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Syed A. Zamin
LSU Health Sciences Center- New Orleans

Kaichen Tang
UTHealth

Emily A. Stevens
UTHealth

Xiaoqian Jiang
UTHealth

Sean Savitz
UTHealth

See next page for additional authors

Presenter Information

Syed A. Zamin, Kaichen Tang, Emily A. Stevens, Xiaoqian Jiang, Sean Savitz, and Shayan Shams

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Syed A. Zamin[1], Kaichen Tang[2], Emily A. Stevens[3], Xiaoqian Jiang[2], Sean Savitz[3], and Shayan Shams[2]

[1] School of Medicine, Louisiana State University Health Sciences Center New Orleans, LA
[2] School of Biomedical Informatics, UTHealth, TX
[3] Department of Neurology, McGovern Medical School of Medicine, UTHealth, TX

UTHealth The University of Texas Health Science Center at Houston

NIH National Institutes of Health Turning Discovery Into Health

Introduction

The incidence of stroke and stroke-related hemiparesis has been steadily increasing and is projected to become a serious social, financial, and physical burden on the aging population. Studies report up to 85% of stroke survivors experience upper extremity (UE) hemiparesis in at least one arm[1] and 78% fail to achieve the average UE function for their age, even after 3 months of treatment and rehabilitation[2]. Reaching these populations has also become increasingly difficult. Poor accessibility to healthcare for people with disabilities in rural areas is attributable to several factors. Stark geographic disparities between rural and urban America are apparent, for example, in Texas: 71% of rural counties lack outpatient rehabilitation clinics for stroke patients, which greatly exceeds the 19% of urban counties[3]. Patient disabilities and comorbidities further reduce patient compliance and stand in the way of physical rehabilitation that is best realized by active participation. These reasons inspire us to advance technologies to reach an increasingly isolated patient demographic via tele-evaluation. The Fugl-Meyer assessment is the golden standard for evaluation of UE function in post-stroke hemiplegic patients. It is used extensively as the primary metric to quantify post-stroke recovery, even in shorter modified forms. In this study, we present a novel method to assess functional ability in stroke patients that can be implemented practically with pre-existing technology in remote settings and does not require the labor and time from a clinician or physical therapist.

Table 1. Modified Fugl-Meyer Assessment Items

Group	Fugl-Meyer Item	Abbreviation
AI. Reflexes	Flexors	R
	Extensors	R
AII. Flexor Synergy	Shoulder retraction during hand to ear activity	U
	Shoulder elevation during hand to ear activity	U
	Shoulder abduction during hand to ear activity	FM-0
	Shoulder external rotation during hand to ear activity	U
	Elbow flexion during hand to ear activity	FM-1
	Forearm supination during hand to ear activity	FM-2
AII. Extensor Synergy	Shoulder adduction during hand to ear activity	FM-3
	Elbow extension during hand to knee activity	FM-4
	Forearm pronation during hand to knee activity	FM-5
AIII. Mixed Synergies	Hand to lumbar spine	U
	Shoulder flexion to 90°	FM-6
	Forearm pronation/supination with elbow at 90°	FM-7
AIV. Low Synergy	Shoulder abduction to 90°	FM-8
	Shoulder flexion to 180°	FM-9
	Forearm pronation/supination with shoulder flexed	FM-10
AV. Normal Reflexes	Biceps, triceps, and fingers	R
B. Wrist	Wrist stability with elbow at 90°	S
	Wrist flexion/extension with elbow at 90°	FM-11
	Wrist stability with elbow at 180°	S
	Wrist flexion/extension with elbow at 180°	FM-12
	Wrist circumduction	FM-13
C. Hand	Mass flexion	FM-14
	Mass extension	FM-15
C. Grasp	Hook grasp	S
	Thumb adduction	S
	Pincer grasp	S
	Cylinder grasp	S
	Spherical grasp	S
D. Coordination/Speed	Tremor during finger from knee to nose activity	FM-16*
	Dysmetria during finger from knee to nose activity	FM-17*
	Time to complete finger from knee to nose activity	FM-18*

Note that 18 of 33 tests (55%) in the Fugl-Meyer can theoretically be scored using the presented model and are abbreviated with the prefix "FM-". Other abbreviations: R, requiring physical examination; U, involving occluded joints or undetectable motion; S, requiring strength assessment; *, unscorable due to class imbalances.

Patient Information Summary

Table 2. Summary of Patient Population

Characteristic	Missing, n (%)	Categories	Count, n (%) or μ ∓ σ
Demographics			
Age	1 (2.2 %)		60.4 ∓ 16.5
Sex	1 (2.2 %)	Male	24
		Female	20
Race	1 (2.2 %)	White	12
		Black	12
		Asian	0
		Hispanic	0
		Other / Unknown	20
Presenting Condition			
Stroke Type	1 (2.2%)	Ischemic	30
		Hemorrhagic	12
		Unspecified	2
Paretic Side	0 (0%)	Left	25
		Right	10
		No difference	10
Lesion Location	1 (2.2%)	Cortical	7
		Subcortical	24
		Other	13
NIHSS	3 (6.7%)		6.9 ∓ 5.8

Abbreviations: μ, mean; σ, standard deviation; NIHSS, National Institute of Health Stroke Scale.

Methods

Patient Recruitment and Study Activities

45 adult study participants (Table 2) with acute or subacute weakness and unilateral hemiplegia as a result of ischemic or hemorrhagic stroke were recruited after admission to inpatient rehabilitation facilities within the Memorial Hermann Health System. Investigators performed Fugl-Meyer assessments with subjects every 2 days and recorded activity items using as video camera at a resolution of 1080p and a frame rate of 60 Hz placed 3-5 meters away on a tripod 1.5 meters in height.

Deep-learning Motion Detection

We modified a joint recognition pipeline[4] that uses YOLOv3 object detection[5] and the HDRNet model[6] to extract *xy*-positional body joint locations from videos (Figure 1, top). A finger joint detection model[7] fits a palm detector to produce a bounding box which is then analyzed for hand joint locations (Figure 1, bottom).

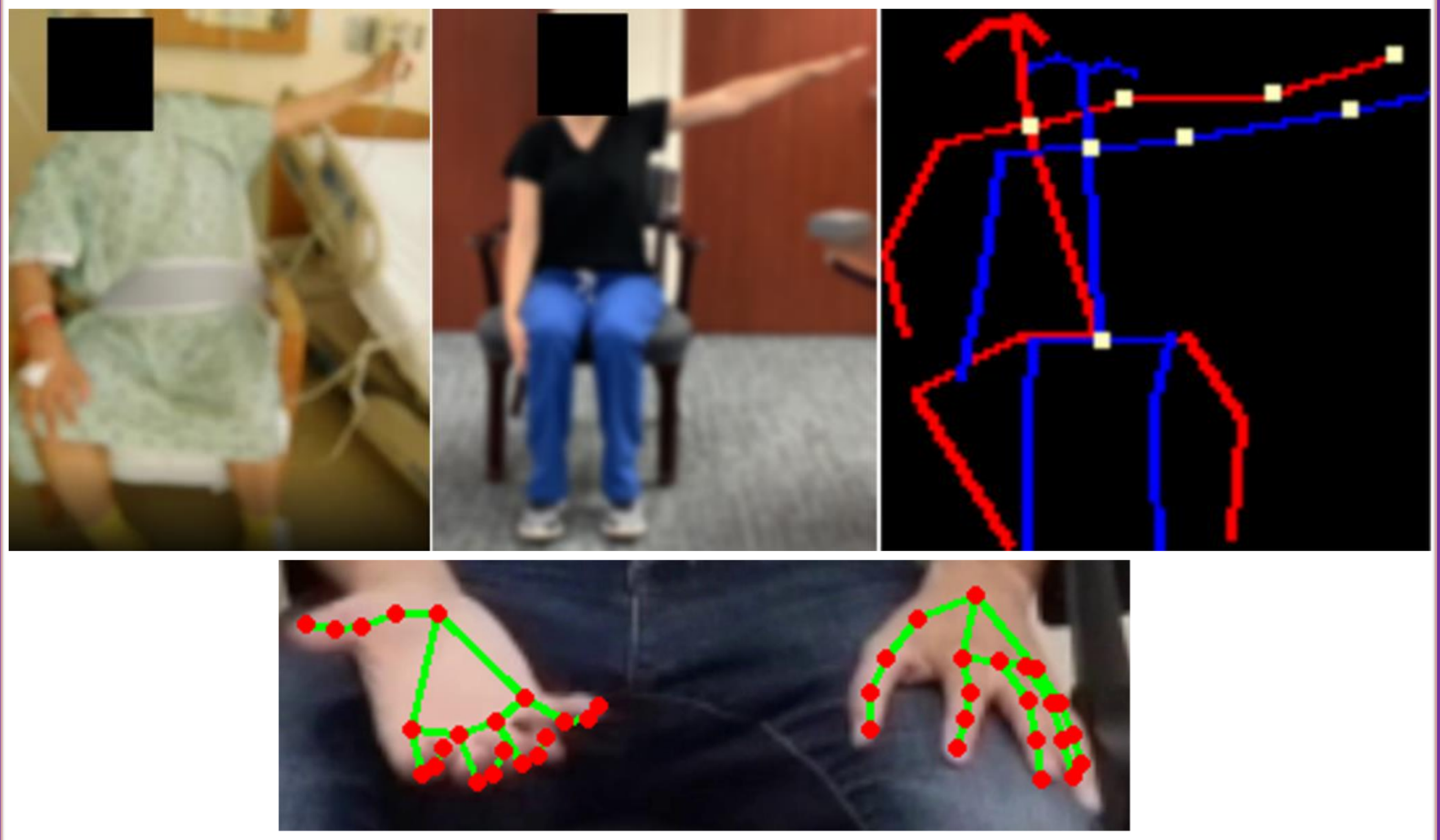

Fig 1. Visual representation of normalized joint coordinates depicting final position of shoulder abduction performed poorly by subject (left, red) and correctly by investigator (middle, blue) with important joints identified (right, yellow). A hand detection model depicting joints (red) is superimposed on the input image (bottom). Images are blurred for privacy.

Auto-scoring Machine Learning Models

For each video, tensors of size $2 \times n \times J_b$ and $2 \times n \times J_h$, where n is 15 frames selected from each video and J is the number of joints, representing the body (b) and hand (h) are input into a convolutional neural network, recurrent neural network, and dilated convolutional neural network to predict Fugl-Meyer scores. An eXtreme Gradient Boosting model is employed as the benchmark using features extracted designed for rule-based classification methods.

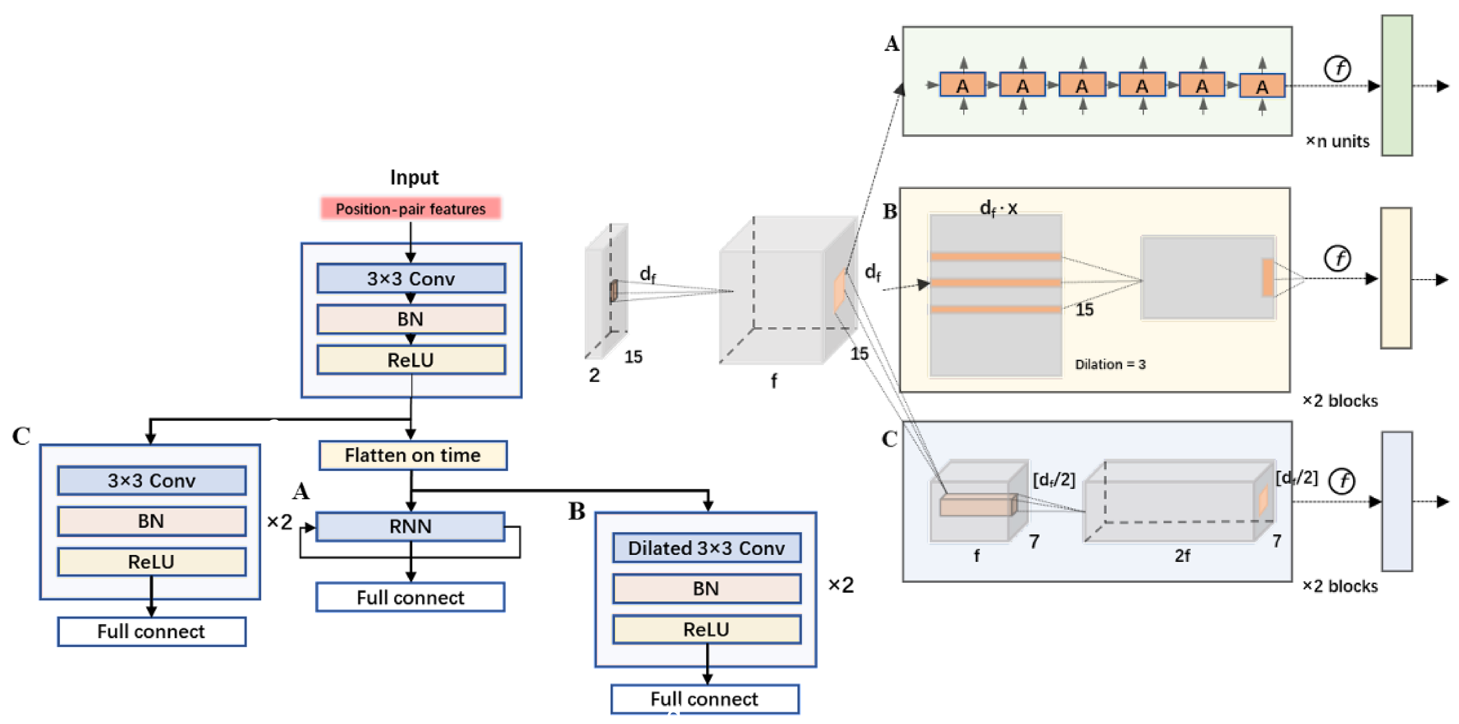

Fig 2. Model structure overview (left) and detailed neural network presentation (right). After feeding with the same input of extracted temporal features matrix, the data goes through a block of feature-wise convolution and then goes to one of three branches: A is the Recurrent Neural Network, B is temporal-wise dilated Convolutional Neural Network of two blocks, and C is feature-wise Convolutional Neural Network of two blocks. For all 3 branches, a fully connected layer is attached as the last layer for score classification.

Results

Item-Wise Prediction Accuracies

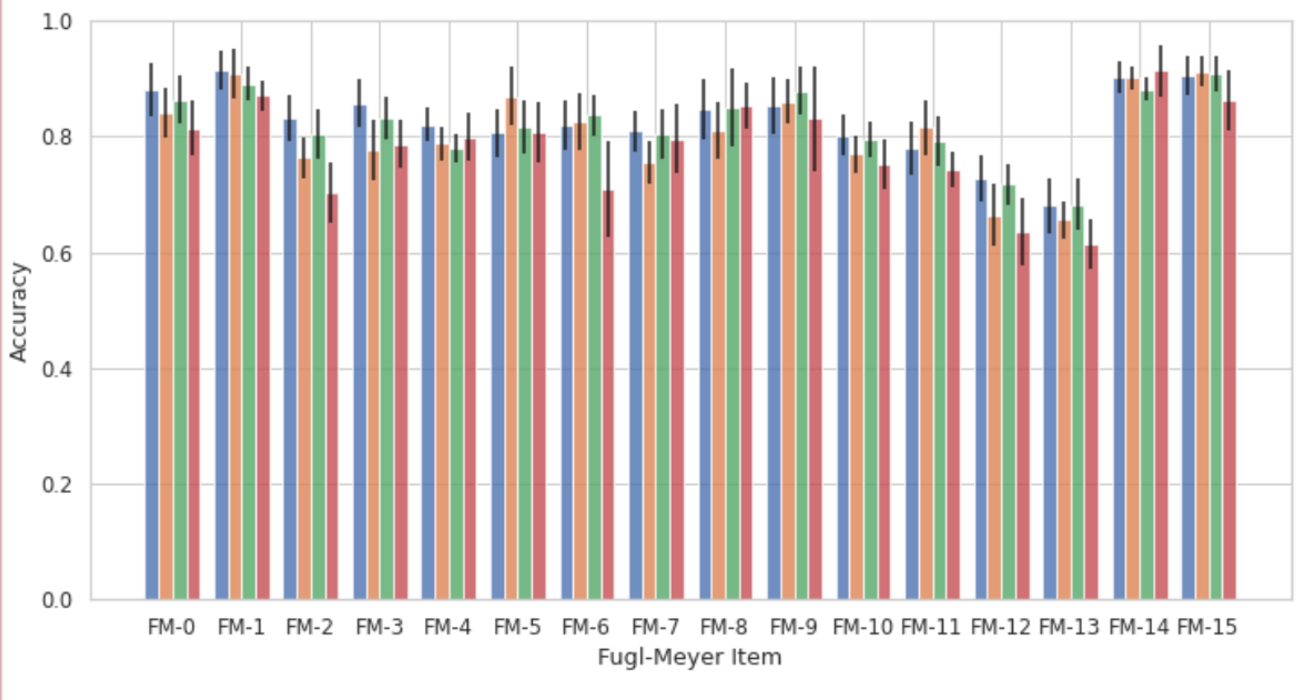

Fig 3. Prediction accuracies with standard deviation bars grouped by Fugl-Meyer item generated from the convolutional neural network (green), recurrent neural network (orange), dilated convolutional neural network (blue), and eXtreme Gradient Boost (red) models.

Group-Wise Prediction Accuracies

Table 3. Group-Wise Prediction Accuracies

Groups	S_{Total}	S_{avg} (std)	R^2	$RMSE_{pred}$
AII. Flexor Synergy	6	4.37∓1.337	0.865	0.643
AIII. Extensor Synergy	6	4.28∓1.284	0.883	0.619
AIV. Mixed Synergy	4	2.94∓0.739	0.897	0.587
AV. Low Synergy	6	4.82∓1.151	0.912	0.599
B. Wrist	6	4.15∓1.463	0.83	0.682
C. Hand	6	5.37∓0.061	0.951	0.476
D. Coordination / Speed	6	/	/	/

Abbreviations: S_{Total}, total possible scores; S_{avg}, total average of all available samples in group; std, standard deviation; R^2, correlation coefficient; $RMSE_{pred}$, root mean square error; /, unscorable due to class imbalances.

Conclusions

This paper presents a method for low-cost automatic assessment of stroke patient upper extremity disability. We show the designed models can score 16 of 33 (48%) items in the Fugl-Meyer assessment, with accuracies ranging from 0.781 and 0.827 for each item. When grouped by Fugl-Meyer category, strong correlations between model prediction and actual scores were achieved (R^2 =0.89). This novel method is demonstrated with potential to conduct telehealth rehabilitation evaluations with accuracy and reliability. This system should reduce physician and therapist burden, improve accessibility to rehabilitation, and improve the flexibility of treatment plans.

Future Studies

In future studies, we envision several changes that could help establish this method as an effective telehealth option for stroke patients:

- Several experts scoring the FMA to confirm inter-rater reliability
- Data collection in an outpatient clinical setting or subject's home

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* Corresponding author: shayan.shams@uth.tmc.edu