An Unsupervised Model for Physical Rehabilitation Exercise Assessment

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Motivation

- Participation in physical therapy and rehabilitation programs is often compulsory and critical in postoperative recovery or for treatment of a wide array of musculoskeletal conditions.

- It is infeasible and economically unjustified to offer patient access to a clinician for every single rehabilitation session.

- Most of the patients need to depend on home-based rehabilitation after receiving inpatient followed by outpatient rehabilitations.

- There is still a lack of versatile and robust systems for automatic monitoring and assessment of patient performance.

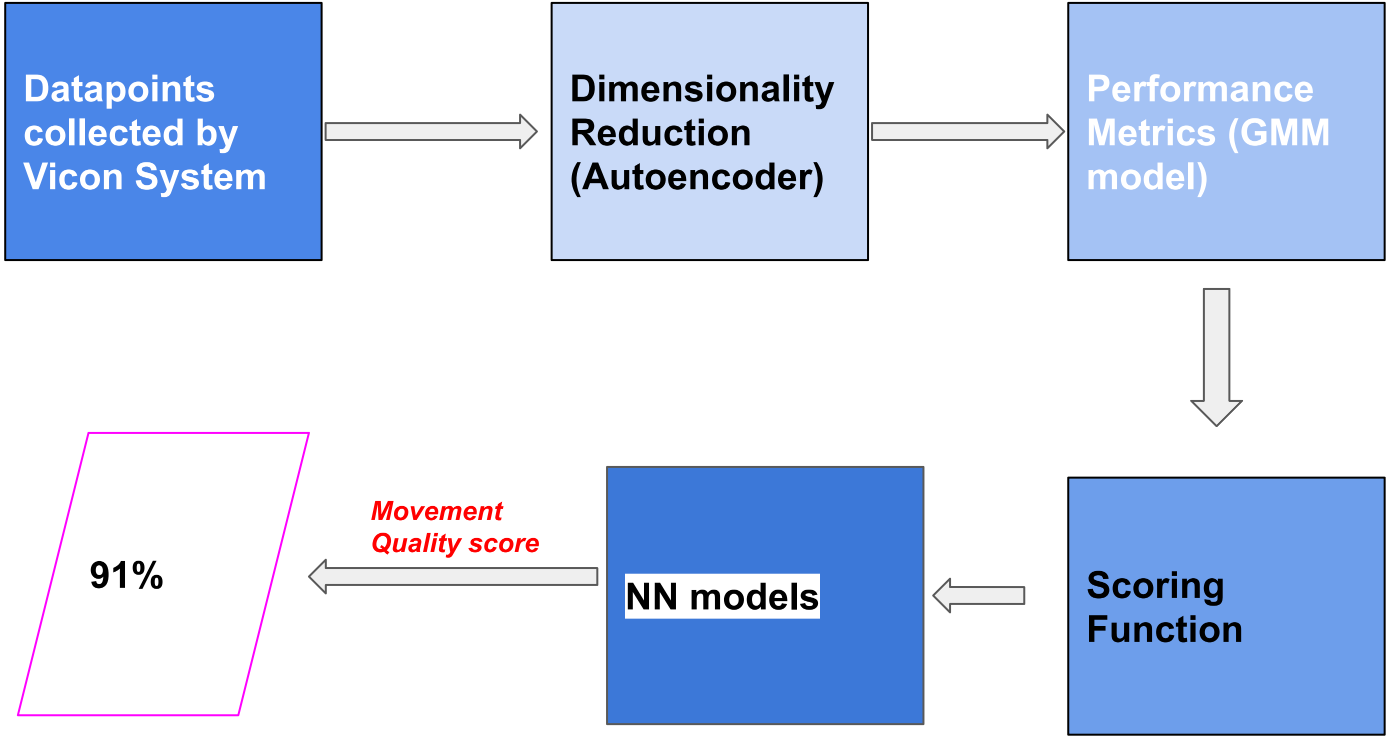
Abstract

- With the improvement of sensor systems, computer aided assessment of physical exercises can be associated with manual evaluation.

- Deep Learning models can be trained with proper physical movement data and therefore, can be evaluated to distinguish the appropriate movement of a patient during his training/practice sessions.

- This study goal is to build models to assess ten distinct exercises.

Proposed Framework



Dataset Description

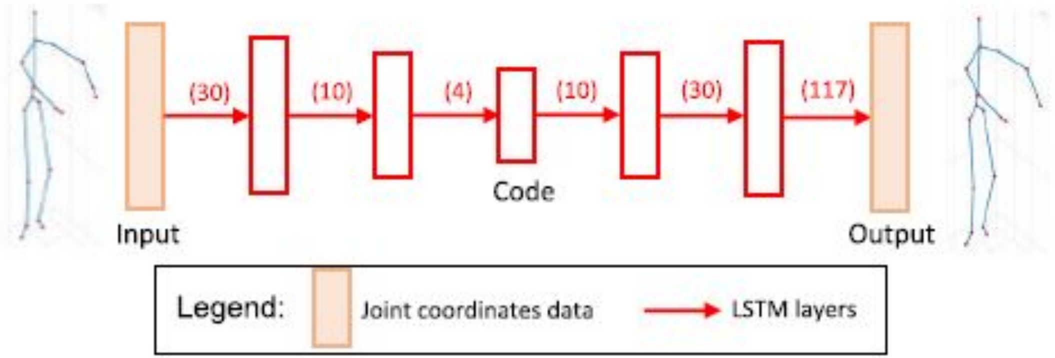
The following 10 movements were selected for the data set:
(1) deep squat,
(2) hurdle step,
(3) inline lunge,
(4) side lunge,
(5) sit to stand,
(6) standing active straight leg raise,
(7) standing shoulder abduction,
(8) standing shoulder extension,
(9) standing shoulder internal-external rotation, and
(10) standing shoulder scaption

System used for data collection : Vicon

Dimensionality Reduction

Autoencoder:

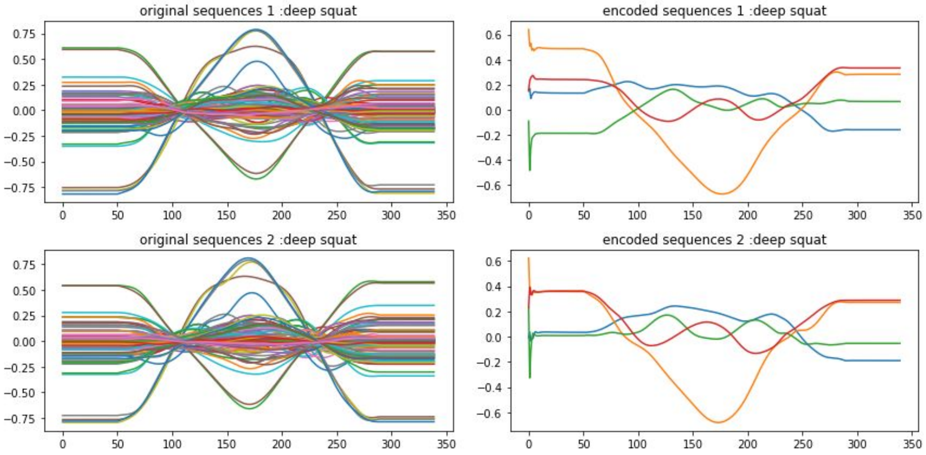
Autoencoders are trained to find which minimize the mean squared deviation between input and output Data.

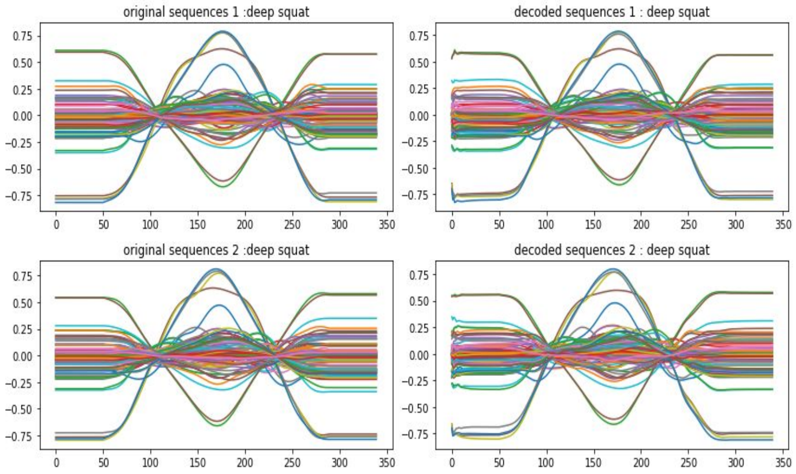


The encoder portion consists of three intermediate layers of LSTM recurrent units with 30, 10, and 4 computational units.

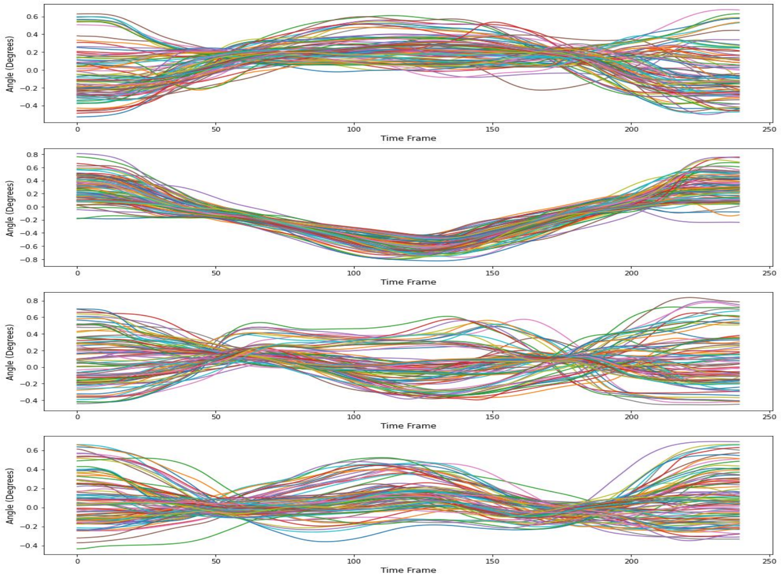
The decoder portion has three intermediate layers of LSTM units.

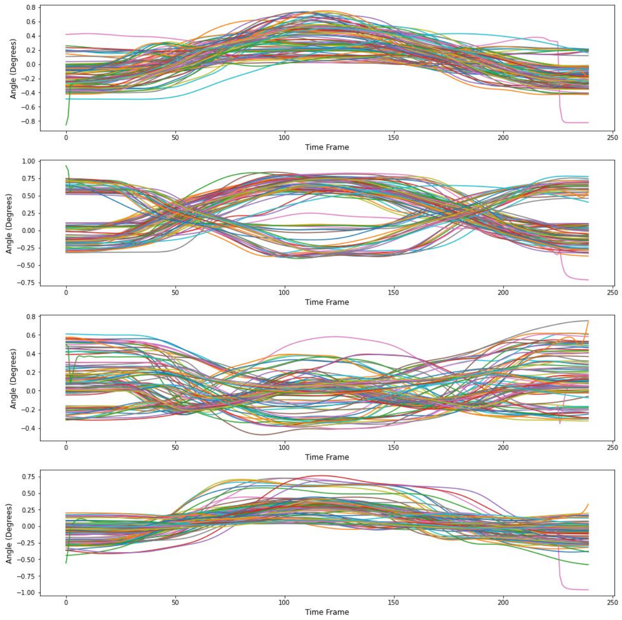
Encoded and Decoded Sequences





Autoencoder

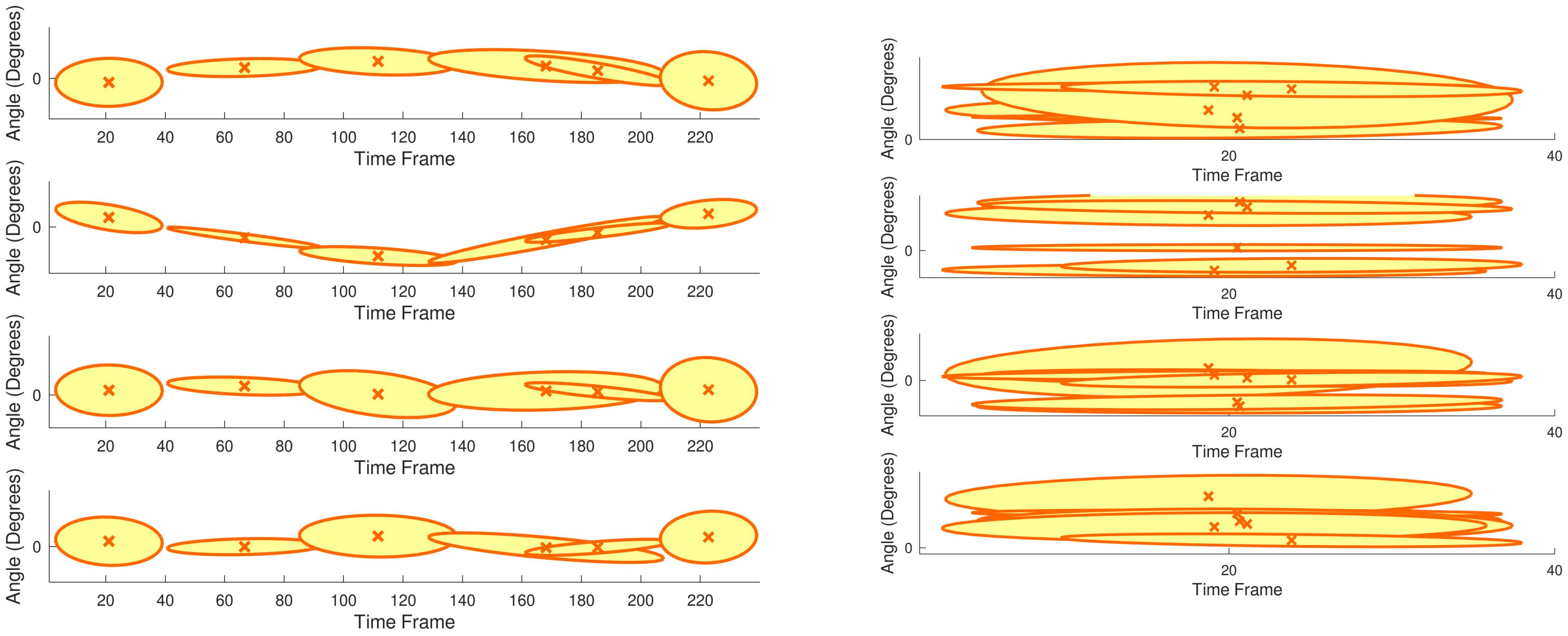




Performance Metric

- A metric based on Gaussian mixture model (GMM) log-likelihood is adopted.
- Log-likelihood of a movement data for a given model is a natural choice for evaluation of data instances in probabilistic models.
- GMM is a parametric probabilistic model for representing data with a mixture of Gaussian probability density functions
- The method used for estimating the model parameters λ in GMM is the expectation maximization (EM) algorithm

Gaussian mixture model (GMM)



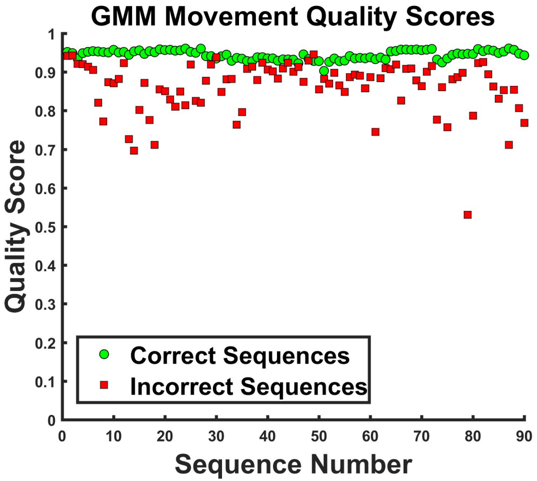
Scoring Function

In the presented framework, a scoring function maps the values of the performance metrics into a movement quality score in the range between 0 and 1.

$$xk = (1 + e\hat{}(xk/(\mu+3\delta)-\alpha 1)-1 \;\ldots\ldots\; (1)$$

$$\bar{y}k = (1 + e\hat{}(xk/(\mu+3\delta)-\alpha 1\ ) + (yk - xk)/\alpha 2\ (\mu + 3\delta))-1 \;\ldots\ldots(2)$$

The proposed scoring function is monotonically decreasing, and is designed to preserve the distribution of the values of the performance metric.



RNN Model (Using LSTM)

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
bidirectional_3 (Bidirection (None, 240, 40)           22080
_________________________________________________________________
dropout_4 (Dropout)          (None, 240, 40)           0
_________________________________________________________________
dense_3 (Dense)              (None, 240, 30)           1230
_________________________________________________________________
dropout_5 (Dropout)          (None, 240, 30)           0
_________________________________________________________________
bidirectional_4 (Bidirection (None, 20)                3280
_________________________________________________________________
dropout_6 (Dropout)          (None, 20)                0
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 21
_________________________________________________________________
activation_2 (Activation)    (None, 1)                 0
=================================================================
Total params: 26,611
Trainable params: 26,611
Non-trainable params: 0
_________________________________________________________________
```

Comparison of Scores from RNN

Exercises	Mean Absolute Deviation	RMS Deviation
Deep Squat	0.01653842172724859 6	0.0516887967520600 5
Hurdle step	0.041030974583625 8	0.0671334960553133 2
Inline lunge	0.0408358373849732 6	0.052247374260963 1
Side lunge	0.0328841031285694 65	0.0676390904012942 3
Sit to stand	0.0263670324117796 8	0.0403551680890222 5

CNN model

```
_________________________________________________________________
leaky_re_lu_5 (LeakyReLU)    (None, 200)               0
_________________________________________________________________
dropout_5 (Dropout)          (None, 200)               0
_________________________________________________________________
dense_3 (Dense)              (None, 100)               20100
_________________________________________________________________
leaky_re_lu_6 (LeakyReLU)    (None, 100)               0
_________________________________________________________________
dropout_6 (Dropout)          (None, 100)               0
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 101
_________________________________________________________________
activation_1 (Activation)    (None, 1)                 0
=================================================================
Total params: 302,201
Trainable params: 302,201
Non-trainable params: 0
```

Average Mean absolute deviation

0.018011

RMS deviation

0.030595

Average Movement Quality score

90.47%

Comparison table for performance metric mean deviation

Exercises	Mean absolute deviation	Mean absolute deviation of existing work[1]
Deep Squat	**0.01026**	0.01077
Hurdle step	0.08177	**0.02824**
Inline lunge	**0.00713**	0.03980
Side lunge	**0.00779**	0.01185
Sit to stand	**0.01302**	0.01870
Standing active straight leg raise	**0.01357**	0.01779
Standing shoulder abduction	**0.01223**	0.03819

Exercises	Mean absolute deviation	Mean absolute deviation of existing work
Standing shoulder extension	**0.01561**	0.02305
Standing shoulder internal-external rotation	**0.00967**	0.02271
Standing shoulder scaption	**0.009024**	0.04162
Avg	**0.018011**	0.02527

Movement Quality Score Prediction

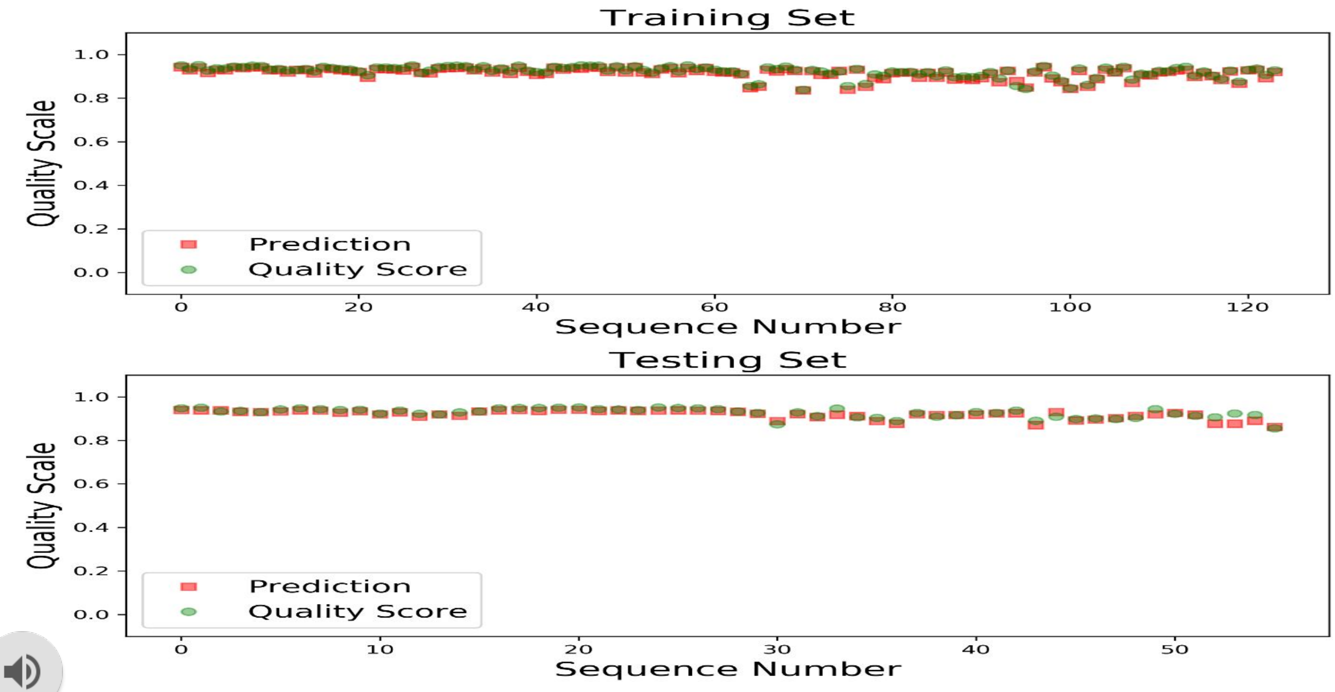


Fig: movement quality score prediction by our CNN

Discussion

- For training the deep neural networks, the movement quality scores based on the GMM log-likelihood calculated with autoencoder-reduced data are employed. Only the case of between-subject is considered, since for the within-subject case the number of repetitions per subject is too small to train NNs.

- For CNN we tried to predict movement quality score both from angle and position data of vicon sensor. Adding an extra layer and using the autoencoder output data makes our CNN giving higher accuracy than existing work.

References

- **https://arxiv.org/abs/1901.10435**
- https://ieeexplore.ieee.org/abstract/document/8957502
- https://webpages.uidaho.edu/ui-prmd/
- A Deep Learning Framework for Assessing Physical Rehabilitation Exercises