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Smart Phone ROM Measurements Based On Action Recognition In Rehabilitation Using Deep Learning

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Abstract

Computer-assisted physical therapy (rehabilitation) assessment includes assessing patient performance in undertaking recommended recovery tasks, based on interpreting movements from activity which are recorded through a sensory interface. For assessing rehabilitation as well as for determining permanent disability scores in workers' compensation situations by evaluating Range of Motion (ROM) following injury or action is needed. Smartphone technology developers have built software (apps) in recent years that imitate ROM measurement instruments, such as the universal goniometer. This paper explores the approaches to Activity Recognition (AR) using a smartphone application that utilizes the on-board accelerometer sensor with the goal of tracking people's physical activity at home. In addition, HAR may provide useful information about the level of daily physical activity via smartphone or wearable sensor, especially in circumstances where a physically AR are normally exists, as in modern environments. This paper suggest a deep convolution neural network system (DCNN) using a smartphone ROM measurement of various joints, such as leg, foot and ankle based on AR. Datasets are collected from android phones for the exercise movements done by patients and predict 88% recovery score. The proposed DCNN method obtained the highest training rate of 94.08% and higher testing accuracy of 94.17% than the LSTM method. DCNN method has spends 87sec less computation time.

Keywords: *Smart Phone, ROM measurements, rehabilitation, Activity Recognition*

1. Introduction

Human activity Recognition (HAR) is an important and convenient field of research, with the increasing use of wearable and portable smart devices. Numerous embedded sensors collect data on human motion using the approach suggested by the authors [1]. Continuous HAR technologies are built as part of mechanism for tracking long-term human activities including living environment support, sport trauma identification and surveillance [2]. Reporting on the everyday practices of patients outside of a hospital environment is projected to become an important method for assessing health care strategies and making clinical decisions [3]. The wearable sensor technology can possibly promote many applications in a home environment, such as guidance on recovery, movement assessment, behavior recollection, and fall detection [4]. HAR is an increasingly important function which improves the quality of life at a person and promotes health. HAR helps close the difference between the low-level sensor and high-level patient based technologies of assisted living environments. Due to its low invasiveness, simplicity and high adhesion, the smartphone is commonly used among the numerous available sensing components.

Generally, routine physical activity testing provides an important guideline for health services, such as diabetes avoidance or decline, blood pressure regulation, cardiovascular disease and heart failure. Smartphones provides quite so much flexibility to track the physical and physiological measurements of humans while integrating multiple appropriate sensors, including the Inertial Measurement Unit (IMU), oximeter and thermometer [5]. Such kinds of smartphones are presently prevalent in society.

The most frequently injured joints namely, ankle, foot and leg joint ROM has become an important concern for post-injury treatment in the wider community as well as in particular categories such as the elderly or physical therapy patients. In the past 60 years, many methods of measuring distance from basic visual estimation to high-speed cinematography, to the more commonly used standardized goniometer were used and tested to improve measurement precision and the possible sources of error. Throughout the rise of mobile applications (apps) designed to turn smartphones, many developers have developed applications for calculating ROM around specific joints. As a result, the detection and elimination of sources of measurement error resulting from the particular measurement system used for measuring ROM has become increasingly important [6]. The major purpose of the research work has been to determine whether the smartphone apps Goniometer Pro (Gonio), Dr. Goniometer (DrG), and Clinometer (Clino) measure ankle ROM as accurately as the clinical standard UG, by evaluating the correlations between UG measurements and smartphone app measurements. The development of Deep Learning (DL), artificial intelligence (AL), and techniques of computational powers [7–9] overlooked the step of manually extracting data. The DL approach has been implemented for the automated learning of features in various fields such as healthcare, image recognition, and recently for specific HAR in smartphones and wearable sensors [10]. A significant number of DL algorithms have been effectively introduced in HAR recently by automatically choosing the set of functionality. An efficient HAR model based on a DCNN [11] has been proposed to manipulate the goniometer and intrinsic movement characteristics. Eight events were successfully defined for a DCNN model of three CNN layers and two max pooling layers. In this paper proposed a DCNN classifier model for movement recognition using smartphone ROM measurement on different joints, such as leg, foot and ankle. The organizations of this paper are as follows. Section 2 describes the related survey regarding technique based methodological contributions from existing work, Section 3 describes the proposed methodology based on Smartphone ROM measurement using DCNN, Section 4, discusses evaluation based on accuracy and computation time, Section 5 concludes the evaluation work.

2. Literature Review

Ding and Ren has proposed an algorithm based on Hierarchical features of Conventional Neural Networks (HCNN) in order to focus on overcoming the drawback of conventional technique of medical image recognition in which a medical exercise consists of rehabilitation image segmentation algorithm are not only stimulate the speed of network convergence and also reduced the time consumption during training [12]. In addition, the major feature is to increase the segmentation algorithm accuracy in medical exercise of rehabilitation image and also perform better practical value. Spinsante et.al has introduced HAR based on the goal of tracking people's physical activity over workspace with a smartphone application using the on-board accessible accelerometer sensor [13]. The proposed technique has the ability in classifying the six different activities by differentiating among non-active state and active state with approximately 99% accuracy. Shun Lin et.al has proposed an approach of classifier based on their research in which the issue of motion segmentation has been formulated with two-class issue of classification that classify among non-segment and segment portions [14]. The proposed method is not aware about domain knowledge of exercise and established in form of groups with participants and exercises which are not considered as a portion of training set that allowed to more robust in clinical applications. Zheng et.al has analyzed the segmentation effect in performing DL models, and comparing the method of four data transformation. The 97.20% is the best overall accuracy gets accomplished from eight activities in accordance with data of seven wearable sensors that has exceeded several Machine Learning (ML) techniques [15]. Buck et.al has illustrated about analysis of goniometer applications and comparing their measurements with an electronic goniometer gold standard for determining the best reliable application [16]. Cox et.al has illustrated about the participants' health statuses are not resolved. Therefore, the small bolster is utilized for standardizing measurement for the participant's ankles [17]. Moreover, the stabilization of few ankles plays a significant role in generating stable measurements but considering time for better stability in ankle is not regularly practical over clinical practice while caretaker required for measuring ankle ROM as quick as possible. Behnoush et.al has illustrated about maximum elbow ROM for positioning and forearm supination have been investigated for 60 healthy volunteers with smartphone and UG [18]. Qi et.al has proposed a recent model to HAR by smartphone whereas this recent model is Fast and Robust-Deep CNN (FR-DCNN) which required 0.0028 sec for predicting the performance of an electronic mode with accuracy of about 95.27% [19].

3. Proposed Methodology

3.1 Data preparation

The senior researcher's foot and ankle clinics have been measured for 24 patients as a pathologic ankles whereas this study has introduced all patients with the age 18 and above years old and patients with ankle arthrodesis, acute fracture and exhibited severely with ROM limitation are excluded [20-23]. However, the approval of human subjects is acknowledged and written informed approval has accomplished from any participants before all measurements are considered whereas participants has an average of 52 years. In this experiment, 21 patients out of 24 have done prior ankle surgery. Hence, the average time elapse among participant's surgery and its measurement over clinic are 146 days [24-27]. Moreover, this study aims to analyze dissimilar application types for determining while the application approach is considered for measurement might be an essential leverage of correlation among application estimation and measurements of UG.

3.2 Procedure

The senior researcher's foot and ankle clinics have been represented with all participants as patients who meet their inclusion and exclusion of studies criteria which are included in this study once the clinical appointments is introduced. When the written informed approval has provided then the measurement of ROM are accomplished over isolated examination room at their official visit. The person's leg placed on the side of the pathological ankle has rolled up to each particular measurement protocol is illustrated to reveal the participant's leg and foot [28-30]. During measuring process, the knee posture is fixed so that the knee joint of each person has flexed at an angle of 90 degrees. In order to remove bias because of patient exhaustion in every patient and the procedure present in this measurements are considered by smartphone get randomized. Once completing all kind of measurements get accomplished for patient is requested to finish the survey. There are various measurement protocol are given below [32-36].

3.2.1 Universal Goniometer Protocol

The investigator has laterally located themselves from each person's pathological ankle in which UG is placed so that the goniometer axis present is perpendicular to the lateral malleolus of the patient, with its stationary arm stretching further towards the fibular head and the mobile arm is made parallel to the fifth metatarsal longitudinal axis shown in Figure 1. Once the inspector modified the mobile arm in order to fascinate measurement from the reveal UG side, the recorder has recorded the observed angle over neutral position but in the case of plantar flexed or dorsiflexed position present in whole degrees.

Figure 1. The position of UG based on goniometer axis

3.2.2 Gonio Protocol

The lateral positioned from investigator for the inhibition's pathologic ankle whereas the mobile has located in such a way that the phone's bottom corner has been centered based on lateral malleolus of person with the phone's side edge parallel to the person's fifth metatarsal longitudinal axis is shown in Figure 2.

Figure 2. Bottom corner positioned for the Gonio measurements through phone

The investigator has selected start button of the application after neutral position gets accomplished and it assist to record the neutral positioned angle. Moreover, the person plantar flexed or dorsiflexed has been examined from the investigator but while rotating the position of phone. Therefore, the phone side edge gets relocated as parallel to the person's fifth metatarsal longitudinal axis along phone bottom corner until it gets centered on the laterals malleolus of the person. Thus, the selection of examiner is considered with "End" button and the measured angle of both dorsiflexion and plantar flexion as the recorded document is displayed over screen is shown in figure 3.

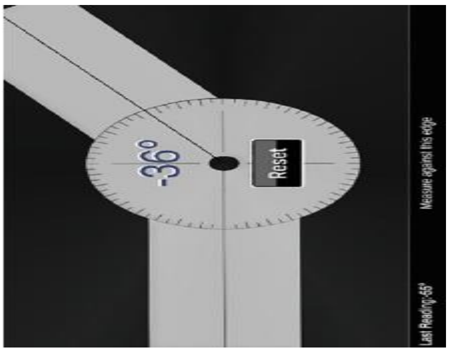

Figure 3. Screen display of recorded document about measured angle from Gonio measurements

3.2.3 Clino Protocol

The positioning of both participant and investigator are same in the Gonio protocol whereas the measurement is also considered in a similar fashion. Once an investigator completes the measurements, the records have been documented with measured angle subsequently dorsiflexion and plantar flexion gets displayed over screen.

3.2.4 DrG Protocol

The person's pathologic ankle has been positioned lateral to investigator from 3 feet of person's ankle whereas the phone is hold vertically by investigator at the position of person's ankle and the application is utilized for taking picture of person's ankle, leg and foot over frame.

3.3 Deep Convolutional Neural Networks

Once the training dataset has collected from the information of smartphone then classifier is created for HAR whereas the training process about DCNN classifier on ($\tilde{s}_j$* , y_j), j = 1, 2, _ _ _ ,M, $\tilde{s}^* \epsilon R^m$ has been considered as an issue of supervised learning. The framework of DCNN design contains four layers inclusive of deep convolutional layers which considered as a drop-out layer [20], a full connection layer and a classification module. Initially, there are three deep convolutional modules consists of a 2D convolution layer Rectified Linear Units (ReLU) and batch normalization layer [21-23]. The final deep convolution modules has incorporated a furthermore layer as max-pooling layer [24].Thus, the DCNN framework details are described as follows.

Inputs: A matrix consists of m dimensions with fixed time length is expressed in term of $\mathbf{s}^*_{\mathbf{n}\times \mathbf{M_b}}$ whereas this model is designed to compare three input types as an experiment. These inputs have illustrated the 3 s input vector of a provided training data size, namely M_b = 150 with 50 Hz sample frequency.

Deep Convolution Modules: There are 3 modules which are designed in DCNN consists of Con.mod#1, Con.mod#2 and Con.mod#3. The first two modules consists of 2D CNN layers, Batch Normalization (BN) layer and Rectified Linear Unit (ReLU) function. There are three window size such as 5, 10 and 15 i,e 3x3 which can performed in convolution operation [25-27]. The size of yielded feature map is (n - 2) x (M_b - 2), (n - 4) x (M_b - 4), and (n - 6) x (M_b – 6). The BN layer can know somewhat more independently of other layers by itself which are adopted to each layer of the CNN network. The aim of the ReLU layer is to solve the disappearing slope and the gradient-explosion problems [28, 29].

Max-pooling: The max-pooling has been performed for selecting maximum feature value and at last the outcome obtained from max-pooled from the final layer of Conv. Module #3 that modify in creating a feature vector to the input matrix.

Dropout: In general, feature vectors of convolved and max-pooled are very large which causes overfitting issue and this experiences may minimize the accuracy of classification. Hence, the dropout layer has been applicable to avoid both overfitting and reduction of training time. Thus, the dropout percentage is set to 0.5 in this evaluation of experiment.

Output: However, the outcome of fully connected layer is considered as SoftMax layer which assist in classifying the activities using probability computation of every node input over softmax layer such as participant's ankle reliability, patients foot and their leg for 3 dissimilar measurements like DrG, Clino and Gonio that related to UG. Hence, the high probability of measurement can be determined to be predicted activity.

4. Result and Discussion

In order to validate the interest of metrics for the proposed DCNN technique, this experiment has suggested with various design in comparing it with existing algorithm based on various metrics. However, this investigation is implemented and estimated in MATLAB Version 2018b. whereas the initial experiment gets implemented for comparing the classification of training time, training and testing accuracy between three kind of inputs. Hence, the ROM measurement efficiency has been evaluated for identifying the assess reliability of those three technique measurement related to UG. Thus, the accuracy of training and testing is calculated based on training and testing dataset correspondingly and total training time indicates the cost time required to build the proposed technique as DCNN classifier. In addition, the comparative results between these three measurements are represented as $\tilde{s}^{*}_{3\times M_b}$ have been shown in Table.1.

Table.1 Proposed DCNN classifier-based Smartphone ROM measurement for various Joints

Smartphone Measurement	Various Joints	Training Accuracy (%)	Testing accuracy (%)	Training time(sec)
Gonio	Leg	91	94	88
	Foot	90	95	84
	ankle	93	92	82
Clino	Leg	85	80	71
	Foot	80	91	74
	ankle	75	85	80
DrG	Leg	73	95	118.32
	Foot	85	94	226.11
	ankle	71	90	105

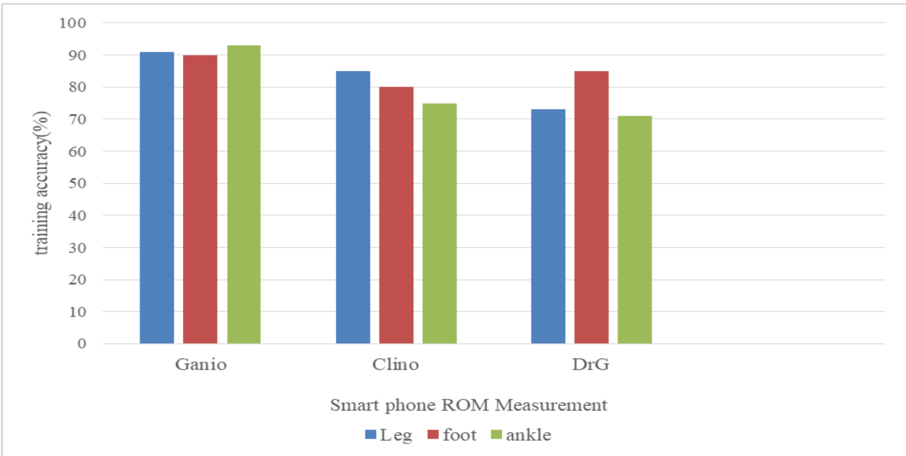

Figure 4 Training accuracy using DCNN classifier-based Smartphone ROM measurement

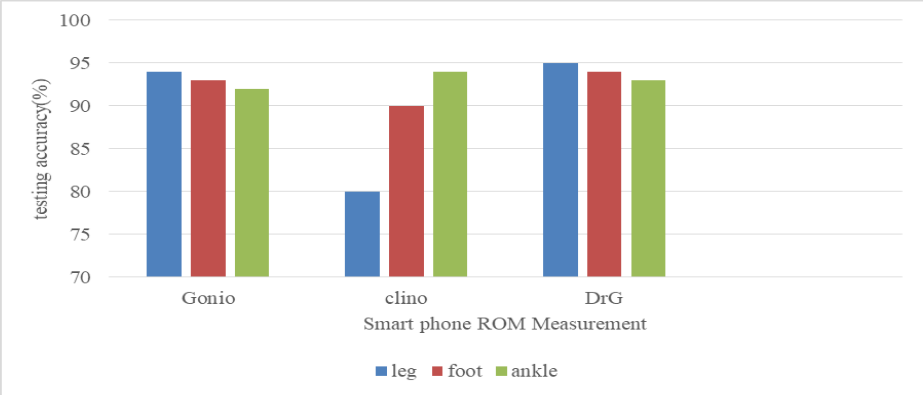

Figure 5 Testing accuracy using DCNN classifier-based Smartphone ROM measurement

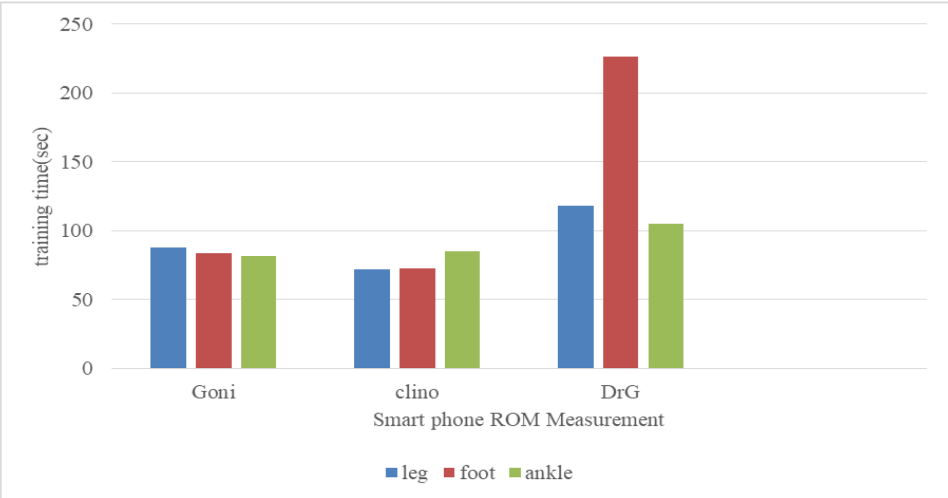

Figure.6 Training time using DCNN classifier-based Smartphone ROM measurement

Figure.4, 5 and 6 represents the training accuracy, testing accuracy and training time using DCNN classifier depends upon clinical standard UG and three dissimilar application types to measure ankle, foot and leg ROM in clinical setting. By comparing the results on accuracy training data in DCNN classifier, the Gonio smartphone measurement acquires the highest accuracy than the DrG and clino smartphone measurement, on testing accuracy in DCNN classifier, the Gonio and DrG smartphone measurement obtains excellent interrater reliability than the clino smartphone measurement and training time in DCNN classifier, clino smartphone measurement acquires the less time consumption than the of other two.

The performance of ROM measurement in smartphone among proposed method and existing DL classifier namely Long Short Term Memory (LSTM) is shown in table 2. The collected dataset with 18 subjected records get segregated as 90% of data for training and 10% of data for testing the sample in which proposed method has four convolutional modules introducing 2D layer of CNN, Rectified Linear Unit (ReLU) layer and normalization (BN) layer but in the case of LSTM technique it consists of classification layer, fully connected layer and softmax layer. Additionally, the LSTM model contains one LSTM layer that has 50 minibatch size and 50 neurons with learn rate of 0.001, drop factor as 0.1 and drop period as 100.

Table.2 Comparison of time consumption and accuracy for proposed DCNN and LSTM classifier

Algorithm	Accuracy		Computation time	
	Training	Testing	Training	Testing
DCNN	94.08%	94.17%	87sec	0.22sec
LSTM	92.05%	93.39%	118.12 sec	0.32sec

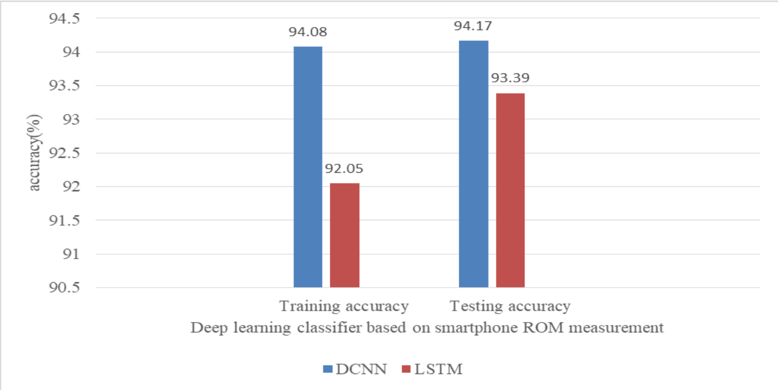

Figure.7 Comparison of DCNN with LSTM based on smartphone ROM measurement using accuracy

However, comparison of classification accuracy has been calculated for both training and testing dataset in both proposed DCNN and existing LSTM classifier are shown in Figure.4. Hence, the illustration of figure 4 has delivered that proposed DCNN technique has high training rate of 94.08% while compare to LSTM classifier whereas testing rate is also high in DCNN with 94.17% when compared to existing method of LSTM classifier.

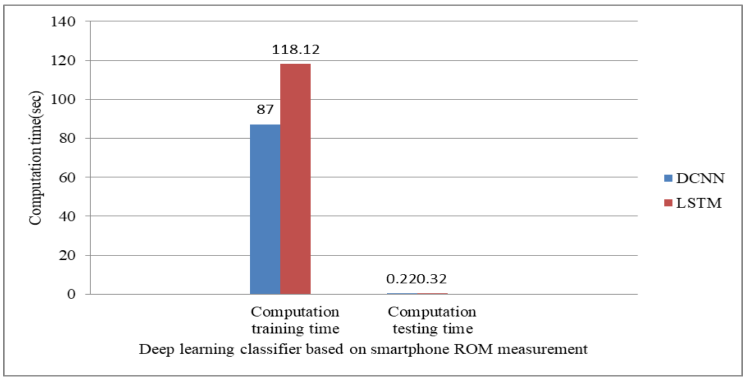

Figure.8 Comparison of DCNN with LSTM based on smartphone ROM measurement using computation time

Similarly, time consumption for processing the training and testing dataset has been shown in figure 5 which illustrated that proposed DCNN method consumes less time as 87 sec while compared to LSTM classifier that consume 118.12 sec in training dataset due to 90% of dataset but in the case of testing dataset the time consumption is very less compared to that of training dataset for both proposed and existing method but the individual comparison of time consumption describe proposed DCNN has better time consumption as 0.22 sec when comparing it with existing LSTM classifier which consumed time as 0.32 sec.

Thus, the quality score of resulting movement plays a dual role over framework but initially during real-time setup exercise assessment has provided quality score for inherent consideration of calculated value of utilizing performance metrics. At an instance, the measured quality score of about 88% obtained for patient is simple to understand and has the ability to allow the patient for self-monitoring their growth towards functional recovery in accordance with received scores in an interval of time.

5. Conclusion

This paper illustrated the design and architecture of proposed DCNN. In this paper suggested profoundly DCNN architecture to perform complex AR from smartphone sensors. This system reduces the computational time to train a DCNN classifier using the ROM mobile applications, since most of the patients already own smartphones and can access ROM-measuring devices that are considerably cheaper than a UG, patients will be able to measure knee, foot and leg more often using non-clinical environments in their own home. Most of the patients examined in this study indicated that if they could conveniently do it themselves (15 more frequently; 7 same amount; 2 less frequently) they would more commonly test their ankle ROM at home. Most participants were very relaxed in this study, having their ankle, foot and leg ROM tested by a smartphone. The proposed DCNN method gets the highest training rate (94.08%) and higher testing accuracy (94.17%) than the LSTM method. DCNN method only spends 87s for training the dataset which has less computation time than the LSTM. The exercise done by the patients from their smartphone and predict 88% recovery score. The proposed DCNN is the best suited algorithm for ROM measurement in rehabilitation patients.

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