

Rehab-Net: Deep Learning framework for Arm Movement Classification using Wearable Sensors for Stroke Rehabilitation

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Abstract—In this paper, we present a deep learning framework ‘*Rehab-Net*’ for effectively classifying three upper limb movements of the human arm, involving extension, flexion and rotation of the forearm which over the time could provide a measure of rehabilitation progress. The proposed framework, *Rehab-Net* is formulated with a personalized, light weight and low-complex, customized CNN model, using 2-layers of Convolutional neural network (CNN), interleaved with pooling layers, followed by a fully-connected layer that classifies the three movements from tri-axial acceleration input data collected from the wrist. The proposed *Rehab-net* framework was validated on sensor data collected in two situations—**a) semi-naturalistic environment involving an archetypal activity of ‘making-tea’ with 4 stroke survivors and b) natural environment, where 10 stroke survivors were free to perform any desired arm movement for a duration of 120 minutes. We achieve an overall accuracy of 97.89% on semi-naturalistic data and 88.87% on naturalistic data which exceeded state-of-the-art learning algorithms namely, Linear Discriminant Analysis, Support Vector Machines, and k -means clustering with an average accuracy of 48.89%, 44.14% and 27.64%. Subsequently, a computational complexity analysis of the proposed model has been discussed with an eye towards hardware implementation. The clinical significance of this study is to accurately monitor the clinical progress of the rehabilitated subjects under the ambulatory settings.**

Index Terms— Convolutional Neural Network, Deep learning, Human Activity Recognition, Rehabilitation, Times-series Classification.

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I. INTRODUCTION

Stroke is a global public health issue, being the second leading cause of death worldwide, besides post-stroke outcomes such as disability affects the quality of life [1],[2]. Impairment of the upper limb is a common post-stroke episode, having a major impact on performing activities of daily living (ADL) [3]. Rehabilitation is an effective way to treat and promote motor recovery which helps in improving the ability of performing ADL among the stroke survivors. However, clinical rehabilitation of survivors is a long, inconvenient and expensive process, necessitating home/remote-based rehabilitation techniques [4], [5]. This requires the monitoring of the ADL performed by the patients’ rehabilitation to evaluate their progress. Development in wireless sensor network (WSN) technologies have facilitated remote monitoring through body-worn miniaturized sensors enabling objective assessment of rehabilitation progress, aiding clinical decision-making [6-8].

In this context, Human activity recognition (HAR) presents a solution towards continuous ADL monitoring for evaluating patient performance [9]. The principal objective of activity recognition is to identify human behavior in real time scenario to provide proactive assistance to users even outside the conventional clinical setting [10]. Moreover, monitoring of ADL, reduces burden of hospital stay and improves both recovery, and diagnosis and prognosis reliability which increases the patient’s quality of life and minimizes cost [11]. ADL monitoring helps to ascertain the degree of participation of rehabilitating patients, further acting as a rehabilitation indicator [12], [13]. Body-worn inertial sensors have the distinct advantage of being non-intrusive over camera-based vision sensors and hence have been the preferred modality in HAR applications. Accelerometers are the most widely used wearable technology for HAR since they usually lead to good

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results in recognition of physical activities, require relatively less energy and processing power and are insensitive to the environmental conditions [14], [15].

The most challenging task of HAR using sensor data in real time scenario is getting accurate and opportune information of people's activities and behaviors which is usually achieved by a good classifier. A range of classifiers such as K-Nearest Neighbor (KNN) [16-18], Decision Trees (DT), Multi-Layer Perceptron (MLP), support Vector Machine (SVM) [19-21], Naive Bayes classifier [22], Artificial Neural Networks (ANN) and Hidden Markov model (HMM) [23-25] have been applied for HAR using wearable sensors [26]. Majority of these state-of-the-art algorithms have been used in classifying a host of activities ranging from gross, dynamic movements including walking, running, gestures etc. However, these methods have relied on heuristic feature engineering (hand-crafted feature extraction, appropriate selection of features), which cannot find the discriminative features to accurately classify different human activities.

Deep neural network (DNN) represents a data driven approach where inference can be drawn directly from raw sensor data. DNN allows feature extraction directly from in-domain data, thus enabling the learning of task-adapted feature representations. In recent years, DNN has been widely used successfully across various fields such as speech recognition, computer vision, and natural language processing [27-30]. Convolutional Neural Network (CNN) is the most widely used DNN algorithm, characterized by an initial layer of convolutional filters (a set of weights which slide over the input), followed by non-linearity (activation function – rectified linear units), sub-sampling (pooling), and a fully connected layer which realizes the classification. CNNs often consist of stacked filters, activation, and pooling layers to enable the network to integrate the information from the different filters and various levels of abstraction. The stacking of multiple convolutional layers helps to achieve automatic feature extraction, where denser layers capture more complex or differentiating features. A *proof-of-concept* application of CNN for HAR using wrist accelerometer data, collected from healthy subjects and respective preliminary results reported in our earlier work [31], illustrating successful classification of the three fundamental forearm movements – (1) *Task A*: reach and retrieve (extension and flexion of the forearm), (2) *Task B*: lift arm (rotation of the forearm about the elbow) and (3) *Task C*: rotate arm (rotation of the wrist about long axis of forearm).

Being motivated by our initial results as reported in [31], in this paper, we further extend the concept to develop a deep learning framework with a personalized, light weight and low-complex, customized CNN model for classifying arm movements of stroke survivors in a “*semi-naturalistic*” and a “*naturalistic*” environment. The basic premise of this work is developing a data driven framework to classify fundamental arm movements performed with the paretic arm involved in ADL, using data from a minimal number of sensor, i.e. wrist-worn accelerometer. Enumeration of classified movements over a longitudinal scale could be used as an indicator of rehabilitation progress in neurodegenerative pathologies such

as stroke. Our proposed framework, *Rehab-Net* is successfully evaluated on a cohort of 4 stroke survivors participating in an archetypal activity of ‘*making-tea*’ comprising three fundamental movements in an inter-leaved manner (semi-naturalistic environment) and on 10 survivors left on their own to perform activities of their choice (*naturalistic* environment). We achieve an overall movement classification accuracy of 97.89% and 88.87% respectively in the two mentioned scenarios respectively, demonstrating the usefulness of CNN in inferring movement information from time-series data collected through pervasive means in an uncontrolled natural setting reflecting its use to monitor patient activity in remote monitoring setting.

Furthermore, it can be noted that the proposed *Rehab-Net* framework for identification of HAR also includes the stroke survivors, exhibiting moderate levels of tremor therefore the proposed *Rehab-Net* framework, could be extended for the use with the patients suffering from other neurodegenerative disorders (Parkinson's disease, multiple sclerosis, chronic kidney disease) that might demonstrate greater levels of tremor. This can not only help the clinicians to detect and quantify the tremor but also understand the link among different activities and tremor to analyze the cause of tremor [32]. The proposed *Rehab-Net* framework, therefore, can add further insights to the state-of-the-art based tremor identification in stroke survivors during rehabilitation and thereby can complement the existing methods.

The novelty of this work rests in developing deep learning framework with a personalized, light weight and low-complex, customized CNN model for HAR during ADL using a minimal number of inertial sensor data. The exploration further involves a detailed analysis on hyper parameter optimization, a key factor in CNN based formulation, leading to an optimal model for personalized evaluation on stroke survivors who were at varying stages of post-stroke rehabilitation, also exhibiting the moderate level of tremor. Furthermore, the efficacy of the proposed model was demonstrated in comparison with existing classification algorithms, *viz.* Linear Discriminant Analysis (LDA), Support Vector Machines (SVM) and *k*-means clustering. We further analyze the computational complexity of the developed framework and discuss ways to minimize the complexity making it amenable for implementing on resource-constrained wearable platform for real-time inference. The rest of the paper is organized as follows. Section II discusses about the motivation and background of this work, Section III describes the experimental protocol. The movement classification framework using the proposed CNN topology has been discussed in Section IV. The results, comparison with state-of-the-art models and complexity analysis have been mentioned in Section V, whereas Section VI concludes the paper.

II. BACKGROUND AND MOTIVATION

HAR using wearable sensors has been a popular research area with applications covering medical diagnosis, home monitoring, assisted living, sports and rehabilitation [33]. Inertial sensors have been commonly used, especially most of the research has focused on accelerometers for classifying

activities [34-35]. The study on HAR has been further aided by recently published surveys which provide a detailed account on activities being monitored, sensors, algorithm and performance [33-36]. Upper limb rehabilitation for survivors of neurodegenerative disease (e.g. stroke) has also received due attention in literature [37], [38], with [39-44] focusing on monitoring rehabilitation outcomes of stroke survivors during motor activities, using accelerometer attached to the arm and trunk. Machine learning algorithms, ranging from Random Forest, transfer wise learning, *k*-means clustering, incurring hand-crafted features and subsequent processing, have been employed in these studies.

To accelerate the generalization capability of such activity classification models/approaches and to achieve higher accuracy for ADL, recent work has focused on using DNN, which has been covered in detail in the review [30],[45]. CNN has come across as the most widely used DNN algorithm [46-48] owing to its strong discriminatory capabilities on time-series data. A CNN-based generalized framework was effectively demonstrated in our previous study [31] for classifying three upper limb movements of four healthy subjects, using tri-axial accelerometer on the wrist. This motivated us to explore CNN in conjunction with a fully connected layer for classifying three target tasks (*A*, *B* and *C*). The deep structure of CNN with multiple layers (convolution, rectifier, pooling, and fully connected) allows characterization of the salient features of the sensor signals, making it effective for activity classification.

TABLE I- ACTIVITY LIST FOR ‘MAKING-TEA’

Definition of Tasks		
A	Reach and retrieve (extension and flexion of the forearm)	
B	lift arm (rotation of the forearm about the elbow)	
C	Rotate arm (rotation of the wrist about long axis of forearm)	
Activity	Task	
1.	Fetch cup from desk	A
2.	Place cup on kitchen surface	A
3.	Fetch kettle	A
4.	Pour out extra water from kettle	C
5.	Put kettle onto charging point	A
6.	Reach out for the power switch on the wall	A
7.	Drink a glass of water while waiting for kettle to boil	B
8.	Reach out to switch off the kettle	A
9.	Pour hot water from the kettle in to cup	C
10.	Fetch milk from the shelf	A
11.	Pour milk into cup	C
12.	Put the bottle of milk back on shelf	A
13.	Fetch cup from kitchen surface	A
14.	Have a sip and taste the drink	B
15.	Have another sip while walking back to desk	B
16.	Unlock drawer	C
17.	Retrieve biscuits from drawer	A
18.	Eat a biscuit	B
19.	Lock drawer	C
20.	Have a drink	B

III. DATA ACQUISITION SYSTEM AND METHOD

The data for the algorithmic exploration were collected in

two situations from four and ten stroke survivors in consultation and supervision of expert clinicians.

A. Semi-naturalistic Dataset (D1):

Data were collected in a semi-naturalistic environment, from four stroke survivors (age range 45–73, both sexes, both left and right arm dominant, at various stages of rehabilitation) at the Brandenburg Klinik (BBK) in Berlin (Germany). Participants performed an archetypal activity of daily living, namely ‘making-tea’, comprising of 20 arm movements representing 10 repetitions of *Tasks A* and five each of *B* and *C* in an interleaved manner (cf. Table I).

Participants gave their kind consent for the experiments and were encouraged to perform the movements in a natural way without restricting physical factors such as height/distance/position of tables/chairs/working surface, with respect to the subject’s position, pace of performing the designated task. This was done to ensure a wide range of variability within the kinematic data aiding the development of a robust activity classification mechanism which would produce acceptable level of accuracy in real-world scenario. The data were collected for total 5 days from each stroke patient, wherein each day two repetitions of ‘making-tea’ were performed by each stroke survivors to ensure patient remain comfortable. Therefore, the semi-naturalistic dataset consists total 10 repetitions (2 repetitions/day), adding up to 200 arm movements (100 *Task A*, 50 each of *Task B* and *C*). Among these collected data, the preliminary studies [44] [51] have been reported by the coauthors using two repetitions of ‘making-tea’.

Shimmer 9DoF wireless kinematic sensor module was used as the sensing platform which contains mutually orthogonal tri-axial accelerometer, magnetometer, and gyroscope. For our experiments, only a tri-axial accelerometer (range ± 1.5 g) was used to collect from the impaired arm at a sampling rate of 50 Hz. The data pertaining to each task was segmented in accordance with annotations from a researcher accompanying the experiment.

B. Naturalistic Dataset (D2):

Data were collected from 10 chronic stroke survivors (age 61.4 ± 11.7 years old, both sexes, both left and right arm dominant, at various stages of rehabilitation) with varying degrees of severity of *Hemiplegia* at Ecole Polytechnique Federale de Lausanne. Each subject was requested to perform different arm movements during 2 hours of a weekday, within their home environment with exclusion of taking a shower or leaving the house. After the measurement period, participants gave feedback on the activities performed to have an estimated reference on the time spent in each activity. Data were collected using Physilog wearable sensor, comprising of tri-axial accelerometer, gyroscope and magnetometer, on the wrist/elbow of both arms as well as one on the sternum. For our analysis, we focus only on the tri-axial acceleration data (sampled at 200 Hz) collected from the wrist of the impaired arm for our analysis. Although collected in completely uncontrolled environment, participants were encouraged to use their upper limb to perform various daily motor activities.

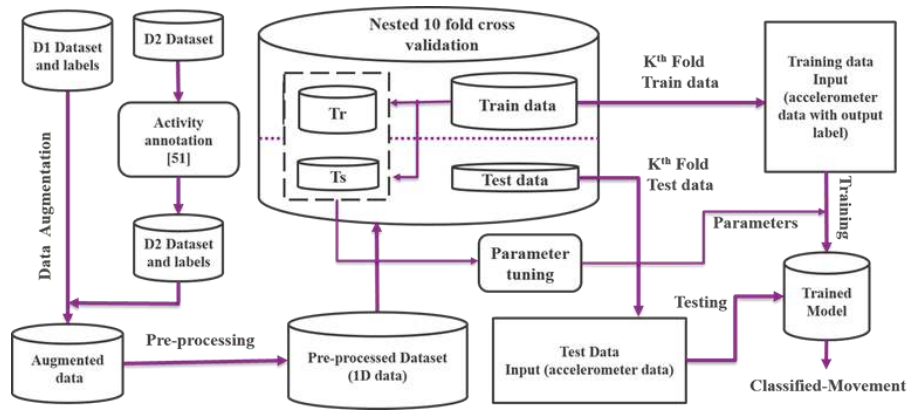


Fig. 1 Proposed Rehab-Net framework of upper limb movement recognition where Tr and Ts represent training and testing subset respectively.

TABLE II: ARCHITECTURAL AND TRAINING INFORMATION OF PROPOSED REHAB-NET (Where $D1$ and $D2$ are dataset of semi-naturalistic and natural environment respectively.)

Layer(type)	Output Shape		Total Parameters (Weights + biases)
	$D1$	$D2$	
Input layer	(64,1)	(256,1)	0
Conv1D_1 (9,1,20)	(56,20)	(248,20)	200
MaxPooling_1 (2,1)	(28,20)	(124,20)	0
Dropout_1 (0.5)	(28,20)	(124,20)	0
Conv1D_2 (9,1,20)	(20,20)	(116,20)	3620
Maxpooling_2 (2,1)	(10,20)	(58,20)	0
Dropout_2 (0.5)	(10,20)	(58,20)	0
Fully connected layer	200	1160	0
Output layer	3	4	603 ($D1$) 4644 ($D2$)

Since, these data were collected in an uncontrolled setting, the precise class labels for various human activities were not available for a supervised learning framework. This posed a challenge to translate the proposed supervised learning model from semi-naturalistic environment to a completely uncontrolled setting. However, similar problems were overcome recently by [49] [50] by applying certain algorithms to extract the class information. But in an attempt to do so, off course, the precision in the class information would be degraded. Nevertheless, since our first of its kind attempt here is to resolve a practically challenging problem in an uncontrolled setting in the context of stroke-survivors during rehabilitation process, following [49] [50], we also adopt movement recognition algorithm [51] in our proposed framework only for validation. This works by mapping six standard orientations of a tri-axial accelerometer to the three investigated arm movements (Tasks A , B , C and U). The algorithm was used in conjunction with 1024 data samples (approximately 5.12 seconds, a representative timeframe for completion of one of the interested Tasks), with an overlapping

window size of 50% to yield an annotation (A , B or C) for each window. The dataset is partitioned into training and testing set using the nested 10-fold cross validation. Since these data were collected in natural environment, it would also incur subjects performing a host of other movements therefore we focus on Unknown Task (U) along with Task A , B and C . Hence, the adopted CNN based activity recognition would focus on classifying 4 activities (including U) for $D2$ dataset.

IV. PROPOSED DEEP LEARNING FRAMEWORK

The proposed framework revolves around developing a personalized, light weight and low-complex, customized CNN model for recognizing elementary arm movements which constitute majority of upper limb activities performed in daily life using only a wrist-worn tri-axial accelerometer. The personalized framework helps to model the variability inherent within the data distribution of a given subject who is at various stages of their rehabilitation process. An overview of the proposed *Rehab-Net* framework for movement recognition is shown in Fig. 1 and presented in further detail.

A. Stage 1: Data Augmentation

Deep learning algorithm requires large amount of data to ensure better generalization capability as well as performance. Given the application area, it was difficult to collect data for long duration from stroke survivors, since they tend to tire out quickly which sometimes results in over fitting problem. Data augmentation is a preferred technique to build a powerful classifier with very less amount of data in deep learning [52]. A fundamental idea for using data augmentation is that the deformations/variance applied to the labeled data only changes the way of representation while keeping the semantic meaning of the labels same making the network more robust against real data which is unseen or untrained. Based on the approach described in one of the recent study [53], data augmentation is performed by adding the Gaussian noise to the raw data to create different possible variations of the input which may occur in real time scenario, resultant in 20x larger dataset size. This data augmentation technique can be expressed as-

$$S_v = S_o + w(\sigma, \mu) \quad (1)$$

Where, S_v is virtual data, S_o is the original input data and w is a weighting parameter that generates random numbers from the normal distribution with mean 0 and standard deviation 0.1.

B. Stage 2: Pre-processing

The main motivation behind this stage is to reduce the computational complexity for real-time execution which can be helpful to develop a low power, less area and less complexity architecture design for resource constrained applications. To meet the requirement of CNN model, all inputs must have the same length therefore each activity data is analyzed and fixed to 5.12s which is sufficient to capture the different arm movements of stroke survivors. Further, length of the input signal is compressed while preserving the useful information where down-sampling with scaling factor 4 is performed by averaging each set of four samples. Next, we have transformed the tri-axis signal into 1D signal shown in Fig. 2, followed by normalization step. Signal transformation is done through estimation of acceleration magnitude of three axis data as it always contains the significant information from all the axes [54] which can be expressed as-

$$A_R = \sqrt{(A_x)^2 + (A_y)^2 + (A_z)^2} \quad (2)$$

Where A_x, A_y and A_z are acceleration data in x, y and z direction. Moreover, this reduces the huge amount of computational which is detailed in section V-C.

C. Stage 2: Hyper-parameters tuning

Selection of optimally tuned hyper-parameters is a key towards neural network performance. These parameters can be divided into two types: architectural and training parameters. Architectural parameters involve selecting the number of layers, number of filters/kernels in each layer, size of each filter, stride rate and type of pooling which are paramount in model formulation. Training parameters include learning rate, type of back propagation algorithm, activation function, loss function, dropout and number of epochs, etc. In our study, to estimate the impact of training parameters on the performance of the model, a Grid search cross validation method using the GridSearchCV instance [55] has been employed. It works through multiple combinations of tuning the parameters, cross validates and determines the one which gives the best performance. Architectural parameters such as depth, filter size, filter length and pooling size are optimized using a heuristic grid search method where filter size from 3 to 11, filter length from 5 to 25 are considered for analysis which are detailed in Table III. Several experiments have been carried out to select the optimally tuned parameters for training and selecting the appropriate architecture where best configuration of these parameters are shown in Table II.

D. Stage 3: Proposed 'Rehab-Net' Model

The proposed network architecture comprises of two convolutional layers followed by ReLU activation function, two pooling layers, and one fully connected layer as shown in Fig. 3. The first convolutional layer formed by 20 unique 9×1 (stride 1) filters which are convolved with the input data, resulting in 20 feature maps. Each of these feature maps are then passed through the ReLU activation function to introduce non-linearity which are followed by Pooling Layer 1 that does 2×1 max pooling separately over all the 20 rectified feature maps.

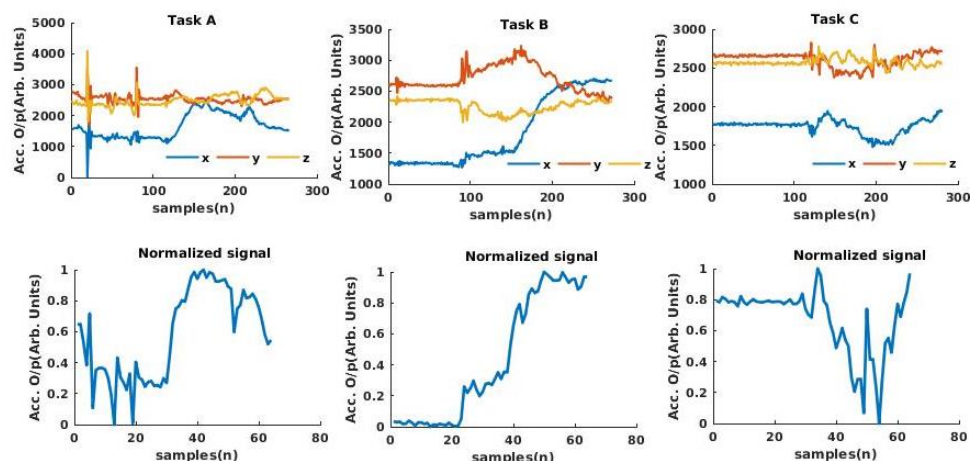


Fig. 2: Transformation of Tri-axis accelerometer signal into 1D signal

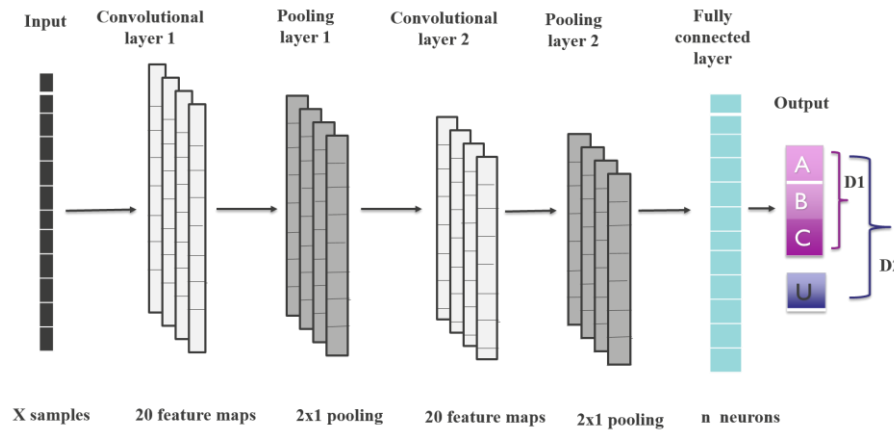


Fig. 3 Proposed Model Architecture (where X is no. of samples 64 (D1) and 256 (D2) and n is no. of neurons in the fully connected layer which are 200 and 1160 for D1 and D2 dataset respectively).

This progressively reduces the spatial size of each rectified feature map and allows a form of translation invariance, besides controlling over-fitting and reducing computation. Similar to the first convolutional and pooling layer, same process is repeated for second convolutional and pooling layer without any changes in the parameters. The output of Pooling Layer 2 is flattened which acts as an input to the Fully Connected Layer. Finally, the output of fully connected layer is passed to the softmax activation function to classify the particular task. The full architecture can be simplified by $C(20,9,1)-R-P(2,1)-C(20,9,1)-R-P(2,1)-FC(n)$ where $C(N,k,s)$ indicates convolutional layer with N kernels of spatial size $k \times l$, applied to the input with stride s , R is rectified unit, P is pooling layer and $FC(n)$ is a fully connected layer with n neurons where n is 200 and 1160 for dataset D1 and D2 respectively.

The proposed model is trained on the data of each subject with a dropout probability of 0.5 to drops out a random set of activations in particular layer with 50% probability. This assured the network is not getting too ‘fitted’ to the training data and thus helps to alleviate the over-fitting problem. Sparse categorical cross-entropy loss function and ‘Adam optimizer’ [56] is used to update the weights faster than the popularly used stochastic gradient descent (SGD). Training was done with maximum of 100 epochs and mini-batch size of 15. After each epoch of training, model performance is evaluated on testing set and early stopping criteria is set to halt the training process when there is no decrement in training error during the 100 epochs. The best model having lowest error on testing set is saved for real-time evaluation.

V. RESULTS AND DISCUSSION

Experiments are conducted to get an efficient and computationally less-complex model, suitable for embedded platform. The proposed model was evaluated on D1 and D2 dataset and the results have been analyzed in this section.

The proposed model has been implemented in Keras 2.0.5 [57] using Theano 0.9.0 as a backend engine, running on a workstation with a 64 bit Ubuntu operating system, an Intel(R) Xeon (R) CPU E5-1607 v3 @ 3.10 GHz, 24 GB RAM and

trained and tested utilizing the Nvidia GTX 1080 GPU having 4GB dedicated memory.

A. Evaluation criteria

In our study, we have used nested 10-fold cross validation for evaluating the proposed *Rehab-Net* performance. Further, these results are averaged to compute the optimum test performance of the *Rehab-Net* model. Accuracy, precision, recall, F1-score and ROC curve, are the effective metrics for imbalance class distribution therefore, included to validate the robustness of the proposed model which can be defined as-

- Accuracy*- ratio of correctly predicted observation to the total observations.
- Precision*- ratio of correctly predicted positive observations to the total predicted positive observations.
- Recall*- ratio of correctly predicted positive observations to the all observations in actual class.
- F1 Score*- weighted average of precision and recall.
- ROC curve* - A Receiver Operating Characteristic (ROC) curve illustrates the true positive rate (sensitivity) against the false positive rate for the different threshold points.

B. Performance assessment

In the first evaluation, experiments are done to select the optimum training parameters which are explained in previous section (Section IV-B). For initialization, 2 convolutional layers, 10 filters with size 7×1 are fixed and then experiments are performed separately for different depths, filters length and filter size by keeping the other parameters constant. The second evaluation is performed for selection of architectural parameters where depths (1,2,3) filter sizes (3,5,7,9,11) and filter length (5,10,15,20,25) are included for the analysis. This was done using the nested 10 fold validation wherein parameters with less variance in the performance selected for further evaluation of the proposed *Rehab-Net* model. Table III shows the averaged model performance of different architectural parameters. It can be seen that there is a steady increment in the classification accuracy on both the datasets with increment in filter size and filter length as shown in Table

III. However, performance increment for filter length 20 to 25 and filter size 9 to 11 is very little therefore, filter length 20 and filter size 9 are chosen as optimum parameters as they exhibit less complexity compared to filter length 25 and filter size 11. Furthermore, we have found that adding an extra convolutional layer, results in a decrease in accuracy from depth 2 to 3. This shows that as more layers are added, more complex features are indeed extracted, wherein sometimes some features may be irrelevant providing no useful information for classification, results in degradation in performance. Based on the first evaluation, depth 2, filter size 9 and filter length 20 are chosen as optimum parameters which are highlighted in bold face in Table III.

TABLE III. PERFORMANCE ANALYSIS OF DIFFERENT ARCHITECTURAL PARAMETERS

Parameters	No.	Classification Accuracy	
		<i>D1</i>	<i>D2</i>
	1	80.97	76.32
Depth (convolutional layers)	2	84.56	83.25
	3	78.91	82.34
Filter length (Number of filters)	5	75.24	82.05
	10	84.56	83.25
	15	91.66	85.93
	20	96.78	86.64
25	96.89	86.83	
Filter size (size of each filter)	3	81.09	80.71
	5	83.27	82.9
	7	84.56	83.25
	9	88.01	86.11
	11	89.53	86.53

Similar exhaustive exploration was also done with the pooling size where 2*1 provided the best performance in conjunction with the demonstrated architecture. After the parameters tuning, the proposed model is trained and tested again using the optimum selected parameters with 50% dropout probability and reported the results to make sure that information is not leaked to the model. This provided the average performance of 97.89% and 88.87% accuracy for *D1* and *D2* respectively for our investigated problem.

The classification results for each subject of *D1* (semi-naturalistic) and *D2* (natural environment) datasets are presented in Table IV and V respectively with the average performance over all the subjects highlighted in bold face. It can be observed that *D2* is having less accuracy than *D1* due to the facts of evaluation in an uncontrolled setting or/and performance of activity annotation algorithm (mislabeling). Subsequently, ROC curves are plotted to visualize the classification ability of the proposed model as shown in Fig. 5.

C. Impact of Preprocessing

The proposed *Rehab-Net* model is optimized in algorithmic level to reduce the memory and computation cost which involved down-sampling followed by conversion of Tri-axis signal into 1D signal. To understand the influence of these two steps on the performance of the model, comparative analysis is done for 1D and 3D input representing processed input and Tri-axis input respectively.

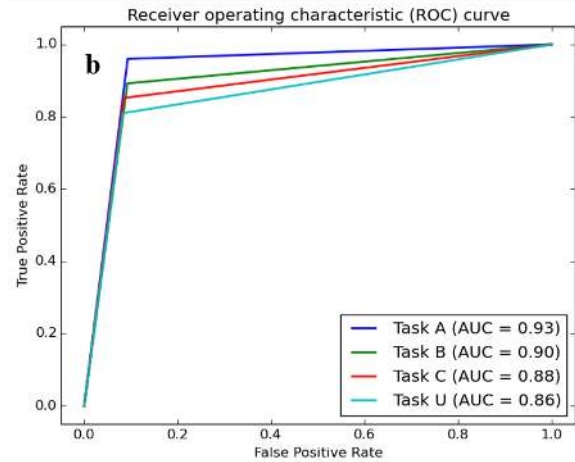
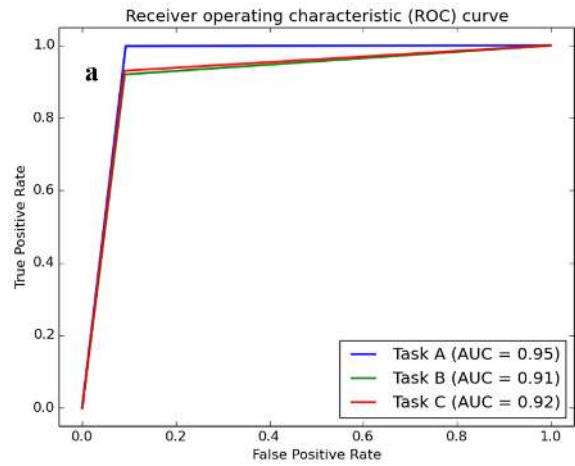


Fig. 5 (a) and (b) represent the ROC curves of dataset *D1* and *D2* respectively.

It is found that with a trade-off of 0.9% accuracy, complexity reduction of approximately $3 \times \left(\frac{O_v^T}{O_v^1} \right)$ times can be achieved where O_v^T and O_v^1 represent output feature map size of 3D and 1D input respectively.

TABLE IV. PERFORMANCE ANALYSIS ON DATASET *D1*

Subjects	Accuracy	Precision	Recall	F1-score
S1	95.42	95.23	94.92	95.18
S2	98.89	99.82	99.68	99.52
S3	98.34	97.52	98.75	98.24
S4	98.91	99.46	99.8	99.27
Average	97.89	98.01	98.29	98.05

TABLE V. PERFORMANCE ANALYSIS ON DATASET *D2*

Subjects	Accuracy	Precision	Recall	F1-score
S1	90.11	92.82	93.01	93.24
S2	87.56	87.52	87.13	86.93
S3	84.32	83.1	82.99	82.56
S4	90.85	91.11	91.23	91.33
S5	92.41	92.98	91.19	92.72
S6	86.92	87.12	85.27	86.25
S7	83.73	88.17	87.81	87.01
S8	91.25	91.23	91.25	91.51
S9	91.31	95.09	94.38	95.33
S10	90.23	89.94	88.56	90.05
Average	88.87	89.91	89.28	89.69

TABLE VI. COMPARISON OF PROPOSED REHAB-NET MODEL WITH EXISTING MODELS USING DATASET D1

Method	Features	Sub.	Sensitivities (%)			Average Acc.
			A	B	C	
LDA [44]	19	S1	35	100	40	52
	19	S2	15	0	100	32
	21	S3	60	100	20	60
	8	S4	95	0	20	52
SVM [44]	19	S1	50	95	0	48
	19	S2	80	5	80	61
	21	S3	45	95	10	49
	8	S4	65	95	5	57
k-means [44]	19	S1	80	90	100	88
	19	S2	90	20	100	75
	21	S3	95	100	20	78
	8	S4	10	80	60	40
Proposed Model	-	S1	96.06	98.22	90.47	95.42
	-	S2	99.41	99.69	99.93	98.89
	-	S3	97.58	99.28	99.39	98.34
	-	S4	99.82	99.88	99.69	98.91

D. Comparison with State-of-the-Art models-

To evaluate the performance of the *Rehab-Net*, comparative study is conducted with other state-of-the-art models which have used the same dataset. Time domain feature extraction, optimal feature selection and classification using LDA, SVM, and *k*-means were employed on the ‘*making-tea*’ data (two repetitions for each of the four subjects) in earlier study [44], which accounted in best average accuracies of 49%, 54% and 70% respectively. However, in all the above study [44], data collected in a completely controlled environment (resembling exercises performed in a controlled clinical setting) and was tested on the ‘*making-tea*’ data. In the present study, we chose to train and test both using the semi-naturalistic ‘*making-tea*’ data (using 10 repetitions instead of only 2 repetitions as in [44]) as we feel this represents a more objective reflection of a classifier being trained and tested on data with inherent variability. Hence, a direct comparison although not fair, would however present the advantage of our proposed approach which does not employ feature engineering. It can be seen from Table VI that our method outperformed with an average of 48.89%, 44.14% and 27.64 % improvement against LDA, SVM, and *k*-means using the same dataset (*D1*). For naturalistic dataset, same features used in [44] are extracted and performance is analyzed using app of MATLAB R2016a toolbox for SVM and LDA. It should also be emphasized that our model achieved the average 88.87% performance for *D2* (natural conditions) beating the LDA, SVM and *k*-means by 26.17%, 19.57% and 15.7% respectively as shown in Fig. 6, indicating our method was not biased by favoring the Task A, over Task B and C. These results are favorable with comparison to existing methods, as we have eliminated feature extraction as well as the complexity involved in 3D input while achieving the better performance. This made the process more amenable for resource constrained platform such as embedded and mobile devices.

E. Computational complexity analysis

The computational complexity of *Rehab-Net* is analyzed

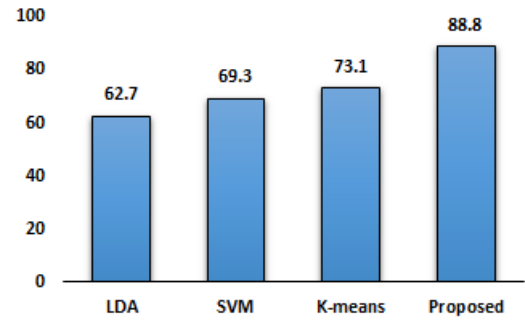


Fig. 6 Comparative analysis of naturalistic dataset

with an aim towards real-time implementation, focusing on the most compute- intensive part of CNN i.e. convolutional layer. This layer contains approximately 90% computation of the model which essentially involves power hungry multiply-accumulate units. Therefore, estimation of complexity is done based on resources involved in computation of convolutional layers - convolution of input feature maps with kernels which can be illustrated as follows.

Let's consider in the j^{th} convolutional layer, N kernels of size $K_v = K^r \times K^c$ are getting convolved with D input feature maps of size $I_v = I^r \times I^c$ using the stride rate of s which results in N output feature maps of size $O_v = O^r \times O^c$ then the estimation of total number of multiplier (M_j) and adder (A_j) operations involved in that layer can be represented as-

$$M_j = [(O_v \times K_v) \times D] \times N \quad (3)$$

$$A_j = [\{O_v \times (K_v - 1)\} \times D] \times N \quad (4)$$

This represents the total multiplier and adder operations involved in the j^{th} convolutional layer. However, the resource utilization for implementation of any architecture depends on the type of data processing strategy. Here, there can be four data processing strategies for processing among kernels and stride in each kernel which are as follows.

1) Serial stride and serial kernel

All the N kernels work one after other wherein convolution of kernel with each stride of input happens in serial manner. This requires resource utilization equal to one kernel in the j^{th} convolutional layer.

2) Serial stride and parallel kernel

In this case, convolution of kernel with each stride of input is processing serially whereas kernels used in the j^{th} convolutional layer work parallel to each other. Therefore, resource utilization is N times of strategy 1.

3) Parallel stride and serial kernel-

This case illustrates the parallel computation of all the strides of an input whereas all the kernels of the convolutional layer work serially therefore, total resource utilization can be estimated based on resources involved in computation of all strides of an input.

4) Parallel stride and parallel kernel

In this case, all the kernels of a convolutional layer as well as computation of all the strides of an input are processed parallel to each other requiring resource utilization equal to

number of multipliers and adders operations involved in computation of convolution of j^{th} convolutional layer.

It is feasible to select parallel processing of kernel for convolution neural network due to the fact that next convolutional layer requires all the feature maps to start the computation. Among these, strategy 2 and 4 involving parallel processing of kernels whereas strategy 4 requires higher resources. Therefore, we have selected strategy 2 for further analysis of our proposed model. For data processing of serial stride and parallel kernel in both the architectures of $D1$ and $D2$, required the same amount of resources, however time consumption is different as shown in Table VII. Further, we have also analyzed the actual run-time complexity of our proposed model wherein $D1$ and $D2$ dataset took approximately 255 and 980 microseconds/step for classifying the arm movements. .

The proposed model involved approximately $K_v \times N \times D = 180$ (conv1) and 3600 (conv2) multiplier units and $(K_v - 1) \times N \times D = 160$ (conv1) and 3200 (conv2) adder units where D is 1 for convolutional layer 1 and 20 for convolutional layer 2. These power-hungry MAC units can be easily eliminated using the modified distributed arithmetic (MDA) based methodology which helps to formulate a low-complexity, multiplier-less design, aiding energy efficiency [58]. It is a bit-serial computational operation of multiply and accumulate which transforms MAC operations by a series of LUT access and summations as additions, therefore requires computation time depending on the bit length of the input sequence to produce the output. The recent advancement in architecture development along with the memory efficient methodology hold promise for real-time execution on resource constrained wearable devices [58-59].

TABLE VII: HARDWARE COMPLEXITY ANALYSIS
(Where C is no. of clock cycles required for one stride)

Layer	Multiplier units	Adders	Time (Clock Cycles)	
			D1	D2
Convolutional layer 1	180	160	56C	248C
Convolutional layer 2	3600	3200	20C	116C
Total	3780	3740	76C	364C

F. Discussion

In this work, we have proposed a deep learning framework to recognize the fundamental arm movements of stroke survivors in ambulatory setting. The movements were selected in consultation with clinicians, constituting majority upper limb movements performed in daily living, besides resembling a subset of wolf motor function test (WMFT) activities, an established clinical test battery for stroke rehabilitation. A key feature in such remote monitoring systems is the need for adaptation to change in movement patterns specific to each subject with respect to their rehabilitation. Hence, we train and evaluate the proposed Rehab-Net framework in a personalized manner, catering towards inter-subject and intra-subject variability inherent within rehabilitating movement profiles. A series of studies conducted by Gebruers [60] and Uswatte [40]

have proven the reliability and validity of accelerometer data with clinical measures and provided significant evidence to be considered as a clinical predictor of recovery in measuring the upper-limb activity in stroke. Therefore, in this study an accelerometer sensor is used as it contains the clinically interpretive features about rehabilitation tasks. Enumerating occurrences of specific arm movements performed in daily life, over a longitudinal scale, could provide an indication on the degree of usage of the impaired arm and thereby act as a measure of rehabilitation progress, helping to perform a clinical profiling of the individual subject with respect to their movement quality.

Furthermore, the applicability of deep learning framework in measurement of upper limb movements in stroke survivors, is motivated by the success of deep learning in various clinical studies reported for Alzheimer diagnosis, retinopathy and skin cancer detection, congestive heart failure and osteoarthritis risk prediction, breast nodules and lesions prediction, health monitoring, freezing of gait detection in Parkinson disease, etc. [61]. This increasing usability of deep learning in clinical applications is due to hierarchical structure which provides end-to-end learning of data. Thus, it enables high level features extractions which helps in understanding, discovering and detecting the hidden information from the data about their clinical patterns. Moreover, deep learning provides the better generalization capability than the traditional methods which is also verified in our study in terms of accuracy, precision, recall, F-score and also with ROC curve, one of the important metric used in clinical studies. The performance of Rehab-Net is also cross-validated with the defined label information by the clinicians and researchers. The high performance of deep learning models in clinical studies showing a way toward developing the new generation predictive systems to solve health related problems in real-world.

One of the main primary challenges for developing the framework with deep learning algorithm is over-fitting, limiting the use of models for real-time deployment. To mitigate this, in our study we have taken the following measures: a) generation of virtual data using the widely used technique in machine learning i.e. data augmentation, incorporating possible variations in the training set, b) employed a personalized training-validation strategy, wherein the proposed Rehab-Net framework is trained and validated on each subject's data thereby catering for subject-specific variations in arm dexterity (at various stages of their rehabilitation), c) used a dropout probability of 0.5 which drops out a random set of activations in a particular layer with 50% probability, ensuring generalization capability of the proposed Rehab-Net.

Since the wearable's sensor are deployed in highly dynamic and uncontrolled environment, this degrades the performance of the neural models in real time due to training in controlled environment. Nevertheless, proposing the model and applying in naturalistic environment is also challenging. However, the practical problem of HAR under the rehabilitation setup for the stroke survivors demands an engineering solution to be incorporated in the uncontrolled setting (naturalistic scenario). This tradeoff between the need of having an engineering solution and unavailability of the ground truth under the uncontrolled setting motivated us to translate the proposed supervised learning model from the semi-naturalistic

environment to a completely uncontrolled conditions where the ground truths are not available. Similar problems were overcome recently by [49] [50] by applying certain algorithms to extract the class information, however, trading-off precision in class information. Nevertheless, since our first of its kind attempt here is to resolve a practically challenging problem in an uncontrolled setting in the context of stroke-survivors during rehabilitation process, following [49] [50], we have adopted the movement recognition algorithm [51] in our proposed framework only for validation. The performance analysis on naturalistic environment achieved the average 88.87% performance beating the LDA and SVM by 26.17% and 19.57% respectively which validates the usability of proposed framework in real time settings.

The real time execution of deep learning model on resource constrained platform is another challenge. Therefore, hyper-parameterization is used to select the best model with optimum parameters. Further, to reduce the complexity and computational cost associated with 3D accelerometer data without sacrificing the performance, we have pre-processed data in such a way that reduced computational cost approximately by 3x with negligible loss in performance, making Rehab-Net efficient for implementation on mobile and embedded platforms.

This study is a step towards developing an IoT based solution to assist stroke survivors in tracking their rehabilitation progress in ambulatory settings. To include the proposed system into rehabilitation procedures and protocols, we plan to introduce wearable device as a monitoring system for rehabilitation process, having embedded accelerometer sensor integrated with Rehab-Net for decision making related to ADL activities. This will provide an energy efficient system due to integration of decision making algorithm on sensor node itself, eliminating energy expenditure incurred in data transfer. Later, the information can be sent to the server accessible by clinicians and subject's mobile phone to interpret the progress remotely. Here, we have aimed at detecting arm movements in ambulatory settings to track the progress of stroke survivors during rehabilitation as a case study, however the proposed framework can be suitably used in monitoring elderly people, critical event monitoring such as fall detection or in sports medicine and other health monitoring applications. There are number of advantages of proposed framework which indicate the usability of proposed system for practical cases as follows: 1) An inertial sensor (accelerometer) based solution as opposed to vision based monitoring making the most convenient solution for users for real-time monitoring; 2) Automatic feature extraction from data using deep learning is providing cost effective solution and also reduces the latency which makes the system very responsive; 3) Preprocessing helps to reduce the complexity, making memory and energy efficient solution for implementation on resource constrained platforms; 4) Personalized validation helping to track inter-subject and intra-subject variability inherent within rehabilitating movement profiles; 5) Validation on naturalistic dataset is providing performance analysis in real time settings.

VI. CONCLUSION

This paper presents a deep learning framework *Rehab-Net*

for effectively classifying the three upper limb movements, involving extension, flexion and rotation of the forearm during ADL without using any feature engineering. The proposed personalized, light weight and low-complex, customized CNN model, *Rehab-Net* was able to perform automatic feature extraction on pre-processed acceleration data (collected from the wrist) and classify the three movements from stroke survivors under semi-naturalistic and naturalistic conditions. In conclusion, our proposed framework, *Rehab-Net* achieved overall 97.89% and 88.87% accuracy when evaluated in the two situations, reporting an overall better performance compared to state-of-the-art models. In future, we plan to extend our work further by including the followings: validation of the proposed methodology with data collected for more subjects and diverse types of ADL activities in real time settings, investigate the different traditional machine learning methods and their comparative analysis for all collected data, development of accurate and automatic data annotation algorithm, real-time implementation of the *Rehab-Net*, focusing on an energy efficient implementation of the inference mode on resource constrained platforms.

ACKNOWLEDGMENT

Madhuri Panwar research was supported by Visvesvaraya PhD Scheme for Electronics & IT by the Ministry of Electronics and Information Technology (MeitY). Amit Acharyya acknowledges his Visvesvaraya Young Faculty Research Fellowship from MeitY. This work was partially supported by the Early Career Research Grant from the Science and Engineering Research Board, Government of India, under Grant ECR/2015/000148dated 14th July, 2016.

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