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Applying Deep Learning to Establish a Telemedicine Assistance System: A Case Study of the Stage Classification of Pressure Injuries

Ming-Chuan CHIU [a,1], Tsung-Yu TSENG[b], Chi-Chang CHANG[c], Chun-Chia CHEN[d]
[a b] *Department of Industrial Engineering and Engineering Management, National Tsing Hua University, Hsinchu, Taiwan*
[c] *School of Medical Informatics, Chung Shan Medical University, Taichung, Taiwan*
[d] *Institute of Medicine, Chung Shan Medical University, Taichung, Taiwan*

Abstract. The current medical system still uses manual work for the assessment of pressure injuries. For medical staff, it consumes lots of time and energy, and is difficult to maintain a consistent judgment. In recent years, Covid-19 has worsened the shortage of medical resources and manpower, and has promoted telemedicine. However, limited by the inability to actually touch the affected part of the patient, the medical staff will also have deviations in the judgment of the wound, which will affect the treatment effect. At present, there are only a few studies on the stage identification of pressure injuries, and the accuracy is unsatisfactory. Therefore, this study aims to establish a telemedicine assistance system based on YOLOv7, which is a deep learning model with classification and real-time judgment ability. The front-end interface of this system includes iOS, Android, and Web pages to address the shortcomings of previous studies and provide more real-time pressure injuries wound information in the process of telemedicine. The contributions of this research include providing an available pressure injuries stage classification model with a classification F1 Score value of 0.9246, which can support medical staff to make quick and accurate decisions clinically, and carry out corresponding medical measures according to each stage of symptoms; and can help patients who are inconvenient to visit the hospital to obtain real-time and correct diagnostic information during telemedicine, and seek different medical assistance according to the severity of symptoms; furthermore, immediately remind the medical staff when tracking the improvement or deterioration of pressure injuries, and make corresponding adjustments in treatment techniques and medication.

Keywords. Deep learning, YOLOv7, Pressure injuries identification, Telemedicine assistance system

Introduction

Pressure injuries often affect bedridden patients, and elderly patients and patients with multiple comorbidities are more prone to develop this condition because of their thin skin and poor blood circulation [1]. The complications associated with pressure injuries are even more fatal, such as cellulitis, sepsis, and osteomyelitis. Not only does the

[1] Corresponding Author, Mail: mcchiu@ie.nthu.edu.tw

patient's health deteriorate, but the prolonged treatment also adds to the burden of family members and health care providers and increases medical costs [2].

Despite the existence of globally accepted criteria for determining the stage of pressure injuries, the manual assessment method used in today's medical system is not only time-consuming, but also difficult to maintain a consistent judgment. In addition, the Covid-19 epidemic in recent years has resulted in a severe shortage of medical resources and healthcare manpower, which has made the diagnosis and care of pressure injuries patients even more difficult. Patients who are afraid of being diagnosed with Covid-19 due to the large crowds or who live far away from medical facilities will resort to telemedicine. However, due to the quality of communication equipment or the lack of physical access to the patient's affected area, the medical staff may be biased in their judgment of the wound, which may affect the outcome of treatment. Therefore, if the stage of the pressure injuries wound can be accurately determined and corresponding medical support and care can be provided in a timely manner, it can help patients recover from the wound and reduce medical costs.

This study establishes an intelligent telemedicine assistant system based on YOLOv7, a deep learning model with classification and real-time judgment capabilities. The front-end interface of this system includes iOS, Android, and Web pages to determine the stage of pressure injuries wounds, hoping to provide real-time wound information to both doctors and patients during clinical or telemedicine, and to help healthcare professionals make accurate treatment decisions to achieve the purpose of intelligent medicine and telemedicine.

The chapters of this paper are organized as follows: Chapter 1 describes the background of the study and gives a brief introduction; Chapter 2 presents a literature review of related studies; Chapter 3 details the proposed research methodological framework; Chapter 4 provides a case study of the pressure injuries data set provided by the hospital and compares the results with previous studies; Chapter 5 presents the conclusion.

1. Literature Review

This study divides the literature review into three sections: Section 1.1 describes computer vision; Section 1.2 examines computer vision in the identification of pressure injuries wounds; and Section 1.3 describes the concept and importance of telemedicine.

1.1. Computer vision

In computer vision object detection tasks, the used detectors (detectors) were divided into two categories, which were one-stage detector and two-stage detector [3]. Two-stage detector referred to a special method to select objects and their location information, and then to identify the category of each selected object; while one-stage detector predicted both object location information and classification information. The former usually had higher precision in object localization and target identification, while the latter usually had faster model inference [4].

The models used in the intelligent telemedicine assisted system built in this study required real-time judgment capabilities. YOLO models were widely used in object detection because of their faster inference speed and the subsequent versions released to improve detection precision while maintaining speed [5].

The newest YOLO series model, YOLOv7, proposed by Wang et al. in 2022, had been optimized in two major directions: model architecture and training process, and not only surpassed the previous models in terms of average precision, but also had excellent performance in terms of speed [6]. Therefore, in this study, the YOLOv7 model was adopted as a deep learning model for determining the stage of pressure injuries wounds.

1.2. Computer vision in the identification of pressure injuries wounds

The identification of the stage of a pressure injuries wound was very time and energy consuming for healthcare professionals. It had always been an important issue to identify wounds quickly and with a consistent standard. In recent years, the rapid development of artificial intelligence had promoted its application in various industries, and the medical field had also gained a lot [7].

Wu et al. developed an integrated framework system based on supervised learning and machine learning for detecting regions of interest in post-surgical wounds and for accurate classification of wound features [8]. Wang et al. proposed a deep learning model framework based on MobileNetV2 to achieve better image segmentation in foot ulcer wounds to improve patient care [9]. In summary, the application of artificial intelligence techniques to various types of wounds, both for wound image segmentation tasks and wound classification, could achieve good results. Therefore, this study was conducted to identify pressure injuries wounds by using techniques based on artificial intelligence.

However, most of the studies on pressure injuries using artificial intelligence techniques focused on identifying the composition and properties of various tissues in the wound. Zahia et al. proposed a system based on convolutional neural network for accurate wound image segmentation and tissue classification of granulation, slough, and necrotic tissues in pressure injuries wounds [10]. Chae et al. constructed a telemedicine assistant system based on the residual U-Net model for image segmentation of pressure injuries for physician evaluation [11].

Only a few studies had been performed to identify the stage of a pressure injuries wound, and the accuracy of the identification is poor. Orciuoli et al. constructed a clinical decision support system based on MobileNetV2 to classify Stage 1 to Stage 4 pressure injuries to assist operators in making correct decisions [12]. Fergus et al. used a Faster R-CNN model to discriminate between Stage 1, Stage 2, Stage 3, Stage 4, Deep Tissue Injury (DTI), and Unstageable categories of pressure injuries [13]. This study used YOLOv7, a deep learning model with real-time judgment capability applied to classification tasks, to address the shortcomings of previous studies in identifying the stage of pressure injuries wounds with low accuracy and to provide more real-time wound information during telemedicine.

1.3. Telemedicine

The importance of telemedicine as a service was growing in the wake of the Covid-19 epidemic. It had proven itself in a number of medical fields such as medical consultation, radiology, and psychotherapy, and was widely recognized in areas where medical resources were scarce. Telemedicine not only helped to effectively transfer medical expertise to patients in need through communication technology, but also improved the quality and standard of care through the aid of artificial intelligence [14].

Currently, most telemedicine services were still provided through communication technology between doctors and patients for remote visits. Machado et al. used

WhatsApp communication software to provide a local dentist with expert oral health knowledge and to help the dentist successfully diagnose the patient's actual physical condition [15]. Narasimha et al. compared four video conferencing platforms - Doxy.me, Polycom, Vidyo, and Vsee - and used empirical research and questionnaires to identify the most appropriate telemedicine system design and considerations for the elderly population [16].

Liu et al. found that deep learning models could achieve the same level of accuracy in diagnosing diseases in the field of medical imaging as compared to professionals in the medical system [17]. Therefore, artificial intelligence technology could be a good aid in the provision of telemedicine services. Ting et al. provided an artificial intelligence telemedicine platform based on a ResNet pre-training model for cataract diagnosis and screening, and determined the need for referral services [18]. Meeuws et al. used FOX 2G (Otoconsult NV, Antwerp, Belgium), an artificial intelligence application, to assist cochlear implant recipients in performing tele-acoustic self-assessment to confirm the suitability of the cochlear implant for the recipient [19]. Therefore, this study used the YOLOv7 deep learning model to provide accurate information on the stage of pressure injuries wounds to healthcare workers during telemedicine services.

2. Research Method

The methodology of this study can be divided into three stages. In the first stage, the intelligent telemedicine assistant system platform is built, and the system database architecture and system architecture concepts are explained; in the second stage, the deep learning model is built, and the YOLOv7 model is introduced; in the third stage, the model validation is conducted, and the model recognition performance of YOLOv7 is analyzed by confusion matrix, and the three common evaluation metrics, Precision, Recall, and Average Precision (AP), are used to analyze the overall model performance. The research framework is shown in Figure 1.

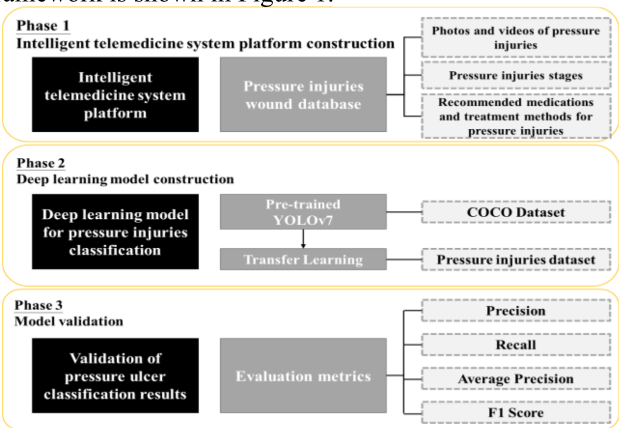

Figure 1. Research framework.

2.1. *Intelligent telemedicine system platform construction*

MVC (Model-View-Controller) is an architectural design structure implemented as a point-of-concern separation structure, and is widely used in user interface design, dividing the interface into three main components: model, view, and controller [20]. Model is responsible for the system logic and data processing; view is responsible for the system UI interface; and controller is responsible for receiving requests and coordinating between the model and the view. The MVC design allows the system to be highly scalable, easy to manage, and more conducive to the team's division of labor. In this study, the intelligent telemedicine system is divided into three parts with reference to MVC structure: model (MySQL), view (iOS, Android, and Web pages) and controller (PHP). The MVC structure of the platform developed in this study is shown in Figure 2 below.

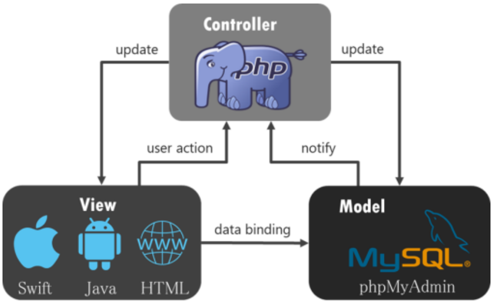

Figure 2. MVC design architecture for intelligent telemedicine assistant system [20].

The intelligent telemedicine assistant system model part of this study, which is the MySQL database management system, has the system database architecture as shown in Figure 3.

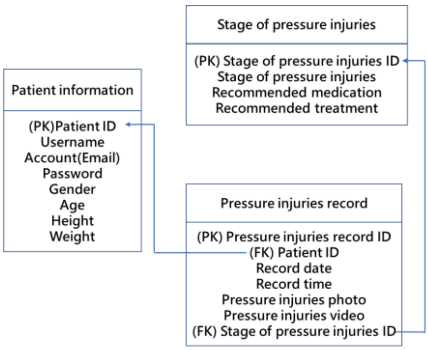

Figure 3. System database architecture.

The intelligent telemedicine assistant system is set up to record the patient's personal information and information about the patient's pressure injuries wound. The patient's basic personal information includes gender, age, height, and weight, etc., which can be used as a reference for medication dosage in addition to presenting an electronic medical record. Patients are also required to record the current status of pressure injuries wounds in the system by uploading the current recording date, time, pictures, and videos of pressure injuries wounds, and the system will use the YOLOv7 model established by this study to perform real-time stage recognition and location identification of the uploaded pictures and videos of pressure injuries wounds. The results of the stage identification will be linked to the table of the stage of pressure injuries, and the results of the stage identification of the pressure injuries of the patient and the recommended medication and treatment method corresponding to the stage will be presented on the system page for the patient's reference, so that the patients can more accurately grasp the situation of their pressure injuries.

2.2. Deep learning model construction

In this study, YOLOv7, a deep learning model with classification and real-time judgment capability, is added to the intelligent telemedicine assistant system established. Whenever a patient uploads a picture or video of a pressure injuries wound, YOLOv7 can automatically recognize the stage of the wound in the picture or video and present the wound location information to help patients record and obtain the actual situation of their own pressure injuries wounds faster and more accurately.

In view of the fact that it is time-consuming to build a deep learning model from scratch and it is difficult to obtain good recognition results, this study uses a transfer learning mechanism. In other words, the model is pre-trained in a dataset with a large number of images, and a pre-trained model with basic object recognition capability and related parameters are obtained; then the model and parameters are used as initial values and put into the target dataset for training, so that a well-performing deep learning model can be built very efficiently with significant training cost savings [21].

Compared to previous object detection models, YOLOv7 achieves the best performance in recognition speed and precision between 5FPS and 160FPS [6].

2.3. Model validation

The confusion matrix is used in this study to evaluate model identification performance [22]. The confusion matrix shows four results: True Positive (TP) represents the case where the actual sample is positive and the predicted sample is also positive; True Negative (TN) represents the case where the actual sample is negative and the predicted sample is also negative; False Positive (FP) represents the case where the actual sample is negative but the predicted sample is positive; and False Negative (FN) represents the case where the actual sample is positive but the predicted sample is negative. The confusion matrix structure is shown in Table 1 below.

Table 1. Confusion matrix.

Confusion matrix		Predicted	
		Positive	**Negative**
Actual	**Positive**	True Positive	False Negative
	Negative	False Positive	True Negative

After obtaining the confusion matrix, we can further calculate three common object detection metrics: Precision, Recall, Average Precision (AP), and F1 Score [23].

Precision reflects the proportion of positive samples predicted by the classification model that are actually positive (Equation (1)); Recall reflects the proportion of positive samples that are successfully predicted positive by the classification model (Equation (2)); the Precision-Recall curve drawn with Recall as the horizontal axis and Precision as the vertical axis is the average Precision-Recall curve. The area under the curve is the Average Precision (Equation (3)); F1 Score reflects the overall performance of a model and is the harmonic mean of Precision and Recall. All four metrics are between 0 and 1, and the higher the value, the better the performance of the model. The four equations are as follows.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{2}$$

$$\text{AP} = \int_0^1 \text{Precision(recall)} \tag{3}$$

$$\text{F1 Score} = \frac{2*\text{Precision}*\text{Recall}}{\text{Precision+Recall}} \tag{4}$$

3. Case study

3.1. Intelligent telemedicine system platform construction

Following the system database architecture shown in Figure 3, this study developed an intelligent telemedicine medical assistance system. The application process is as follows: (1) Patients first create an account and fill in basic personal information such as gender, age, height, and weight, which can be used as an electronic medical record for later reference and as a reference for treatment and medication recommendations. (2) Patients upload photos or videos of their pressure injuries wounds to the front-end of the intelligent telemedicine medical assistance system. The front-end then sends the patient's relevant data and pressure injuries photo or video data to the back-end. (3) Based on the YOLOv7 deep learning model with classification and real-time judgment capabilities, the back-end starts to recognize the category of the pressure injuries wound and track its location information based on the uploaded photo or video data. The analysis results are then provided to the front-end. (4) Finally, the front-end provides the pressure injuries identification results, the stage of the wound, the treatment method for that stage, and suggested medication information to both the doctor and patient. Doctors can also use this information to determine if there are any omissions and provide more professional information to the patient. The schematic diagram of the intelligent telemedicine medical assistance system mentioned above is shown in Figure 4.

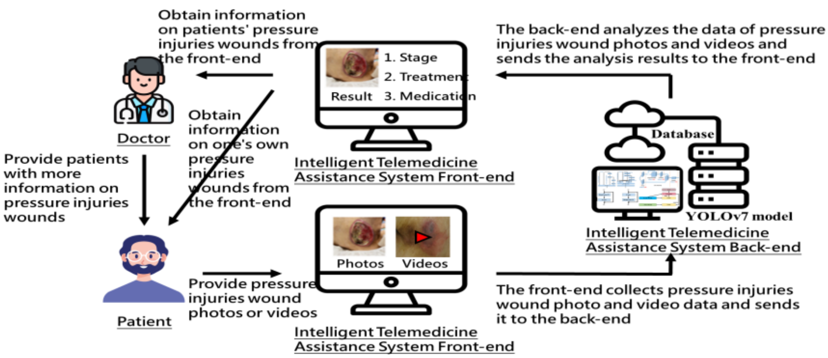

Figure 4. Schematic diagram of the intelligent telemedicine medical assistance system.

3.2. Deep learning model construction

This study utilized the pressure injuries dataset provided by the hospital. The dataset includes 6 categories of pressure injuries: 37 photos of Stage 1 pressure injuries, 146 photos of Stage 2 pressure injuries, 160 photos of Stage 3 pressure injuries, 60 photos of Stage 4 pressure injuries, 59 photos of DTI pressure injuries, and 67 photos of Unstageable pressure injuries. The roboflow© software was used for annotation and data augmentation of the pressure injuries dataset. The dataset of 561 photos was split into training, validation, and testing sets in an 8:1:1 ratio. Data augmentation techniques, including horizontal and vertical flips, 90-degree, 180-degree, and 270-degree rotations, brightness increase of 0-30%, and Mosaic method were applied, increasing the number of training data set to three times the original amount, and resulting in a total of 1365 images in the training set.

This study used YOLOv7 to classify pressure injuries wounds, with input images resized to 640x640 pixels. The model was trained using Python 3.7 in a Windows 10 environment, on a computer with an Intel Core i5-8400 2.8GHz CPU and NVIDIA GeForce RTX 2080 Ti GPU. The training lasted for 100 epochs, with each experiment taking about 2.5 hours.

3.3. Model validation

The YOLOv7 model used in this study achieved optimal classification performance when trained with an Adam optimizer, a learning rate of 10^{-2}, a batch size of 18, and 100 epochs. From the confusion matrix obtained from the test set, it can be seen that the Recall values for all types of pressure injuries except for Stage 2 are 1. The Recall value for Stage 2 is 0.94. The confusion matrix for the classification performance of each type of pressure injuries is shown in Figure 5.

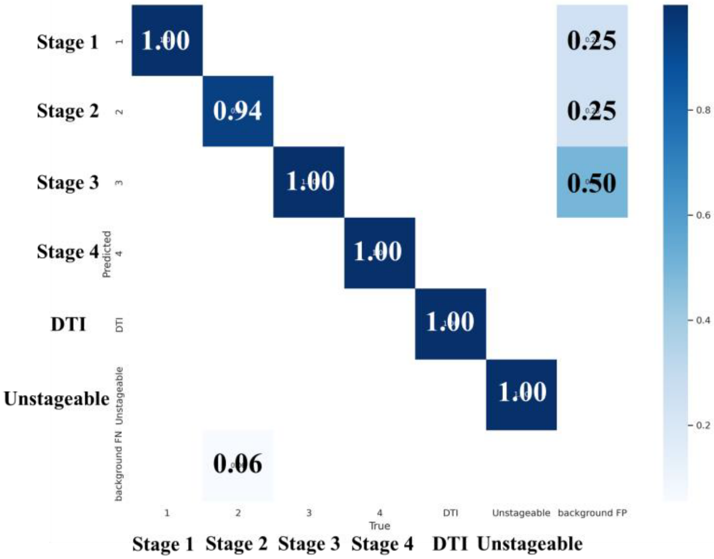

Figure 5. Confusion matrix of the test set.

From the results, it can be seen that there is a small probability for the Stage 2 pressure injuries to be ignored by the classification model, but it is not a classification error; the other types of pressure injuries are correctly classified and not ignored by the classification model. In conclusion, the YOLOv7 model trained in this study has a good performance with an F1 Score value of 0.9246 in the task of pressure injuries classification.

Compared with previous studies that used different classification models for pressure injuries classification tasks, such as MobileNetV2 [12], Faster R-CNN [13], Logistic regression and Artificial neural network [24], our study outperformed previous research in terms of classification performance. The comparison results are shown in Table 2.

Table 2. Performance comparison of pressure injuries classification between this study and related research.

Research	Classification model	Average F1 Score
Orciuoli et al., 2020 [12]	MobileNetV2	0.6-0.86
Fergus et al., 2022 [13]	Faster R-CNN	0.6956
Yilmaz et al., 2021 [24]	Logistic regression	0.742
Yilmaz et al., 2021 [24]	Artificial neural network	0.739
Our research	YOLOv7	0.9246

4. Conclusion

To accurately and consistently determine the stage of pressure injuries and provide timely medical support and care during clinical visits or telemedicine, this study developed an intelligent telemedicine assistance system based on the deep learning model YOLOv7, which has classification and real-time detection capabilities. The system's front-end interface includes iOS, Android, and web pages. In academia, this study addresses the low accuracy of previous research in identifying the stage of pressure injuries. In practice, the contributions of this study include providing a usable pressure injuries stage classification model to support healthcare professionals in making accurate decisions and providing corresponding medical measures based on each category's symptoms. It also helps patients who cannot go to the hospital to obtain real-time and accurate diagnosis information during telemedicine and seek different medical assistance based on the severity of their symptoms. Moreover, this intelligent telemedicine assistance system can track improvements or deterioration in the symptoms of pressure injuries and promptly remind healthcare professionals to make corresponding adjustments in treatment methods and medication.

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