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Wound Image Classification Using Deep Learning

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ABSTRACT: Wounds not only harm the physical and mental health of patients, but also introduce huge medical costs. Meanwhile, there is a shortage of physicians in some areas, and clinical examinations are sometimes unreliable in wound diagnosis. Reliable wound analysis is of great importance in its diagnosis, treatment, and care. Currently, deep learning has developed rapidly in the field of computer vision and medical imaging and has become the most commonly used technique in wound image analysis. This paper studies the current research on deep learning in the field of wound image analysis, including classification, detection, and segmentation. We first review the publicly available datasets from various researches, and study the preprocessing methods used in wound image analysis. Second, we applied the VGG-19 Model in deep learning tasks (classification, detection, and segmentation) and their applications in different types of wounds (e.g., burns, diabetic foot ulcers, and pressure ulcers) are investigated. Finally, we discuss the challenges in the field of wound image analysis using deep learning, and provide an outlook on the research and development prospects.

I. INTRODUCTION

As a "silent epidemic" [1], wounds not only cause severe physical pain to individual patients such as background pain caused by the wound itself and operative pain from clinica interventions [2], but also introduce a certain degree of psychological impact, such as worry an anxiety in patients who suffer from traumatic pain, and in severe cases, it may lead to depression [3]. In addition, since chronic wounds take a long time to heal, patients must undergo continuous care to prevent infection and the ongoing diagnosis and treatment of wounds place a significant financial burden on individuals as well as the society. In the UK, the National Health Ser-vic (NHS) spends ¿1.94 billion and ¿89.6 million annually on managing leg ulcers and burns respectively [4]. At the same time, there is a shortage of surgeons in some regions such as a lac of rotating backups after prolonged physician surgeries, or physicians are busy with othe activities outside the hospital, resulting in patients not receiving timely, high-quality acut surgical care [5], [6] Furthermore, it has been shown that clinical examinations are sometime unreliable in the diagnosis of infections in chronic wounds, even with the participation o experienced physicians [7], as well as in acute wounds [8]. Therefore, there is a need for a low cost, rapid, and accurate wound assessment technique, such as medical imaging based methods to provide assistance in wound diagnosis, prognosis, care, and other related tasks.

Along with the rapid development of smart phones, computer hardware, and Internet techniques research on wound or wound image assessment has started to emerge, including real-time monitoring [9], remote diagnosis [10], and mobile care [11]. Wound images can provide valuable information for an expert to accurately diagnose wounds. However, manual evaluation through wound images is time-consuming. and usually requires a significant amount of experience [12] and training an experienced physician is costly in terms of time. Researchers have made great efforts to address this issue and various solutions have been proposed to assist physicians in wound diagnosis through wound images. Traditional digital image processing using machine learning is one of the most commonly used techniques for wound diagnosis [13], [14], but it has high time costs, since when describing the characteristics of different target images, a large number of parameters need to be manually adjusted, such as using line search techniques to tune free parameters in the support vector machine (SVM) that control the penalty of the classification error [15], and grid search techniques to select the combination of network size and weight decay that give the feed-forward neural networks (NN) the best performance [16]. With a sufficient amount of labeled training data, deep learning techniques can now effectively address this problem. The potential of deep learning in image processing has been widely recognized since the Alex Net architecture based on convolutional neural networks (CNN) achieves impressive results in the Image Net competition. The CNN model is the most commonly used model in deep learning [17]. It has the advantage that it can automatically extract multiple levels of image visual features, and does not need to manually adjust a large number of parameters [18], which effectively improves the efficiency of image processing tasks. With the availability of more and more publicly available datasets, deep learning has made rapid progress in the field of medical imaging [19], including the wound image analysis [20], and diagnostic tools based on deep learning frameworks have proven to be effective in aiding clinical decision-making [21].

Zahia et al. [22] publish a review of machine learning techniques in pressure injury in 2019.
Anisuzzaman et al. [23] publish a review of artificial intelligence techniques in wound assessment in 2021, including a review of rule-based algorithms, machine learning algorithms, and deep learning algorithms. Although these studies cover a large amount of work, we believe that the review in the field of deep learning is not comprehensive. Different from previous work, we provide a more comprehensive overview of deep learning methods, including a review of publicly available datasets used in deep learning tasks, an introduction for data preprocessing methods, and various deep learning models. At the same time, we review the latest research in the field of deep learning as applied to various types of wounds. We retrieve more than 90 research papers through Google scholar searches using the query terms "deep learning", "classification", "detection", "segmentation", "wound" and combinations of various disease names. After determining specific wound types and deep learning tasks, we care-fully screen a total of approximately 50 papers considering the publication date and the number of citations. 64% of the papers were published after 2020.

Existing System:

- A Convolutional Neural Network (CNN) is a type of deep learning algorithm that is particularly well-suited for image recognition and processing tasks. It is made up of multiple layers, including convolutional layers, pooling layers, and fully connected layers.
- The convolutional layers are the key component of a CNN, where filters are applied to the input image to extract features such as edges, textures, and shapes. The output of the convolutional layers is then passed through pooling layers, which are used to down-sample the feature maps, reducing the spatial dimensions while retaining the most important information.
- The output of the pooling layers is then passed through one or more fully connected layers, which are used to make a prediction or classify the image.
- A convolutional neural network, or CNN, is a deep learning neural network sketched for processing structured arrays of data such as portrayals.
- CNN can run directly on a underdone image and do not need any preprocessing.
- CNN contains many convolutional layers assembled on top of each other, each one competent of recognizing more sophisticated shapes.

Proposed System:

- VGG-19 is a convolutional neural network that is 19 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database.
- The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.
- A fixed size of (224 * 224) RGB image was given as input to this network which means that the matrix was of shape (224,224,3).
- The only preprocessing that was done is that they subtracted the mean RGB value from each pixel, computed over the whole training set.
- Used kernels of (3 * 3) size with a stride size of 1 pixel, this enabled them to cover the whole notion of the image.
- Spatial padding was used to preserve the spatial resolution of the image.
- Max pooling was performed over a 2 * 2-pixel windows with sride 2.
- This was followed by Rectified linear unit (ReLu) to introduce non-linearity to make the model classify better and to improve computational time as the previous models used tanh or sigmoid functions this proved much better than those.
- Implemented three fully connected layers from which first two were of size 4096 and after that a layer with 1000 channels for 1000-way ILSVRC classification and the final layer is a softmax function.

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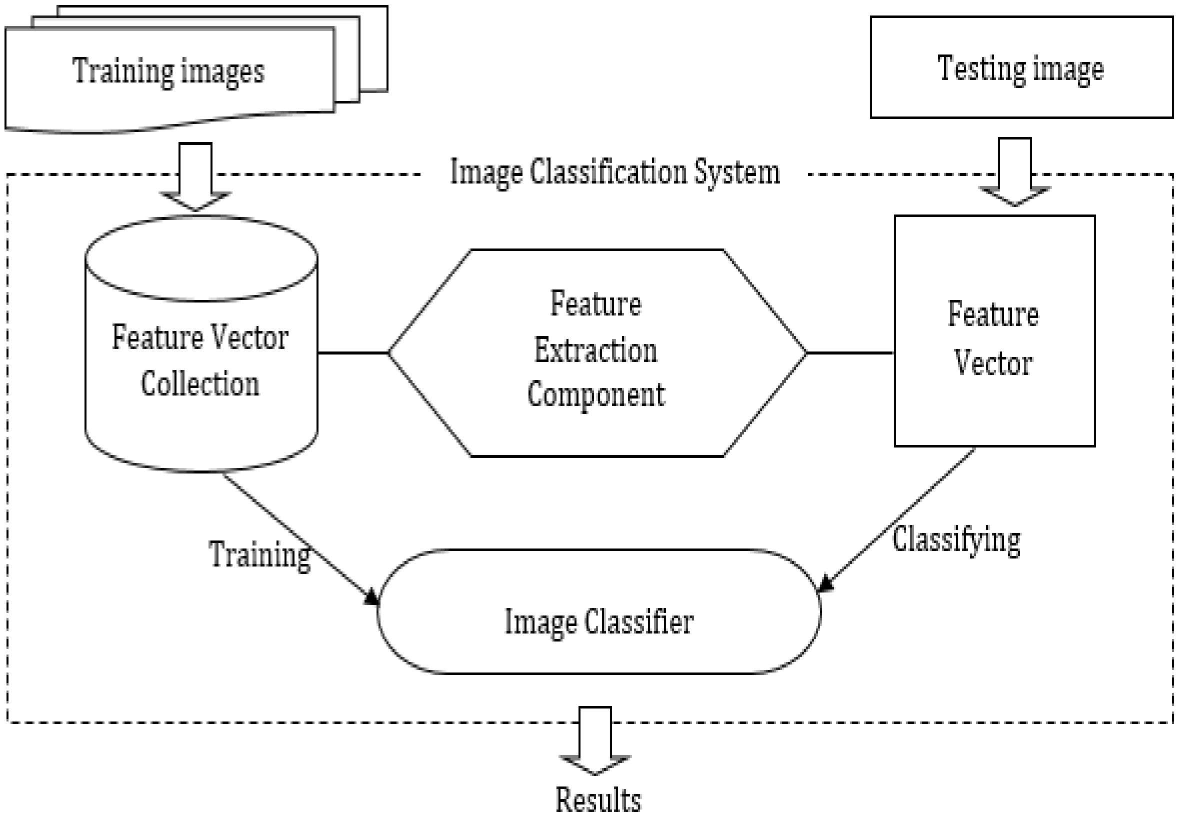
System Architecture:



III. RESEARCH METHODOLOGY

The research methodology for wound image classification using deep learning involves the following steps:
1) DATA AND DATA PREPROCESSING:
DATA
Data is one of the most important parts of deep learning. When deep learning models are trained with many parameters, but the amount of data used for training is insufficient, the network model is prone to overfitting. In the field of medical images, collecting datasets is challenging. First, medical images are more difficult to share publicly due to privacy protection. With the continuous development of medical data analysis methods, even after anonymizing the images, hackers may still be able to identify patients through technical means. Therefore, data in most studies are not publicly available. Second, the primary job of medical professionals is not data collection, and the acquisition of a batch of images may be done by multiple personnel, which can lead to inconsistent standards of the collected images. In addition, due to the different imaging equipment, distance and angle of the capture, the image content can show significant differences, including color mode, light, intensity, edges, etc., making the network model need more parameters to analyze the images. Finally, some medical images cannot be acquired in large quantities, since the capture method can harm the patient's body.

DATA PREPROCESSING
Although deep learning models can be trained directly based on original images when the data is sufficiently clear and of low noise, the training performance of the model still varies depending on data preprocessing methods. Data shortage is one of the common problems in deep learning in the field of wound applications. This is due to the lack of public datasets for some wound types and the difficulty of obtaining the sufficient amount of data through medical institutions. Data augmentation is widely used in preprocessing as a method to expand the number of samples without substantially increasing the existing data. Conventional image augmentation methods include geometric transformation, i.e., rotation, flipping, random scaling, etc., and color transformation, i.e., contrast transformation, color model conversion, Gaussian blur, etc.

2) DEEP LEARNING METHODS:
CNN has been widely used due to its excellent performance and efficiency in image processing.
In 1989, LeCun et al. propose CNN for handwritten character recognition. AlexNet is the first modern deep convolutional neural network (DCNN) model, which first applied techniques such as ReLU, Dropout and GPU operation acceleration in CNN, and achieved excellent performance. With AlexNet winning the ImageNet competition in 2012 with a far superior first place, CNN is able to rapidly spread to various application fields. VGG adopts a larger number of small convolutional kernels in the convolutional layer instead of the otherwise larger ones, thus reducing the number of parameters as well as increasing the number of nonlinear mappings, and significantly improve the classification performance of the network. DeepLab replaces the ordinary convolution of VGG with atrous convolution for segmentation tasks, and then performs post-processing optimization on the obtained segmentation results through Conditional Random Field.

3) EVALUATION METRICS:
The performance of deep learning models can be evaluated through standard metrics. Using different evaluation metrics can make more comprehensive comparisons between models and provide researchers with appropriate directions for optimizing models. The evaluation metrics can be defined by confusion matrices, where the positive and negative instances of correct prediction are denoted as True positive (TP) and True negative (TN), and the negative and positive instances of incorrect prediction are denoted as False positive (FP) and False negative (FN), respectively. Accuracy represents the percentage of correctly classified samples among the total samples, and is the most basic metric for evaluating model performance. The performance of the model can be accurately measured in the class balanced cases. But in the case of class imbalance, using accuracy creates performance evaluation limitations.

4) WOUND CLASSIFICATION:
Burns are a very serious type of wounds, and every year a large number of people are disabled or even die due to burns. Severity assessment of wounds is an initial preparation for burn wound diagnosis, monitoring, and care sessions and is the most common burn injury classification task. deep learning framework that can classify images into four body parts, and three burn levels. It first trains the M-ResNet50 model using non-burn images to predict body parts, and then feeds wound images of specific body parts to train the ResNet50 model to predict severity, and the framework has excellent performance in both classification tasks. Further, use a pretrained CNN

IV. RESULTS

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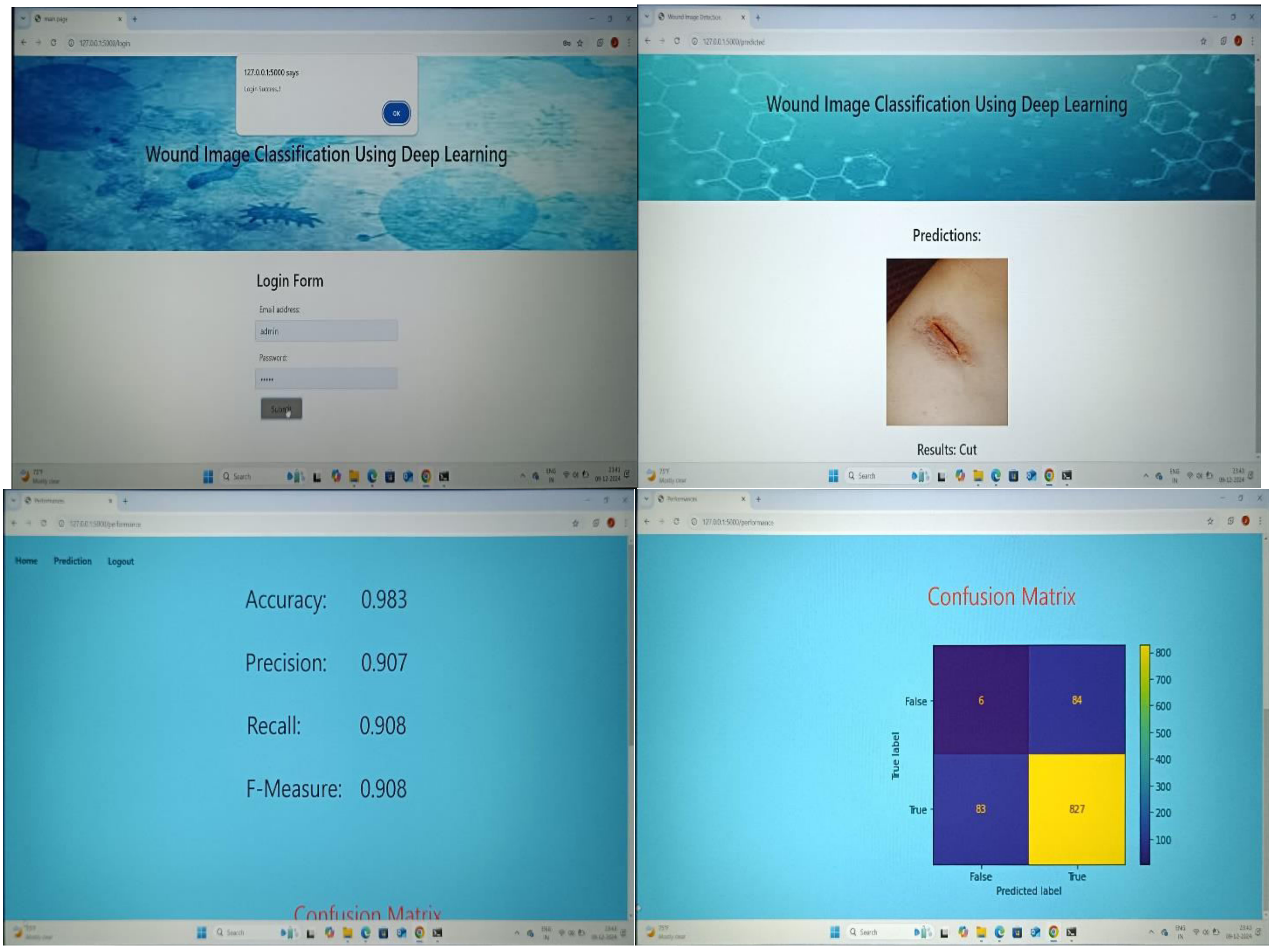

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