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Computer Vision-Based Approach using Deep Learning for Breast Cancer Rehabilitation Evaluation: A Comparative Performance of CNN and RNN using Skeleton Data

Muriati Muda[1,2,*], Azim Zaliha Abd Aziz[2], Chirawat Wattanapanich[3]

[1] Faculty of Computer, Media and Technology Management, University College TATI, Teluk Kalong, 24000, Kemaman, Terengganu, Malaysia
[2] Faculty of Informatics and Computing, Universiti Sultan Zainal Abidin, Tembila Campus, 22200, Besut, Terengganu, Malaysia
[3] School of Engineering and Technology, Walailak University 222 Thaiburi, Thasala District Nakhonsrithammarat 80161, Thailand

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ABSTRACT

Breast cancer rehabilitation plays a crucial role in the recovery process of post-treatment, emphasizing the significance of effective evaluation systems for rehabilitation exercises. This study explores into the utilization of depth-sensing technologies, particularly focusing on skeleton data, in assessing the efficacy of these exercises. Leveraging the ability of deep learning techniques, specifically Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), this study aims to compare their performance in evaluating breast cancer rehabilitation exercises based on skeleton data. The study conducts a comprehensive regression analysis to assess and compare the models' capabilities. The experimental results reveal insights into the comparative effectiveness of CNN and RNN in evaluating the nuances of these exercises, shedding light on their potential applications in enhancing breast cancer rehabilitation evaluation systems

1. Introduction

Breast cancer is one of chronic disease affecting millions of women worldwide. In Malaysia, a parallel trend is evident, with breast cancer emerging as the predominant cancer affecting women [1]. A cancer diagnosis can alter a person's perspective on health and life itself. Female breast cancer survivors are often weighed down by issues of physical lethargy, pain, breast sensitivity and difficulty to concentrate [2]. Physiotherapist plays an important role in the supportive care of breast cancer patients and survivors. Physiotherapy is part of rehabilitation during the hospital period, particularly in the immediate postoperative phase. The goal of therapy treatment is to minimize the side effects and optimize physical function.

Maintaining the physical therapy exercise during and after treatment is an important part of being healthy. Those who participate in physical activity are less likely to experience cancer recurrence than those who maintain a sedentary lifestyle. Early rehabilitation treatment basically

* *Corresponding author*
E-mail address: muriati@uctati.edu.my

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targeting the upper limb exercise to improve muscle strength [3,4]. Patients basically are suggested to start exercise on arm and shoulder. However, as many as 70% of individuals who have survived breast cancer are not adhering to the minimum recommended guidelines for physical activity to maximize health benefits [5,6]. In Malaysia, just 39% of the survivors demonstrated an adequate level of physical activity [7]. Various obstacles have been recognized as factors that hinder the capacity to engage in physical activity. Those patients are fear to perform exercise due to the lack of knowledge and confidence regarding the safety of exercise movement. They also unable to optimize healing benefits due to the absence of supervision and evaluation of home exercises. This situation forces them to incur substantial expenses on Physical Therapists (PT) or Occupational Therapists (OT), contributing to an increased financial burden on families [8-12]. Therefore, there is a demand for development of a model that can assess exercise movement and automatically analyze and evaluate the performance. It will be crucial in helping patients who are enrolled in home-based rehabilitation programs.

In recent years, the integration of depth-sensing technologies and advanced machine learning techniques in the field of Computer Vision (CV) has opened avenues for creating a system that offers greater objectivity in assessing rehabilitation. CV is one of the disciplines in Artificial Intelligent (AI) that is dedicated to the development of automated systems focusing on visual information. Currently information based on skeleton data preferred by many studies in the scope of rehabilitation evaluation as it has many advantages compared to other type of data [13]. The data gives researchers the real time 2D and 3D position of the player's joint. Microsoft Kinect which releases in 2010 became the most utilized tool to track human motion because of its flexibility and affordability, and serves as an alternative to the other high-price motion tracking systems [14]. However, due to difficulties in accessing patients, safety concern, and ethical issues, many study used alternative strategy by using public dataset to complete the finding. The dataset contains human movement of rehabilitation exercises perform by healthy people including the arm and shoulder exercises. UI-PRMD, KIMORE, IRDS, AHA-3D and TRSP are among the most used and popular skeleton-based dataset [13,15-19] in related studies.

Deep Learning (DL) has proved remarkable performance in CV. A key advantage of DL is their ability to handle raw data, automatically extract and represent features using trainable feature extractors, and perform deep processing using multiple hidden layers [20]. It reduces general steps normally taken by studies that implement the traditional machine learning approach [21,22]. Certain studies have indicated that DL methods may lack adequacy for precise analysis when applied to small datasets [21,23]. However, finding from some study reveals that DL methods are able to make significant process and combining skeleton data with DL is a good choice [24]. The Convolutional neural network (CNN) is the most utilized DL network [25-27]. CNN provides great results in processing of images and videos. Another approach of DL is Recurrent Neural Network (RNN) which gives better performance with sequential data [28]. Both of these supervised learning techniques offer simplicity in learning compared to other methods, yet they deliver high-performance results [25,29].

In rehab, CV commonly related to human activity analysis tasks such as Human Activity Recognition (HAR), Human Activity Detection (HAD), Human Activity Prediction (HAP) and Human Activity Evaluation (HAE). Among these, HAE stands out as the most fitting task for assessing rehabilitation progress as the approach is focusing on measuring the movement or action quality, offering feedback on how well the action was performed [13,30]. This type of task uses regression metrics, including mean absolute deviation (MAD), mean absolute error (MAE), root mean square error (RMSE), MAPE, and R-square (R^2) to evaluate the performance of the model. It estimates continuous values, quantify how close model predictions are to actual values [31]. R^2, RMSE, and

MAE are the main or commonly metrics used for model evaluation in the regression task. This study will compare the performance of CNN and RNN towards breast cancer rehabilitation exercises based on skeleton data. The performance evaluation will focus on regression analysis.

2. Methodology

The input dataset has been selected from UI-PRMD dataset collection and then analyzed through the DL approach. The output from the model is analyzed based on HAE task analysis using regression metrics. The overall methodology is shown in Figure 1.

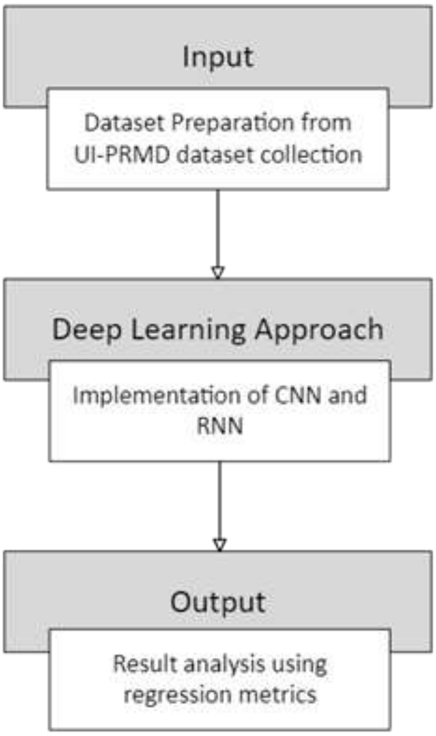

Fig. 1. Overall methodology

2.1 Dataset

A public dataset, UI-PRMD [15] is used to train and validate both models. This dataset was created and published in 2018 to address the lack of publicly available dataset for therapy movements. This dataset includes 10 general rehabilitation exercises performed by 10 healthy individuals for 10 repetitions. The movements performed by those subjects were recorded using Vicon and Kinect system. This public dataset was approved by Institutional Review Board at the University of Idaho under identification code IRB 16-124.

In order to fit the requirements of the study, only skeleton data performed by the female, performed arm and shoulder movement exercises and collected using Kinect are used. The details of the selected data are presented in Table 1 and 2. The final dataset includes 3 rehabilitation movements of 3 female subjects with 22 joints of skeletal model which total up to 502251 of data.

Table 1
Rehabilitation movement of arm and shoulder

Exercise	ID
Standing Shoulder Abduction	M07
Standing Shoulder Internal-External Rotation	M09
Standing Shoulder Scaption	M10

Table 2
Female subjects

Female participants (ID)	Profession	Dominant
S01	Grad Student	Right
S04	Faculty	Right
S09	Grad Student	Right

2.2 DL Model

Two models are designed using CNN and RNN as shown in Figure 2 and 3. CNN model involves a Convolutional layer employing 32 filters with a kernel size of 3 and Rectified Linear Unit (ReLU) activation. This is followed by a MaxPooling layer to subsampling the output. The subsequent Flatten layer reshapes the output into a one-dimensional vector. Following this, a Dense layer with 64 units and ReLU activation is incorporated, culminating in a final Dense layer with a single unit and linear activation, tailored for regression tasks. RNN model consists of an LSTM layer containing 64 units using ReLU activation. Following the LSTM layer, there is a Dense layer comprising a single unit with linear activation, specifically designed for regression tasks. LSTM has been employed to the model to capture the advantage of handling sequential data.

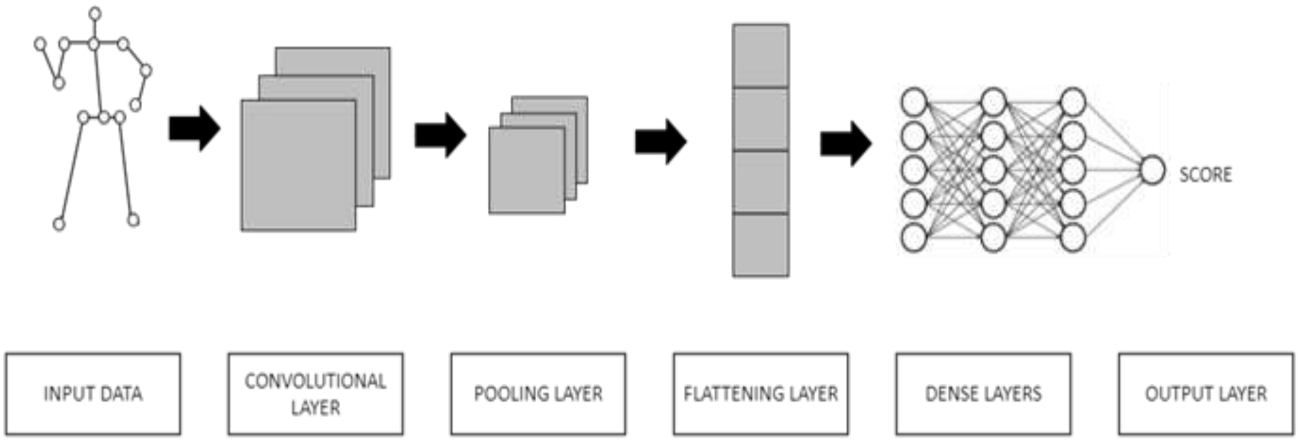

Fig. 2. CNN model

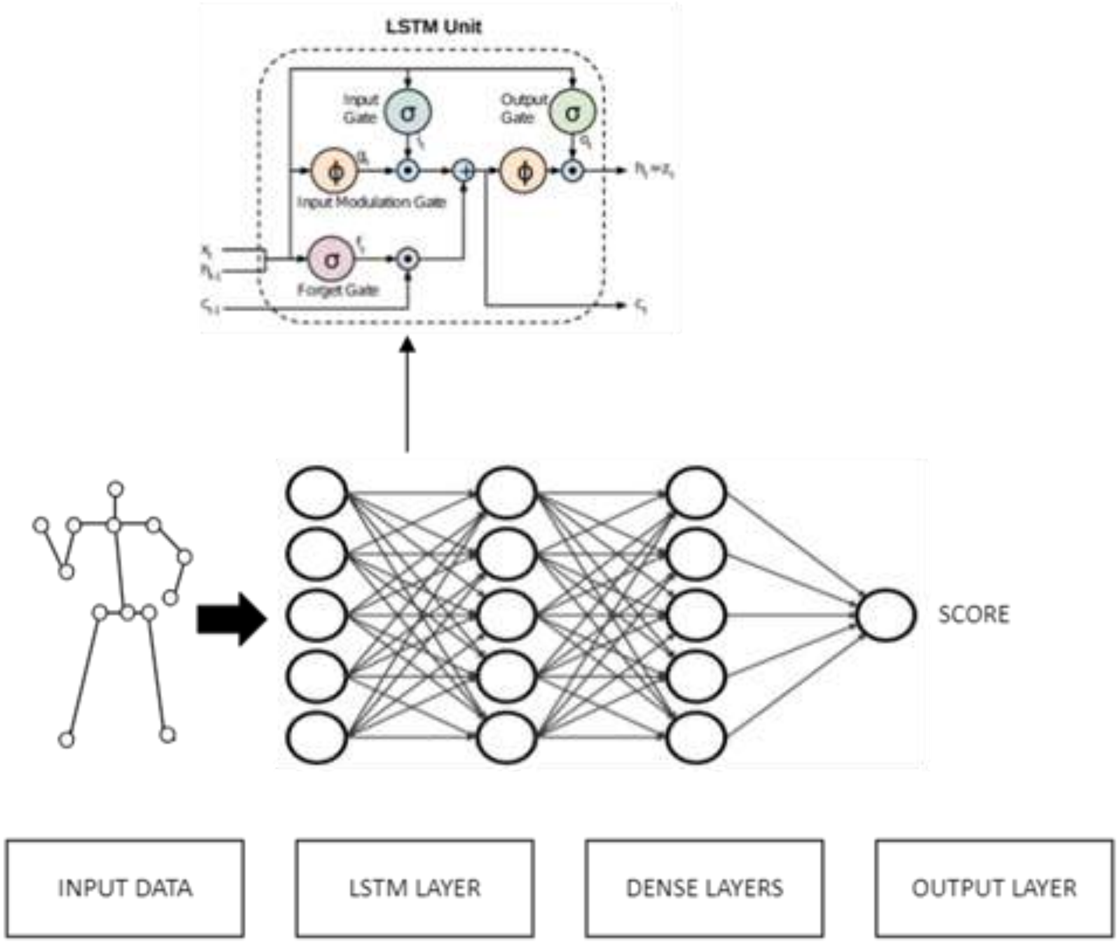

Fig. 3. RNN model

The models are then constructed using Python programming language with several well-known framework and libraries such as Keras, TensorFlow, numpy and Sklearn. Adaptive Moment Estimation (Adam) is utilized as optimization algorithm with default parameters including learning rate of 0.001. To train both models, validation split is set to 0.2 representing 80% of dataset goes to training set and 20% of dataset goes to testing set. The number of epochs is set to 50, and batch size is set to 32. 10-run results are reported for each model to fairly evaluate the performance.

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2.3 Output

To validate the performance of the models, the output was evaluated using regression metrics. All metrics used in this study were calculated using Eq. (1) to (4) [32,33]. RMSE, is an extension of the mean squared error (MSE). The MSE is calculated as the mean or average of the squared differences between predicted and expected target values in a dataset. MSE is used to train a regression predictive model, and RMSE is used to evaluate and report the model performance. The RMSE can be calculated as follows:

$$RMSEV = sqrt(1 / N * sum\ for\ i\ to\ N\ (y\_i - yhat\_i)\text{^}2) \quad (1)$$

Where, *y_i* is the i'th expected value in the dataset, *yhat_i* is the i'th predicted value, and *sqrt()* is the square root function. A perfect RMSE value is 0.0, which means that all predictions matched the expected values exactly. The RMSE in terms of the MSE can be represented as in Eq. (2),

$$RMSE = sqrt(MSE) \quad (2)$$

The MAE and MAD score is calculated as the average of the absolute error values. The values can be calculated as in Eq. (3),

$$MAE/MAD = 1 / N * sum\ for\ i\ to\ N\ abs(y\_i - yhat\_i) \quad (3)$$

Where, *y_i* is the i'th expected value in the dataset, *yhat_i* is the i'th predicted value and *abs()* is the absolute function. A perfect mean absolute error value is 0.0, which means that all predictions matched the expected values exactly.

R^2 sometimes also called *Coefficient of Determination* corresponds to the degree to which the variance in the target variable can be explained by the predicted variables. The following Eq. (4) is used to calculate R^2:

$$R2 = 1 - RSS / TSS = 1 - ((sum\ for\ i\ to\ N\ (y\_i - yhat\_i) \wedge 2) / (sum\ for\ i\ to\ N\ (y\_i - mean(y\_i) \wedge 2)) \quad (4)$$

Where, RSS is the residual sum of squares and TSS is the total sum of squares. A higher value indicates a better fit.

3. Results

Table 3 and Table 4 show the average of 10-run results for CNN and RNN on selected dataset. The results are presented based on various metrics, including Mean Absolute Deviation (MAD) for each selected movement, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-square (R^2). Each metric provides different insights into the model's behaviour and performance. The best result for each metric is shown in bold.

Table 3
MAE, RMSE and R^2 values for CNN and RNN

Metrics	CNN	RNN
MAE	0.5683770735317860	0.2071783385148440
RMSE	1.6019508108010100	0.5895809961050110
R^2	0.6190302736483360	0.4239085611881990

Based on the results obtained in Table 3, it's evident that both the CNN and RNN models showcased commendable performance on the rehabilitation evaluation dataset. These models exhibited low error values and notably high R^2 values, signifying their ability to explain the variance in the data. Detailed analysis indicates that the overall performance of the RNN model outperformed the CNN model significantly. RNN exhibits lower overall MAE, and RMSE compared to CNN. This suggests that, its efficacy in making more accurate predictions across the dataset. However, CNN shows a higher R^2 value, indicating better explanatory power and a better fit of the model compared to RNN.

Table 4
MAD values for CNN and RNN

Movement Type	CNN	RNN
Standing Shoulder Abduction	0.003747	0.004215
Standing Shoulder Rotation	0.024973	0.010345
Standing Shoulder Scaption	1.863758	0.673797

In specific movements of MAD values in Table 4, CNN generally performs better for Standing Shoulder Abduction, while RNN excels in predicting Standing Shoulder Rotation and Standing Shoulder Scaption. These models seem to have different strengths depending on the specific movement being predicted and the overall performance measures considered.

4. Conclusions

The experimental of CNN and RNN models to evaluate breast cancer rehabilitation exercises is presented here. The performances of the models then are discussed based on the regression task. CNN and RNN are both performed commendably well in evaluating the selected dataset derived from UI-PRMD dataset. Each model has its own strength and the implementation of those models should be based on the specific requirements of the task at hand, weighing the importance of the model fit against predictive accuracy. Combining between CNN and RNN is an interesting topic to be explored. Recently hybrid DL models have emerged as a popular and powerful approach, widely implemented across diverse fields. The integration of two or more architectures leverages the strengths of each model type, potentially leading to improved performance and enhanced predictive capabilities. Future study will apply the hybrid concept and explore effectiveness in order to provide better rehabilitation evaluation model for breast cancer patients.

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