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Early Prediction of Pressure Injury with Long Short-term Memory Networks

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Early diagnosis of pressure injury has always been a challenging problem. Pressure injury can spontaneously heal or develop into decubitus ulcers. Few methods are available to predict the growth trend at the early stage of pressure injury, although this stage is a critical time for preventing and treating pressure injury. To address this issue, artificial intelligence algorithms were used in this work with image processing technology to predict the growth trend of early-stage pressure injury. A long short-term memory (LSTM) network, which is a specialized recurrent neural network, was adopted to predict future events based on images collected from hairless rats that made up the pressure injury models. The images were processed with ImageJ software to extract key features, then used to train the LSTM networks. Two types of LSTM network were used to predict the development trend: single-variate and multivariate. The analysis results demonstrated that multivariate LSTM is more effective than single-variate LSTM and has high potential to be applied in the prediction of early-stage pressure injury.

1. Introduction

Pressure injury, also known as decubitus ulcers (DU), pressure ulcers, or bedsores,(1) is a type of partial skin ischemia caused by pressure. Stage 1 pressure injury usually involves non-blanchable erythema of intact skin.(2) At this stage, even experienced medical experts cannot predict whether the pressure injury will spontaneously heal or develop into DU.(3) Once pressure injury develops into DU, it causes extreme pain to patients and may be expensive to treat.(4,5) Diagnosis and monitoring of pressure injury require considerable time and effort from healthcare workers and has become a major and urgent problem. Nevertheless, pressure injury can usually be healed if it is discovered early and the necessary nursing care is provided.(6) Therefore, the early prediction of pressure injury is of great significance in prophylaxis and can avoid complicated therapy.(7)

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Few methods have been successfully applied to predict the early stage of pressure injury, despite early prediction being an essential step in preventing the development of ulcers. Sato *et al.* found that although some clinical observations can be used to predict early pressure injury, these indicators were overdependent on clinical experience and highly subjective.[8] Okonkwo *et al.* conducted clinical studies on the early prediction of pressure injury using subepidermal moisture.[9] However, their conclusion that a substantial quantity of subepidermal moisture indicates a greater risk of pressure injury is questionable. In fact, moisture is lost through evaporation before the skin breaks, the time when the risk of pressure injury is greatest. UV photography was demonstrated by Takashi, a co-author of this work, to be a possible method of detecting skin bleeding and predicting early pressure injury.[10] However, no quantitative method for pressure injury prediction was provided. Xu *et al.* investigated a method using the change in the amount of reflected UV light as an indicator to predict whether early-stage pressure injury spontaneously heals or develops into DU, but the pressure injury region required continuous monitoring for 18 h before the symptoms could be identified.[11] Other limitations of this process are the high cost of the device and the inability to use it with some skin types.

Various sensors have been used in attempts to evaluate and predict pressure injury. Fard *et al.* assessed the risk of pressure injury by monitoring interface pressure and temperature using 64 pressure sensors and 64 temperature sensors.[12] Their approach was based on the theory that temperature is an indicator of pressure ulcer tendency according to the National Pressure Injury Advisory Panel. Sakai *et al.* continuously monitored the interface pressure distribution in intensive care patients using a thermoelastic polymer mattress with a KINOTEX sensor installed in an attempt to prevent pressure ulcers.[13] Yip *et al.* presented a cost-effective monitoring system to continuously detect the pressure between skin and a contact surface. The system consisted of a flexible pressure-sensitive sheet and embedded stainless steel electrodes.[14] Drennan and Southard designed a pressure monitoring system that triggered an alarm to inform patients and caregivers when the soft tissue pressure exceeded a threshold value.[15] The above researchers used various sensors and devices to investigate the relationship between pressure, temperature, and pressure ulcer development, aiming to obtain indirect indicators of pressure ulcer development through the sensor output. However, such devices are expensive and rarely utilized clinically.

Low-cost statistical approaches have also been studied as a means of predicting pressure injury but are subject to controversy. Norton developed the first instrument to assess the risk of pressure ulcer development on the basis of experience in clinical practice, in which the total risk score was the sum of five risk factors.[16] Risk levels and total Norton scores are inversely related. The Norton scale is simple and easy for us, but has received many criticisms because risk factors considered important by other practitioners, such as poor nutrition, are not taken into account.[17] The Waterlow scoring system was developed by introducing normal risk and special risk sections to evaluate the risk of pressure ulcers, which can be considered a more advanced and comprehensive system to evaluate the risk of pressure ulcers.[18] However, the Waterlow scale is complex and its scope of application is relatively small.[19] Other risk assessment scales used in clinical practice include the Braden scale.[20] However, the scales are mostly analogous, and medical staff choose appropriate scales according to the situation in their departments.

Although statistical methods are inexpensive, it is time-consuming and burdensome for the staff to collect and analyze data, which wastes medical resources and makes it difficult to diagnose pressure injury in a timely manner.[21]

To overcome the challenge of predicting early pressure injury, the use of artificial intelligence based on deep learning or machine learning is a potential approach worth attempting. Different from traditional neutral networks, recurrent neural networks (RNNs) allow the continuity of information. Long short-term memory (LSTM), a special RNN introduced in 1997, can learn long-term dependence.[22] Since its introduction, LSTM has been refined and developed and is now applied in a wide range of fields. Owing to its advantages, in this study, LSTM and its variants were used to predict early pressure injury. Multivariate and single-variate LSTM networks were built, and their performances in the prediction of early pressure injury were compared. We built a database based on pressure injury experiments on animals. Images were collected, regions of interest in the images were labeled, and the corresponding features were extracted. Symmetric mean absolute percentage error (SMAPE) and mean absolute error/average value (MAE/MEAN) were used as evaluation criteria to assess the performance of these networks. SMAPE, proposed by Makridakis, reduces the impact of zero and nonzero values on models.[23] Hoover used MAE/MEAN to overcome the problem of division by zero.[24] SMAPE and MAE/MEAN of single-variate LSTM are 0.244 and 0.406, and the values of multivariate LSTM are 0.198 and 0.393, respectively. These values illustrate the high performance and feasibility of the multivariate LSTM network for predicting early pressure injury.

2. Feature Database Obtained from Rat Images

The data this study were obtained from experiments at Nagano College of Nursing conducted on hairless rats. As shown in Fig. 1, the pressure injury model was established by exposing the dorsal skin of five hairless rats to pressure between two circular neodymium magnets for 3.75 h. Four groups of experiments were performed on each hairless rat to obtain a total of 20 sequences of pressure injury images. Ten of the 20 pressure injury models were DU models. The skin of the rats in these 10 DU models was pressed by 4 mm magnets (440 mmHg attraction). The other 10

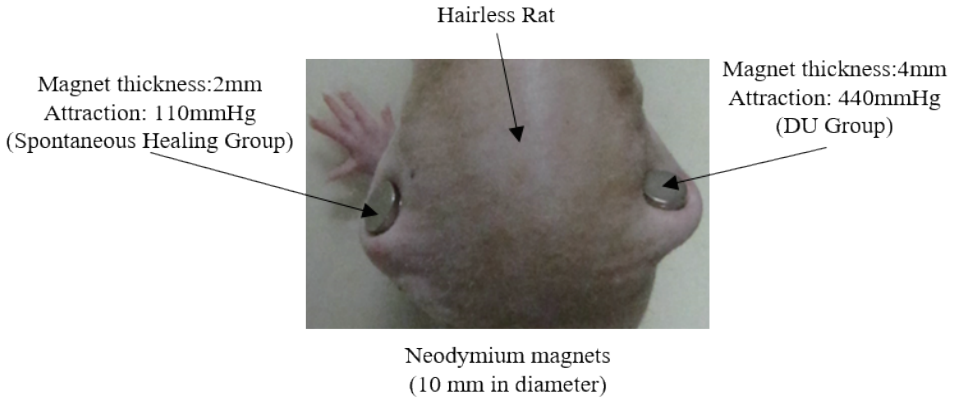
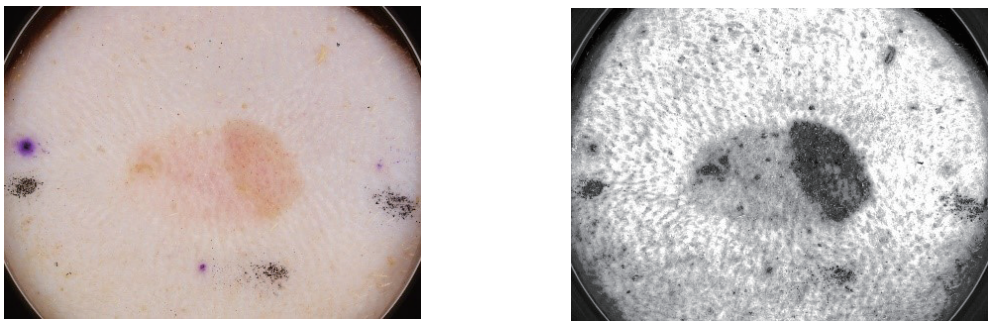


Fig. 1. (Color online) Dorsal skin exposed to pressure between two circular neodymium magnets.

pressure injury models were allowed to spontaneously heal. The dorsal skin of the rats in these 10 models was pressed by 2 mm magnets (110 mmHg attraction). In each experiment, images of skin symptoms of the rats at 11 time points were recorded: 0.5, 3, 6, 12, 18, 24, 30, 36, 48, 72, and 96 h. At each time point, one image of the skin under UV light with a wavelength of 405 nm was taken by a camera specifically designed to capture dermatological symptoms (DZ-100, Casio Co., Japan). Figure 2 shows a comparison of the same pressure injury area under white light and 405 nm UV light; the symptoms are clearer under the UV light. This is because hemoglobin has high absorbance at 405 nm.[25] Olds *et al.* also demonstrated in forensic studies that symptoms of subcutaneous bleeding, which are not visible under white light, can be observed under UV light.[26] Each sequence of images in our experiment included 11 effective images. A total of 220 (11 × 20) samples were obtained from the 20 experiments.

Because our aim was to predict whether pressure injury will develop into DU, the features of the areas including the pressure injury and DU were the research objects. The performance of image processing was affected by noise and uncertainty since the images were acquired from hairless rats. A reference point is critical in determining the relative features of the target area because noise originates from the rotation, offset, or other factors at the same position. The regions of interest include the areas of pressure injury and DU and the selected reference point areas labeled by ImageJ software, as shown in Fig. 3. After comparing various features, we selected the features extracted from regions of interest, which are gray value information (mean, maximum, and minimum gray value) of pressure injury and DU, and the absolute area of each region of interest, as the key features. In addition, owing to the rotation and offset of the images, errors or noise may be introduced into the absolute area. Thus, the relative area was used to represent the region of interest, as defined in Eq. (1). The relative area is equal to the absolute area of pressure injury or DU divided by the reference point area.

$$Relative\ Area = \frac{pressure\ injury(DU)\ area}{reference\ point\ area} \tag{1}$$



(a) (b)

Fig. 2. (Color online) Comparison of pressure injury images obtained after 72 h of pressure under (a) white light and (b) 405 nm light.

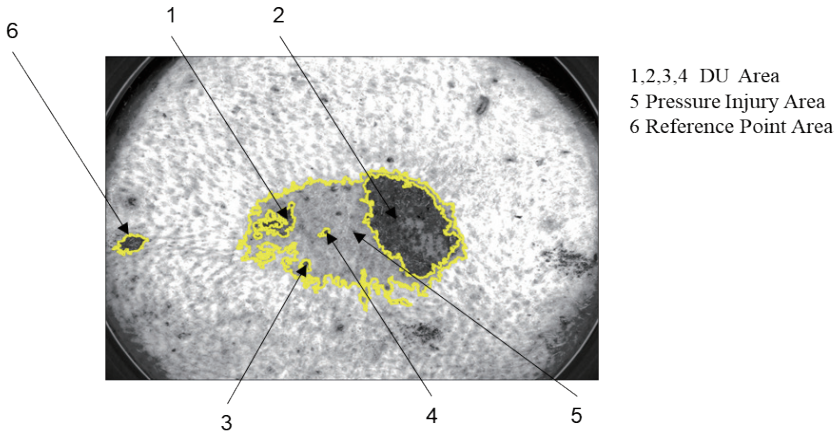


Fig. 3. (Color online) Regions of interest in each image.

3. Framework of Deep Learning

Traditional neural networks can only deal with each input individually; the previous input and the subsequent input are irrelevant. The task in the present study requires better processing of sequential information, namely, the previous input is related to the subsequent input. To solve this problem, we used an RNN model.[28] Nevertheless, an RNN only has short-term memory due to the inherent problems of vanishing and exploding gradients. LSTM is a type of RNN that mitigates these problems by introducing an addition operation into the network through gate control.[22] One of the merits of RNNs is that they can connect previous information to the current task,[27] making them useful in this study. However, RNNs can only be used to solve these problems for relatively short time intervals, and they lose their ability to learn previous information over long time intervals.[29] Thus, we developed an LSTM network with 11 time points to handle long-term dependence.

Multivariate LSTM, an improved version of LSTM, can be used to solve problems with more than one characteristic parameter.[30] The first step is to transform the prediction task into supervised learning, which simplifies the problem. Figure 4 summarizes the inputs of multivariate LSTM. The inputs of the network are the historical data denoted $v(t-1)_1$ to $v(t-1)_8$, and the label is set to the area of the DU of the next time point.

The overall framework of the multivariate LSTM prediction model is shown in Fig. 5, which includes four functional modules: a preprocessing block and input, hidden, and output layers. The preprocessing block cleans the original data, transforming it to a form suitable for supervised learning and normalizing values to the range [0, 1]. The data contained in the input layer consists of the normalized pressure injury and DU gray level information as well as the pressure injury and DU area information at time $(t-1)$ obtained by applying pressure to the skin of the hairless rats. The DU areas at time t are considered as labels. Each input is a vector with the structure (9, 1). The hidden layer employs the LSTM cells to build a prediction network. The sigmoid function was used as the activation function to produce the output of the network in a dense layer. Finally, a postprocessing procedure in the output layer inversely transforms the normalized output value to the original expression.

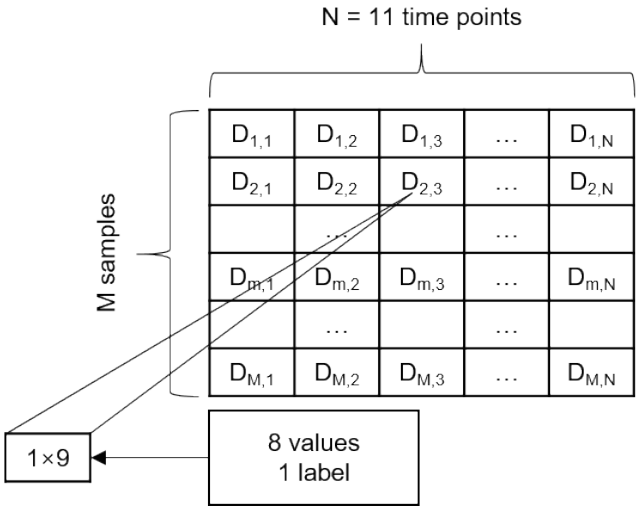


Fig. 4. Input structure of multivariate LSTM network.

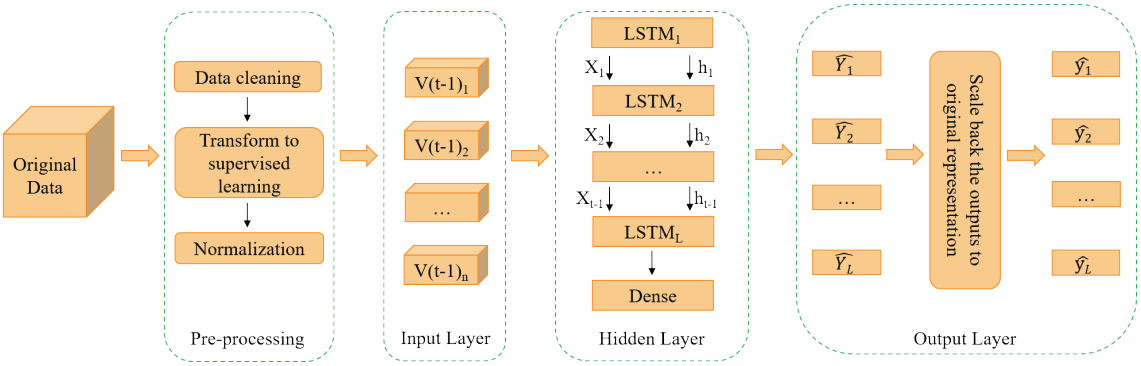


Fig. 5. (Color online) Framework of multivariate LSTM network.

We also built single-variate LSTM to compare the performance of the prediction task with that of the multivariate LSTM. The input of the single-variate LSTM was the sequence data of the DU areas. In the network, we first normalized the dataset and then built the LSTM network with only one variate. A dense layer was added to the last layer of the network to output the prediction value. Finally, an inverse normalization process was used to unify the output and input to the same dimension in the output layer.

4. Results and Discussion

We investigated the performance of the built networks. We divided the database into training and validation sets with a ratio of 9:1. Figure 6 shows a comparison between actual values and values predicted in the final iteration at each time point, where the ordinate represents the relative area of DU and the abscissa represents the number of the time point sequence. Figure 6 demonstrates that the multivariate LSTM network has better performance in terms of the error between the actual values and the values predicted with the training set.

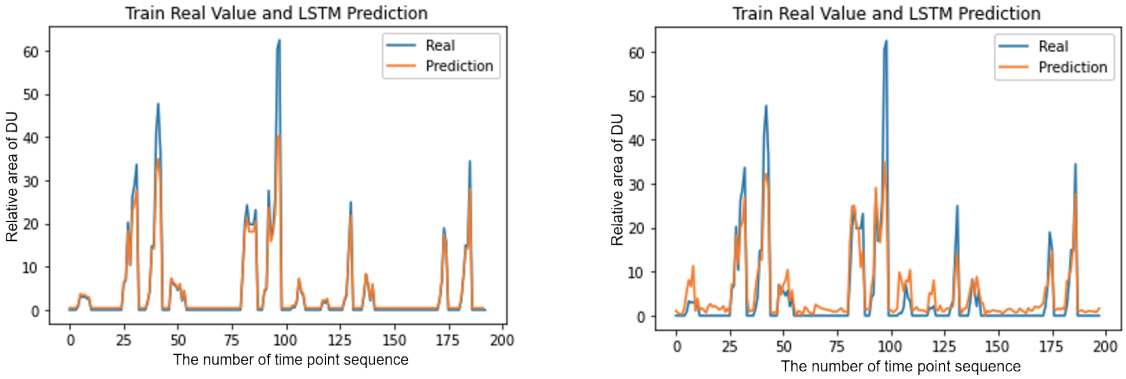


Fig. 6. (Color online) Prediction performance of (a) multivariate LSTM and (b) single-variate LSTM.

To evaluate the built networks, two popular evaluation metrics, SMAPE and MAE/MEAN, were introduced in the work. The two metrics are calculated as

$$SMAPE = \frac{100\%}{N}\sum_{i=1}^{N}\frac{|\hat{y}_i - y_i|}{(|\hat{y}_i| + |y_i|)/2}, \tag{2}$$

$$\frac{MAE}{MEAN} = \frac{\frac{1}{N}\times\sum_{i=1}^{N}|\hat{y}_i - y_i|}{\frac{1}{N}\times\sum_{i=1}^{N}y_i}, \tag{3}$$

where N is the size of the validation dataset and $\hat{y}$ and y are the predicted and actual values of the DU area, respectively. To investigate the effect of the processing parameters on the results, different values of LSTM_units, different loss functions, different optimizers, and different numbers of epochs were set in each model to compare the performance. The results are presented in Table 1.

On the basis of the results in Table 1, 256 LSTM_units, Huber_loss, RMSprop, and 250 epochs were chosen as the parameters in the multivariate LSTM network to develop the prediction network. For these parameters, SMAPE and MAE/MEAN were 0.198 and 0.393, respectively. The performance of the multivariate LSTM network with the validation set was superior to that with the training set as shown in Fig. 7. The loss value was only 0.0022, indicating a relatively small error.

It was found that the model performs well in predicting the development trend of early pressure injury. We used different evaluation indicators to show that the error between the predicted value and the actual value obtained by the prediction network is very small, i.e., the predicted value is very close to the actual value. This result has value for medical treatment because it demonstrates that pressure injury can be predicted and evaluated using multivariate

Table 1
Effect of processing parameters on performance of the two models.

	LSTM_units	Loss	Optimizer	Epochs	SMAPE	MAE/MEAN
Multivariate LSTM	256	Huber_loss	RMSProp	250	0.198	0.393
	128	Huber_loss	Adam	100	0.230	0.454
	64	MSE	Adam	250	0.227	0.456
Single-variate LSTM	256	Huber_loss	RMSProp	100	0.244	0.406
	4	Huber_loss	RMSProp	100	0.258	0.407
	256	MSE	Adam	100	0.263	0.416

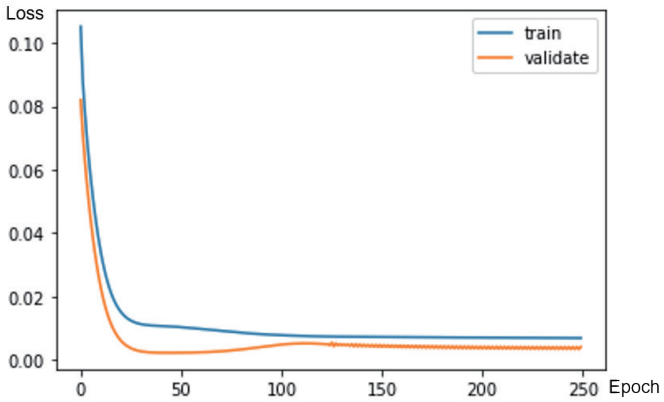


Fig. 7. (Color online) Loss of multivariable LSTM network.

LSTM. Further development of this work is expected to lead to the realization of a suitable approach for clinical use to assist medical staff in diagnosing pressure injury and predicting the development of symptoms.

5. Conclusion

In this study, we built multivariate and single-variate LSTM networks to predict the growth trend of early-stage pressure injury based on time domain features extracted from images of hairless rats. SMAPE and MAE/MEAN were used as key parameters to evaluate the performance of the models. The values of 0.198 and 0.393, respectively, and the loss value of 0.0022 for the multivariate LSTM network demonstrate its high accuracy and potential for predicting early pressure injury.

In future work, more effective methods should be used to optimize the model. As the next step, we plan to acquire frequency domain features from a data set containing more images. There should be more ideal networks for this research, and we will continue to explore and develop such networks. It is possible for this method to predict not only the next time point but also a much later time point, enabling us to achieve our goal of predicting the development of pressure injury at a very early stage.

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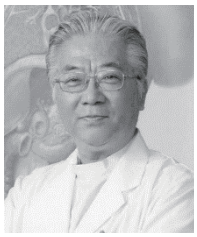

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