant from both. They used PDEs to relate random motion, chemotaxis, capillary tips joins, and tip-sprout joins with respect to the spatial variable in one dimension.

Since solving partial differential equations that model the wound healing process to get time is complex, many attempts have been made to utilize artificial intelligence methods to predict the behaviour of wounds. Kim et al (9) used smartphone images to predict the eventual healing of diabetic foot ulcers. Rosa et al (10) used logistic regression and a tabular data set that contains many wound and patient attributes. Subba et al (11) used the Xception CNN model to classify the wound type along with light gradient-boosted machines to predict the healing time.

3. Methodology

To obtain the time taken by the wound to heal completely, we first tried to use a partial differential equation solver (12), to solve the generic wound model provided in (13). This model consists of 2 equations that model the corneal wound healing process, though the authors stated that this model can be used generally for most wounds.

$$\frac{\partial n}{\partial t} = \nabla(D_n(c)\nabla n) + s(c)n(v - \frac{n}{n_0}) - kn \quad (1)$$

$$\frac{\partial c}{\partial t} = D_c\nabla^2 c + f(n) - h(c)n - \delta c \quad (2)$$

The two partial differential equations relate the cell density in the wound and the concentration of the epithelial growth factor (EGF) with time. The constants of the two equations' are not specific to the area of the cornea. D_c is a constant that resembles the diffusion coefficient of the EGF, K is the cell cycle time, n_0 is the normal skin cell density, δ is the EGF half-life time and v is the rate of cell loss. We note that the previous constants' values can be replaced with the corresponding wound site value. If the normal skin has cell density n_o and normal EGF concentration c_0 then those two equations can be solved to get the time taken by the wound to reach n_0 and c_0 and thus obtain the time needed for the wound healing. For the expected high level of mathematical complexity in equations (1) and (2) we did not manage to obtain time from equations. Since we also couldn't manage to find a public dataset with wound images labelled with the time taken, we decided to look up the average time taken for each class present in our dataset and then labelled each class with that time. Our problem has then shifted from the complex process of obtaining wound healing time directly to classifying the wound type and consequently, the average expected time which is a less complex problem.

3.1. Dataset

We collected wound images from 3 different sources, wound-dataset (14), Medettec (15), and AZH (16) to form a new dataset. We abandoned images that were not taken conveniently, and more importantly, wound classes that did not provide a suitable number of images. We then grouped similar classes of wounds and trained the model on this constructed dataset with 1500 images. Our wound classes are burns, abrasions, lacerations, cuts, diabetic ulcers, venous ulcers, pressure ulcers, surgical ulcers, bruises and normal skin.

We then applied horizontal reflection on the images, which is a data augmentation technique to increase the size of our dataset. By doing this, we increase the variability in our dataset, and also reduce the model's sensitivity to the wounds' orientation, meaning images taken from multiple angles should produce the same results.

To perform the task of wound prioritization we specified a smaller subset of our dataset that contains the wound classes from our dataset that are usually encountered in war zones namely, bruises, burns, abrasions, cuts, and lacerations. These images were assigned to the most significant factors that will affect a wound's priority to be treated. These attributes are the wound class, time taken to heal in normal conditions, severity of the wound, depth and bleeding level. Each attribute is assigned a weight ranging from 0 to 2 indicating its influence.

One can simply calculate the priority of a wound by adding the weights of the attributes and the wound with the highest score will be the the one with the highest priority. However, that will imply that all attributes have the same significance which is not necessarily true. A better approach would be to train a regression head, which, if the data is labelled correctly, would learn the correct significance of each of those attributes.

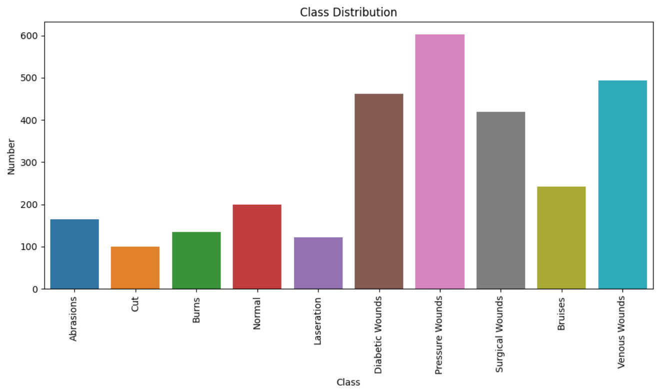

Figure 1: Distribution of wound classes in our dataset

3.2. Deep Learning Model Architecture

Our proposed architecture is a convolutional neural network (CNN) for extracting an arbitrary number of features and classifying the wound. The CNN was designed to extract relevant features from the wound images for subsequent regression. Fig.2 describes the basic structure of a CNN.

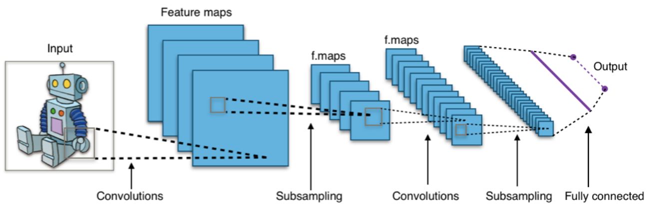

Figure 2: Basic demonstration of a CNN

The CNN architecture consisted of multiple convolutional blocks followed by max-pooling layers to progressively capture hierarchical features. Each convolution block comprised several convolutional layers with learnable filters. These filters convolve over the input wound image, effectively detecting various patterns and features. The convolutional blocks were stacked to allow the model to learn increasingly abstract and hierarchical features as it progressed through the layers. This hierarchical feature extraction was crucial for understanding and representing complex wound characteristics. It followed the ResNet-34 architecture, a pre-trained model that we used in a process called Transfer Learning.

At the heart of our convolutional blocks, we implemented several convolutional layers, each applying a set of filters to the input data. Each filter is responsible for detecting specific patterns that may emerge in the image. Convolution is then done

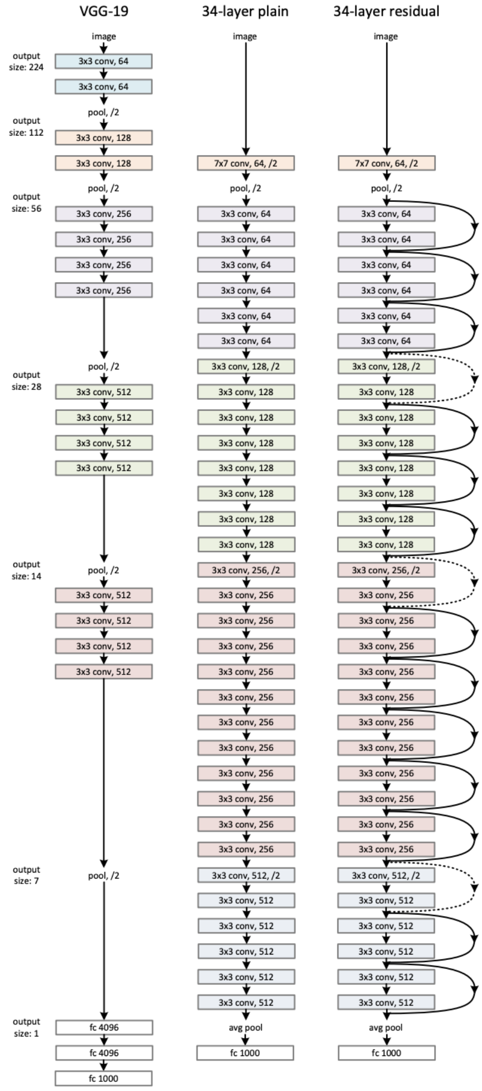

Figure 3: ResNet's architecture
(17)

by sliding these filters over the image and performing element-wise multiplication to produce a feature map. Each map highlights the presence of a certain pattern.

After each convolutional layer, we applied the rectified linear unit (ReLU) activation function to each feature map to introduce non-linearity to the model, by setting negative values to zero and leaving positives unchanged. This allowed the model to reach convergence during training and to learn complex relationships.

Within each convolutional block and after applying several filters to the image, we used max-pooling to reduce the complexity of the data and to focus on the most salient patterns present in the image.

4. Results

We divided the dataset into 2 subsets - 80% training set, and 20 % testing set. We then trained the model with multiple train-

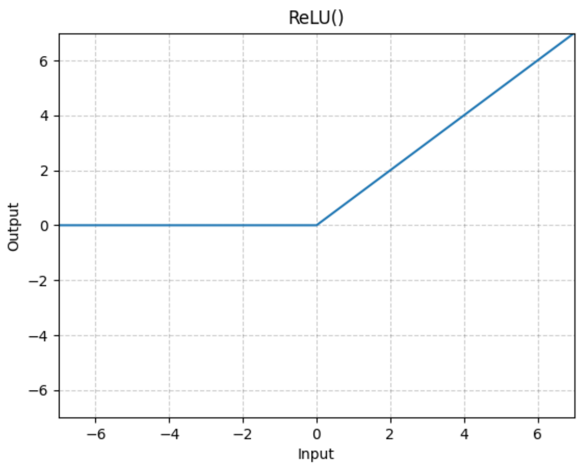

Figure 4: Graphical representation of the ReLU function

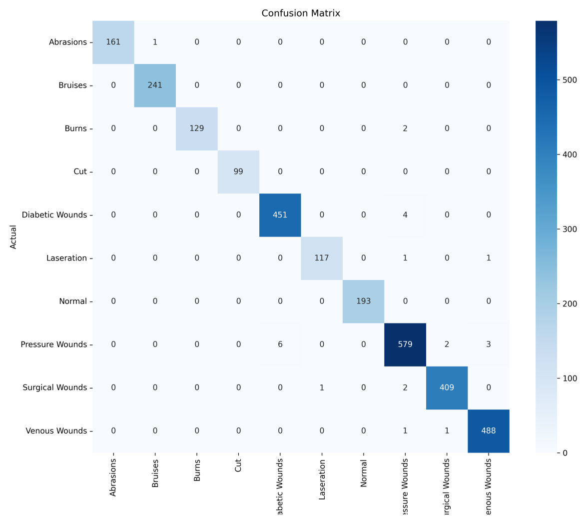

Figure 6: Confusion matrix for 10 different wound classes

ing epochs, and using a quick accuracy test (see Appendix), we determined the most suitable number of iterations to train our model with. Each training iteration involved the application of a classic gradient descent algorithm to optimize the model's weights and filters.

```
epochs = [1, 2, 5, 10, 15 ,20]
acc_s = []
learn = vision_learner(dataloaders, resnet34, metrics=accuracy)

for epoch in epochs:

    learn.fine_tune(epoch)

    interp = ClassificationInterpretation.from_learner(learn)
    acc = interp.confusion_matrix().diagonal().sum() / interp.confusion_matrix().sum()
    acc_s.append(acc)
```

Figure A.7: Our code for determining the most suitable number of iterations

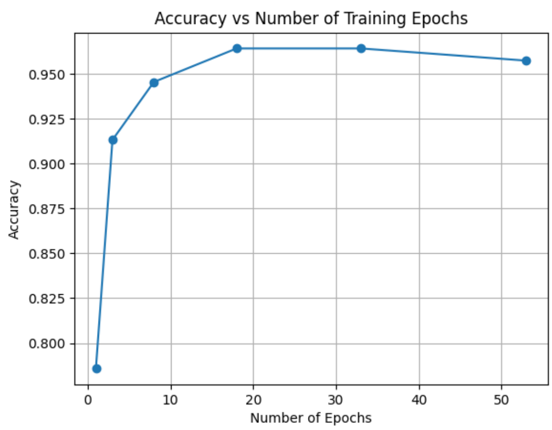

Figure 5: Accuracy versus number of iterations

Our model achieved great accuracy (96%) at distinguishing various wound types, as per our confusion matrix.

5. Conclusion

In this research, we aimed to address the problem of the general shortage of medical staff worldwide in addition to a specific interest in the clinical diagnosis and treatment of wounds in war zones. We explored the possibility of predicting the healing time of different wounds by classifying the wounds into classes each labelled with their average healing time. We also introduced a feature to help medics in war zones assess the priority of wounds. Our dataset was collected from publicly available datasets. The ResNet classifier we used achieved an accuracy of 96% in classifying wound types. Since we couldn't obtain a dataset that contained labelled healing duration, we searched for the average healing duration for different wound classes. Our main contribution is the ability of the user of our application to get a high-accuracy classification of wounds in addition to providing medics with the ability to upload more than one wound and get a priority list of those wounds which will be of great benefit to medics in war zones. A limitation of our work is that we couldn't find labelled wound images with their healing time which would have given more accurate predictions than using average durations of each wound class. This implies that our future work will include seeking an expert to label wound images with their corresponding healing time. We also aim to train a regression head to determine the significance of each wound attribute, allowing for better prioritization. To conclude, using deep learning to assess wound healing has the potential to help clinicians and medical staff in diagnosing wounds and aiding medics during a lack of adequate medical care.

Appendix A. Determining Number of Epochs

Fig.A.7 shows the code we used to determine the most suitable number of epochs to use, and fig.5 shows the results of this cell. We trained the model multiple times, each using a different number of epochs, and determined the number of iterations to use based on the maximum accuracy.

Appendix B. Reproduction

The code and data set needed to reproduce results are found here `https://www.kaggle.com/code/ibrahimfateen/wound-classification-notebook`.

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