EMGHandNet: A Hybrid CNN and Bi-LSTM Architecture for Hand Activity Classification using Surface EMG Signals

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Abstract

Recently, Convolutional Neural Networks (CNNs) have been used for the classification of hand activities from surface Electromyography (sEMG) signals. However, sEMG signal has spatial sparsity due to position of electrodes on hand muscle and temporal dependency due to performance of activity over a period of time. The CNN has the ability to extract spatial features and is limited in extracting temporal dependencies. Whereas, the Long Short-Term Memory (LSTM) aims to encode the temporal relations from sequential data. Hence, in this paper, we propose a hybrid CNN and Bidirectional LSTM (Bi-LSTM) based EMGHandNet architecture to encode the inter-channel and temporal dependencies of sEMG signals for hand activity classification. First, the CNN layers are used to extract deep features from sEMG signals, then these feature maps are processed by the Bi-LSTM to extract the sequential information in both the forward and backward directions. Thus, the proposed model learns both inter-channel and bidirectional temporal information in an end-to-end manner. The proposed model is trained

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and tested on five benchmark datasets, including the NinaPro DB1, NinaPro DB2, NinaPro DB4, BioPatRec DB2 and UCI Gesture. The average classification accuracies for the NinaPro DB1, NinaPro DB2, NinaPro DB4 and UCI Gesture are 95.77%, 95.9%, 91.65%, and 98.33% respectively. They correspond to an improvement of 4.42%, 12.2%, 18.65% and 1.33% over the respective state-of-the-art models. Moreover, for the BioPatRec DB2 dataset, a comparable performance (91.29%) is observed. The experimental results and comparisons confirm the superiority of the proposed model for hand activity classification from the sEMG signals.

Keywords: CNN, Bidirectional LSTM, Deep Learning, Hand Activity Classification, sEMG Signal, exoskeleton control

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1. Introduction

Muscle computer interaction (MCI) is widely used in prostheses [1], robotic control [2], sign language recognition (SLR) systems [3] and human-machine interaction (HMI) [4]. The hand activity classification is a central problem in the MCI technology and it includes analyses of categories such as hand gestures, object grasping and hand movements [5]. The gesture classification is used in many application areas such as computer games, virtual reality, and robot assisted surgeries [6]. A robot assisted surgery requires precise specification of the posture of robotic hand with respect to a patient's body as well as requisite movements to be performed.

The human gestures can be identified directly by classifying gesture images [7] or indirectly through the corresponding surface Electromyography (sEMG) signals [8]. The latter approach has shown immense potential for developing control systems for the exoskeletons and prosthetic devices. The sEMG signal classification can be used to decode the intended motion to control the robotic arm [9]. Specifically, the force, torque and the direction that characterize the intended hand movements have to be decoded by the system [10]. The mapping between the hand movement and the corresponding force was studied in [11] using the ANN and LSTM architectures.

Classification of hand position during object grasping has direct applications in controlling robot arms for pick and place tasks [12, 13]. Similarly, hand movement classification can provide improved degrees of freedom to the exoskeleton arm [14]. The focus of this paper is classification of hand activities using sEMG signals with the pattern recognition methods. The classification of sEMG signals

is traditionally carried out by the machine learning (ML) algorithms and recently with the deep learning (DL) based approaches. A short review of these methods follows.

1.1. Machine Learning Based Approaches

In machine learning techniques, the classification of sEMG signals requires extraction of features, such as the time domain features [15], the frequency domain features [16] and the time-frequency domain features [15]. Shenoy *et al.* [17] classified 8 hand movements with the linear Support Vector Machine (SVM) using the Root Mean Square (RMS) as a feature and was able to control a robotic arm with four degrees of freedom. In Altimemy *et al.* [18], a classification of 15 hand movements for persons with intact-limbs and 12 hand movements for amputees is performed with the Linear Discriminant Analysis (LDA) and the SVM based on the Auto Regressive (AR) features. Shi *et al.* [19] have used features including the Mean Absolute Value (MAV), the Zero Crossing (ZC), the Slope Sign Change (SSC), and the Waveform Length (WL) for hand posture classification with the K-Nearest Neighbor (KNN) classifier to control a bionic hand. In [20], Waris *et al.* classified gesture data extracted through the surface as well as intramuscular EMG signals over a period of seven days and showed that the performance has improved over time with the Artificial Neural Network (ANN) classifier compared to the classical KNN and the SVM classifiers. Tuncer *et al.* [21] extracted the ternary features from the raw sEMG signals. The statistical moments have been used as a feature for the classification with the KNN and the cubic SVM classifiers. Recently, Fatimah *et al.* [22] have decomposed the sEMG signals into Fourier intrinsic band functions (FIBFs) and extracted statistical features for classification with the SVM and the KNN classifiers. The hand gesture identification can be enhanced by capturing the depth information using a leap motion device that improves the relabelling of gestures in training phase[14]. In [23], energy based features were used with the fine KNN for classification of hand gestures based on the sEMG signals. A key limitation of the machine learning approaches is a need for manual design of relevant feature sets for the said problem, which is a very tedious task and may not be sufficiently accurate. Another drawback is the challenge of selection of an optimal classifier for the chosen features.

1.2. Deep Learning Based Approaches

For the sEMG signal classification, though machine learning approaches have reported decent performance, however, in the recent literature, the deep learning

approaches have become popular. It is because they automatically learn the important features [24] and tend to provide an improved performance. Hence with the application of deep learning techniques for the sEMG classification, the control mechanism of exoskeletons can be significantly improved. In this section, we review the recent deep learning techniques for classification of the sEMG signals.

1.2.1. CNN Approaches

In [25], Atzori *et al.* performed the sEMG classification task over NinaPro DB1, NinaPro DB2 and NinaPro DB3 datasets with a deep Convolutional Neural Network (CNN) architecture consisting of two convolutional layers. The authors have shown a performance improvement of 2-5% compared to the existing machine learning classifiers such as the KNN, SVM, Random Forests and the LDA [26]. Among the 2D approaches, Geng *et al.* [27] considered each sample of dimension 1×10 (here, 10 refers to no. of channels) as an instantaneous image and provided as an input to the CNN model and showed that there are patterns within instantaneous image which are similar across samples of the same trial and discriminative across different trials.

Wei *et al.* [28] had split each segment of the data samples into patches of images and processed with a parallel multi-stream CNN architecture and provided patch wise analysis of images. The state of the art accuracies were achieved but the computational complexity is $10-20\%$ higher than the other state of the art architectures. In [29], an evolutionary algorithm is developed which generates the CNN topology to identify the right number of CNN layers, the number of kernels and the kernel size. In [30], deep learning architectures employing three different input modalities such as the raw EMG, the Spectrogram and the Continuous Wavelet Transform (CWT) are analysed with the help of a transfer learning technique. Qi *et al.* [31] used 3D CNN to classify the composite hand motions associated with digit writing. In [32], Betthauser *et al.* have implemented an EMG prediction model with temporal convolutional networks and shown that the sequential prediction of movements is better compared to the frame-wise prediction. In [33], a single channel is randomly selected from the multi-channel data achieving a classification accuracy close to 95% for a subset of NinaPro DB2. From this analysis, It is inferred that sEMG signals can also be classified with only a single channel of data which is very efficient for low memory devices.

1.2.2. RNN Approaches

The recurrent neural network (RNN) is a variation of the neural network which works for sequential and temporal data. In [34], Koch *et al.* have used a Con-

vLSTM cascaded with the LSTM architecture for hand gesture sequence classification. In [35], a two stage network consisting of a fully connected network followed by a stacked RNN is implemented to classify the high density (HD) and sparse sEMG signals. Hu *et al.* [36] developed an attention based CNN-RNN architecture which is able to classify the sEMG images. In [37], a LSTM model is compared with a deep back-propagation (BP) LSTM by using the waveform based classification. In [38], a hybrid CNN-LSTM architecture named as the Long-term Recurrent Convolutional Networks (LRCNs) is used for the task of activity recognition and image and video description. Motivated by this work, Bao *et al.* [39] and Chen *et al.* [40] proposed another CNN-LSTM architecture. Specifically, [39], Bao *et al.* used this joint architecture to estimate wrist angles corresponding to four movements collected from six healthy subjects. Chen *et al.* [40] used hybrid CNN and LSTM architecture for gesture classification through a HD-sEMG dataset using the transfer learning approach. Note that the authors in [40] have only utilised the LSTM for target datasets.

1.3. Motivation for Hybrid Architecture

From the literature, it is observed that the CNN architectures has a capability to understand the spatial features of the human hand activity and the LSTM architectures can capture the temporal information. Moreover, the Bi-LSTM improves over the uni-directional LSTM through learning the forward and the backward inter-relations between the activities and the input sEMG signals. Thus, in this paper, a hybrid CNN and Bi-LSTM framework is proposed to learn both the spatial and bi-directional temporal relations. Our approach differs from existing architectures and methods as follows. The focus is on classification of hand activities with the CNN and Bi-LSTM in contrast to estimation of angles in [39]. The Bi-LSTM based architecture is included in each of the experiments in contrast to [40]. A flattening of activation maps is performed before the Bi-LSTM unit that is in contrast with the architecture in [40] where the dense layers are inserted in between the CNN and LSTM layers which may lead to loss of temporal information. Another difference is in consideration of inputs, specifically window overlap is not considered in contrast to many existing works [28, 29, 36].

1.4. Objectives

The main purpose of this study is to classify human hand activities based on the sEMG signals. The specific objective of this study is to identify the following characteristics of the deep learning model to achieve optimal classification performance: (1) a proper shape of the input data provided to the model, (2) the

number of conv layers and/or the number of LSTM layers, (3) a proper set of hyper parameters for the model and (4) appropriate preprocessing techniques for the sEMG signals.

1.5. Contributions

The main contributions of this work are :

1. A hybrid CNN and Bi-LSTM based EMGHandNet architecture is successfully demonstrated for classification of human hand activities using the sEMG signals.
2. The proposed method exploits the learning of the inter-channel and the temporal features using the 1-D convolutional layers and the Bi-LSTM layers respectively. Specifically, the spatial and short-term temporal relations are encoded by the convolutional layers and the long-term temporal relation are learned by the Bi-LSTM layers.
3. We have performed rigorous experiments on five benchmark sEMG datasets for the classification of hand movements from the sEMG signals. We have also analyzed the impact of the proposed method from different perspectives and compared the performance against that of the recent deep Learning methods.

The rest of this paper is organized as follows: Section II contains the preliminaries required; Section III presents the proposed methodology; Section IV gives details about the experimental setup; Section V demonstrates the experimental results; and Section VI provides a conclusion along with the future scope.

2. Preliminaries

In this section, the basic working of the CNN and the LSTM are illustrated.

2.1. Convolutional Neural Networks (CNN)

The CNNs are commonly used for the feature extraction from images [41]. A CNN consists of the convolution, the activation and the pooling layers. In the convolution (conv) layer, the input is convolved with the filter weights. The number of rows in the kernel is the kernel size and the number of columns in the kernel corresponds to the number of channels in the input data for the first conv layer. For the rest of the conv layers it is the number of filters. An illustration of 1-D convolution is shown in Fig. 1. Consider an input sEMG signal with a two channel data as shown in Fig. 1, the kernel is a two dimensional two column filter

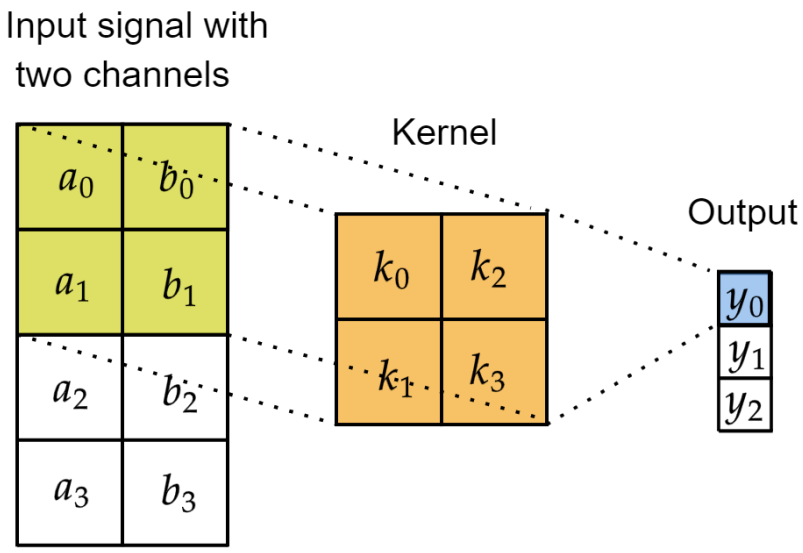


Figure 1: Illustration of 1-D convolution using an example having two channels.

(since the number of channels are two in this example) and the first convolution output is calculated as $\mathbf{y}_0 = a_0 \times k_0 + a_1 \times k_1 + b_0 \times k_2 + b_1 \times k_3$. The remaining outputs are calculated by sliding the kernel in the vertical direction (time stamp direction). Thus, we get a single vector from each filter. The output vectors from each of the filters are concatenated column wise to obtain a 2D feature map which is further processed by the consecutive conv layers. The conv layers are stacked until the abstract features of the signals are obtained. In the activation layer, the input is transformed by a non-linear function such as the $\tanh(\cdot)$ or the ReLU function. The pooling layer reduces the dimensionality of the feature map. The max-pooling is used for selecting prominent features from the feature map. Finally, the output is converted to probability values (classification score) by using the softmax function.

2.2. Long Short-Term Memory (LSTM)

The recurrent neural networks (RNNs) are a type of neural networks capable of analysing sequence of data in which a prediction is dependent on previously computed values. It is commonly used to analyze text, speech and DNA sequence datasets, where any current information is dependent on the preceding time steps.

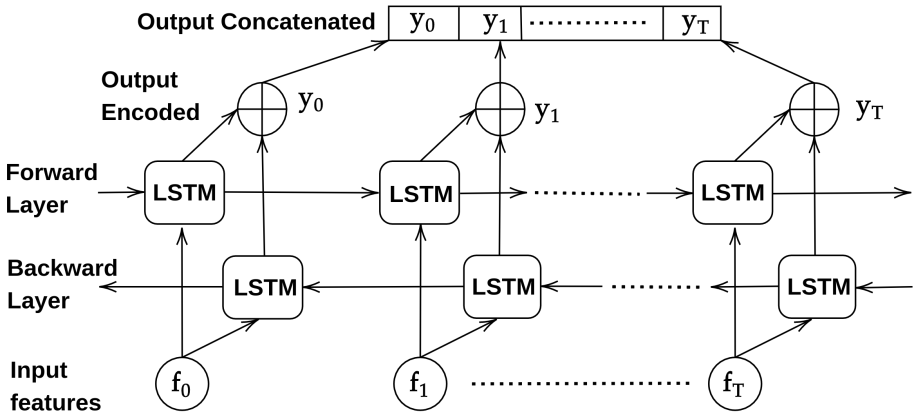


Figure 2: A block diagram of the Bi-directional LSTM

However, the vanishing and exploding gradient issues in RNNs [42] have limited its usability in long input sequence analysis. Hence, Long Short Term Memory (LSTMs) [43] are used for the long sequential data. Within the LSTM, there is a control gate to hold the current hidden state in a memory cell based upon preceding hidden states. The output predictions are encoded based on the previous hidden states. The encoded output, from each LSTM layer is recursively appended to form a complete feature vector. The Bidirectional LSTM (Bi-LSTM), deployed in this work, takes input data in the form of sequences and generates hidden state output predictions for each time step as depicted in the Fig. 2. It considers sequences in both forward and backward directions and encodes the features and concatenates them.

3. Methodology

3.1. Problem Statement

The total number of sEMG patterns in a dataset is $N = S \times N_A \times R$, where S is to the total number of subjects, N_A is the number of different hand activities, and R corresponds to the number of activity repetitions per subject. A full sEMG dataset can be represented as:

$$\mathbf{x} = \{\mathbf{x}_n\}_{n=1}^{N} \tag{1}$$

where each observation array $\mathbf{x}_n$ consists of multiple channels as:

$$\mathbf{x}_n = \{\mathbf{x}_{n,m}\}_{m=1}^{N_C}, \quad n = 1, \cdots, N \tag{2}$$

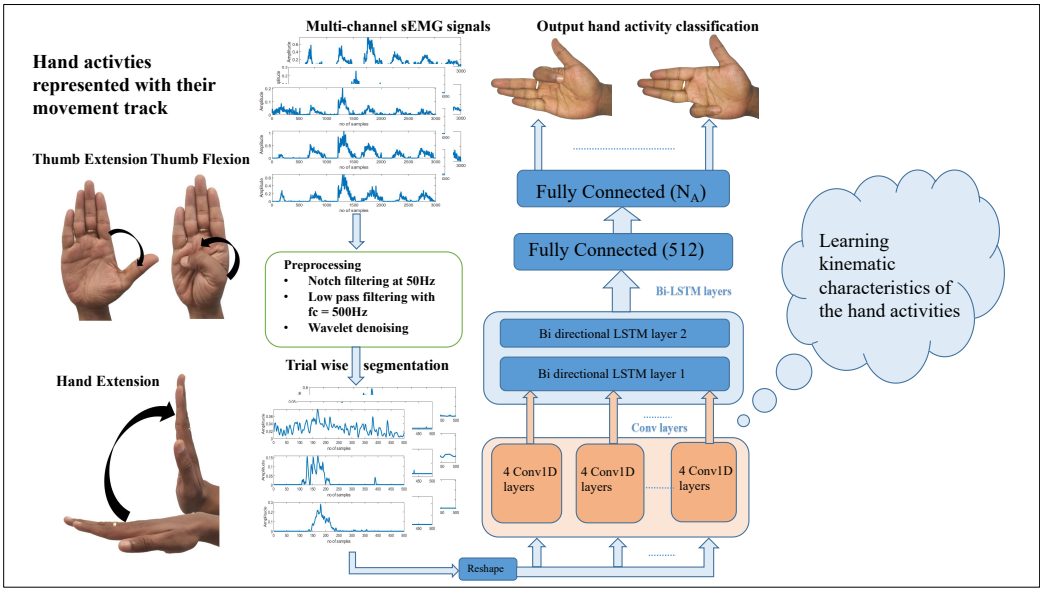


Figure 3: The block diagram depicts learning steps involved in proposed hybrid CNN and Bi-LSTM based EMGHandNet architecture

and N_C is the number of channels (from different electrodes) and each of these channels consists of an array

$$\mathbf{x}_{n,m} = \{x_{n,m}(i)\}_{i=1}^{N_T} \tag{3}$$

where $N_T = N_s \times T$ is the number of values in one trial of duration T and N_s is the sampling rate (samples/sec).

The objective of this study is to map the sEMG signals to the corresponding activity (α - Target labels), which can be formulated as

$$f\{\mathbf{x}_n\} \rightarrow \alpha \tag{4}$$

The mapping function in (4) can be implemented either by a machine learning or a deep learning classifier. For the mapping function, appropriate features are required that represent the underlying inverse kinematic relationships between the sEMG signals and the corresponding activity performed. The feature extraction and mapping is achieved by a hybrid deep learning model described below (see Fig. 3)

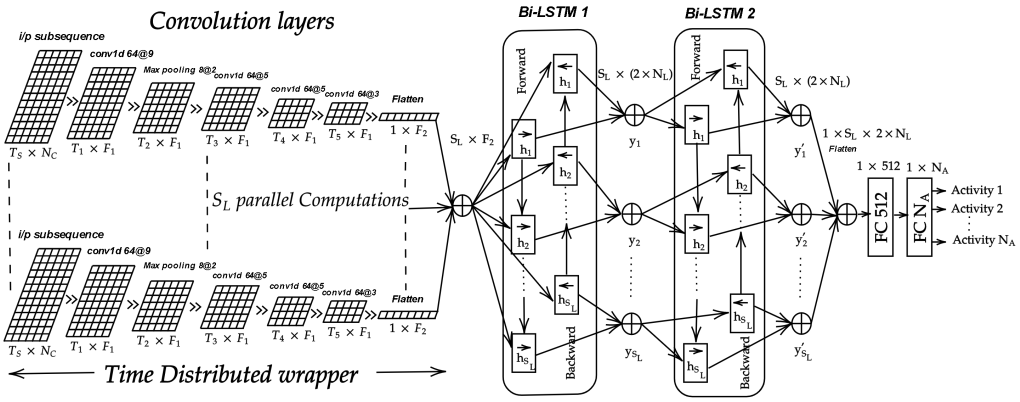


Figure 4: The expanded view of hybrid CNN and Bi-LSTM based EMGHandNet architecture

3.2. Hybrid EMGHandNet Model

The proposed hybrid CNN and Bi-LSTM based EMGHandNet implementation scheme is illustrated in Fig. 3 with the internal architecture depicted in Fig. 4. The sEMG signals are preprocessed, suitably segmented and provided as inputs to a deep learning architecture for classification. The EMGHandNet consists of four one dimensional (1-D) CNN layers with a time distributed wrapper followed by two Bi-LSTM layers and finally two dense layers as shown in Fig. 4. The outputs of the final dense layer are the categories of the hand activities. The deep learning model learns the mapping of neuro muscle activity (sEMG signals) to the limb kinematics. It is able to classify hand activities appropriately by bypassing the need for theoretical neuro-mechanical models (eg. differential equations). This ML based learning of kinematic mapping is demonstrated in [44–47].

The first step is the EMG data setup and preprocessing for feeding to the CNN and is described as follows. The number of samples N_T from each trial is factorized as:

$$\{S_L, T_S\} = fact(N_T) \tag{5}$$

where S_L is no. of sub sequences, T_S is sub-sequence time steps and $fact(N_T)$ is the factorization of (N_T) such that $N_T = S_L T_S$. T_S is chosen such that the minimum (T_S) greater than zero. The class labels are one-hot encoded to compute the cross entropy loss for the multi-class problem. The input shape of the data $N_T \times N_C$ is reshaped to the $S_L \times T_S \times N_C$ using the factorization method in (5). This $3D$ data

is split into train and test samples and sent to 1-D CNN layers. The output size N_o for each CNN layer with a kernel size k is given by

$$N_o = \left\lfloor \frac{i+2p-k}{s} \right\rfloor + 1 \tag{6}$$

where i is the input size, s is the stride and p is the padding given by $p = \lfloor \frac{k}{2} \rfloor$.

The obtained feature map is further processed by three more convolution layers which lead to the generation of an output array of size $T_5 \times F_1$, which is then flattened to a vector size $1 \times F_2$. The feature sets computed in S_L parallel streams are concatenated into a feature array of dimension $S_L \times F_2$, which is provided as input to a stack of Bi-LSTM layers.

Intuitively, Bi-LSTM is able to encode the long-term temporal information better than the uni-directional LSTM. It is because the forward LSTM of Bi-LSTM encodes the sequence from start to end of a trial and the backward LSTM encodes the sequence from the end to start of a trial. The model is better equipped with the temporal representation of the final activity posture from the backward LSTM layer while the forward LSTM layer is able to predict the intermediate movement of activity thus contributing to the improved classification accuracy of the model. The intermediate movement prediction from the backward LSTM layer also reduces the number of possibilities for subsequent movements in terms of prediction and enforces improved separability in the abstract feature space and thus minimizes the class ambiguity. The output dimension of the Bi-LSTM layer with all the sub sequences is $S_L \times 2 \times N_L$ that is flattened and subsequently processed by the two dense layers. Finally, the last dense layer consists of a softmax activation function to obtain output probabilities for each of the hand activity classes.

4. Experimental setup

4.1. Dataset Description

In this section, we briefly discuss the five publicly available benchmark datasets used in the experiments; NinaPro DB1, NinaPro DB2, NinaPro DB4, BioPatRec DB2 and UCI Gesture. In the respective measurement sessions, the sEMG sensors were placed on various muscle locations on the upper limbs. The muscle sites included are Flexor carpi radialis, Flexor carpi ulnaris, Extensor digitorum, Extensor carpi radialis brevis muscle, and Palmaris longus [48]. The datasets consist of hand activities broadly categorized into gestures, wrist movements, grasping

Table 1: Action categories mapped to robotic arm control

Action Category	**Robotic or exoskeleton arm control mapping**
Gestures	To control finger motions of the robotic arm and bionic hand [50, 51]
wrist movements	To control degrees of freedom [51]
grasping objects	To guide an arm for the task such as pick and place objects [12, 13]
hand movements	To provide multiple degrees of freedom for exoskeleton arm [14]

Table 2: Preprocessing steps for each of the datasets

Processing step	**NinaPro DB1**	**NinaPro DB2**	**NinaPro DB4**	**BioPatRec DB2**	**UCI Gesture**
Power line noise filtering at 50Hz	Not applied	Applied	Applied	Not Applied	Not Applied
Low pass filtering with cutoff frequency fc =500Hz	Not applied	Applied	Applied	Not Applied	Not Applied
Wavelet Denoising	Applied	Applied	Applied	Applied	Applied

objects and hand movements. The hand action categories that can be mapped to robotic or exoskeleton arm controls are provided in Table 1. It is assumed that the difference between static and dynamic gestures is the angular velocity of the fingers during activity [49]. In static actions, the angle between fingers does not vary during activity but varies in dynamic activities. The position of the hand can vary in both static and dynamic actions. As per this assumption, the datasets consist of static hand actions only. The datasets are illustrated in detail in the references provided in the descriptions given below.

A brief description of each dataset analyzed is as follows:

1. NinaPro DB1 [26]: The dataset consists of sEMG signals extracted from 27 subjects performing various hand activities are grouped into three exercises namely exercise A, exercise B and exercise C. The exercise A consists of single finger flexion and extension movements. The exercise B consists of multiple finger flexion and extension movements as well as wrist movements. The exercise C consists of grasping of household objects. Each activity is performed for a duration of 5s with a rest period of 3s and repeated over 10 trials.
2. NinaPro DB2 [26]: The dataset consists of sEMG signals extracted from 40 subjects while they performed finger gestures and grasping of objects. The 49 classes of actions are grouped into exercise B, exercise C and exercise D.

The exercises B and C are same as in NinaPro DB1. The exercise D consists of 9 force patterns obtained while pressing fingers on force sensors.

3. NinaPro DB4 [52]: In this dataset, the sEMG signals are collected from 10 subjects. The hand activities are same as in the NinaPro DB1; the only difference is the data is obtained at a higher sampling rate.
4. BioPatRec DB2 [53] : This dataset consists of 26 hand movements obtained from 17 subjects. These activities include six basic hand movements such as open/close, hand pronation/supination and wrist flexion and extension and 20 movements made up of combinations of the six basic movements. Each movement is performed for a duration of 3s with a rest duration of 3s.
5. UCI Gesture [54]: This dataset consists of 7 hand movements obtained from 36 subjects. The activities include seven basic movements such as a hand clenched in a fist, the wrist flexion and extension, radial and ulnar deviation of the wrist, the extended palm, and the rest state. Since the extended palm is not performed by each of the subjects, we have considered first six classes of data for the classification task.

4.2. Dataset Preprocessing and Preparation

As summarized in the Table 2, each trial of the data $\mathbf{x}_n$ is preprocessed differently for each of the dataset used. The data pre-processing is performed in MATLAB R2020 to obtain the train and test data files. As the sEMG signals are contaminated by unwanted components such as the line-noise and the receiver noise. To mitigate their effects, the following three steps are used, a) Line noise filtering at 50Hz to remove power supply noise, b) First order Butterworth low pass filtering at a cut-off frequency of 500Hz (since sEMG signal lies in the band of $20-380$Hz), c) Wavelet denoising at an order of 8, with the symlet mother wavelet. The prepossessing steps are applied as per requirement on each of the datasets. Different preprocessing steps are applied to different datasets due to the following reasons. For the NinaPro DB1, since the data is already filtered with 50Hz line noise only wavelet denoising is applied. As the data is sampled at 100Hz, it does not require low pass filtering with a 500Hz cut-off frequency. For the NinaPro DB2 and NinaPro DB4, since the sampling rate is 2kHz, filters for 50Hz line noise and a low pass filter with a cutoff at 500Hz are applied. The filtered data is denoised with a wavelet-based method. Since the BioPatRec DB2 is available pre-filtered for the 50Hz line noise and band-pass filtered with a pass-band frequencies of 20Hz and 400Hz, no further filtering is required. Similarly,

Table 3: Dataset characteristics and setup for numerical experiments

Parameter	**NinaPro DB1**	**NinaPro DB2**	**NinaPro DB4**	**BioPatRec DB2**	**UCI Gesture**
no. of subjects (S)	27	40	10	17	36
no. of classes (N_A)	52	49	52	26	6
no. of channels (N_C)	10	12	12	8	8
no. of repetitions (R)	10	6	6	3	4
Sampling frequency (N_s) (samples/sec)	100	2000	2000	2000	1000
Trial length (N_T)	500	10000	10000	6000	1500
Activity duration (T) (sec)	5	5	5	3	3
Rest period (sec)	3	3	3	3	3
Sensor type	Otto Bock	Delsys Trigno Wireless	Cometa MiniWave	Bipolar Silver Electrodes	MYO Thalmic bracelet
Total Patterns (N)	14040	11760	3120	1326	864
Patterns per class	270	240	60	51	24
Train patterns (Aggregate data)	9828	7840	2080	884	648
Test patterns (Aggregate data)	4212	3920	1040	442	216
Train patterns (Sub-wise data)	364	196	208	52	18
Test patterns (Sub-wise data)	156	98	104	26	6
Train trial numbers	1,3,4, 6,8,9, 10	1,3,4, 6	1,3,4, 6	1,3	1,3,4
Test trial numbers	2,5,7	2, 5	2,5	2	2

the UCI Gesture data is also available pre-filtered; only wavelet denoising is applied.

For a given trial, if the number of samples are exceeding N_T, the excess data is truncated. In other case, if the number of samples is less than N_T, zero padding is used. The data is split trial-wise into 70% for training as mentioned in Table 3 and 30% for testing [29]. The train and test data sets are standardised channel wise, so that the resultant data has zero mean and unit variance. These files are converted into pandas data frames with TensorFlow back-end. The tensor shapes for each layer are given in the Table 4.

Table 4: Tensor shapes obtained during implementation - Aggregate data scheme. For NinaPro DB1, $T_S = 20$, for NinaPro DB2, NinaPro DB4 and BioPatRec DB2, $T_S = 400$ and for UCI Gesture, $T_S = 50$ (Time segment of 50ms))

Shape of Tensor	**Values for NinaPro DB1**	**Values for NinaPro DB2 and NinaPro DB4**	**Values for BioPatRec DB2**	**Values for UCI Gesture**
$N_T \times N_C$	500×10	10000×12	6000×8	1500×8
$S_L \times T_S \times N_C$	$25 \times 20 \times 10$	$25 \times 400 \times 12$	$15 \times 400 \times 8$	$30 \times 50 \times 8$
$S_L \times T_1 \times F_1$	$25 \times 10 \times 64$	$25 \times 200 \times 64$	$15 \times 200 \times 64$	$30 \times 25 \times 64$
$S_L \times T_2 \times F_1$	$25 \times 2 \times 64$	$25 \times 97 \times 64$	$15 \times 97 \times 64$	$30 \times 9 \times 64$
$S_L \times T_3 \times F_1$	$25 \times 1 \times 64$	$25 \times 49 \times 64$	$15 \times 49 \times 64$	$30 \times 5 \times 64$
$S_L \times T_4 \times F_1$	$25 \times 1 \times 64$	$25 \times 25 \times 64$	$15 \times 25 \times 64$	$30 \times 3 \times 64$
$S_L \times T_5 \times F_1$	$25 \times 1 \times 64$	$25 \times 13 \times 64$	$15 \times 13 \times 64$	$30 \times 2 \times 64$
$S_L \times 1 \times F_2$	$25 \times 1 \times 64$	$25 \times 1 \times 832$	$15 \times 1 \times 832$	$30 \times 1 \times 128$
$S_L \times F_2$	25×64	25×832	15×832	30×128
$S_L \times (2 \times N_L)$	$25 \times (2 \times 200)$	$25 \times (2 \times 200)$	$15 \times (2 \times 200)$	$30 \times (2 \times 200)$
$1 \times S_L \times 2 \times N_L$	1×10000	1×10000	1×6000	1×12000
$1 \times N_A$	1×52	1×49 /1×52	1×26	1×6

4.3. Network Settings and Model Training

The EMGHandNet is implemented with the following parameters. The learning rate (lr) is initialized to 10^{-3} with a batch size of 16. The hyper parameters tuned for an improved performance are given in the Table 5. The number of filters at each convolution layer and the kernel size are mentioned in the Fig. 4, for example conv1d 64@9 refers to 64 filters with a kernel size 9. The EMGHandNet is trained and tested separately for each dataset and corresponding classification accuracy is evaluated as follows

$$\text{Accuracy} = \frac{\text{Number of correctly classified trials}}{\text{Total number of trials}} \times 100. \tag{7}$$

The experiments are carried out on a machine consisting of Nvidia Quadro RTX 6000 24 GB RAM Graphical Processing Unit (GPU) card. The model deployment is done in TensorFlow 2.2.0 framework with python.

Table 5: Tuned hyper parameters for the EMGHandNet

Layer	**Parameter Name**	**Value**
Convolution hyper parameters	Kernel initializer:	he_normal
	Strides:	2
	Kernel regularizer:	10^{-4}
Batch Normalization	ε:	10^{-6}
	Momentum:	0.95
Batch size		16
Learning rate		$l1 = 10^{-3}$
Optimizer	Adam $\beta 1$:, $\beta 2$:	0.9, 0.999
Activation		Tanh & Relu
Dropout		0.2093
no. of epochs		200
Bi-LSTM	Cells:	200
TensorFlow version		2.2.0

5. Results and discussion

The following models are trained and tested on the five benchmark datasets mentioned earlier.

1. EMGHandNet: The proposed hybrid CNN and Bi-LSTM architecture
2. MsCNN: The Multistream-CNN architecture by Wei *et al.* [28]
3. EvCNN: Evolved CNN by Olsson *et al.* [29]
4. CNNLM: Combined CNN - LSTM architecture by Chen *et al.* [40]
5. Energy features: KNN classifier using energy features by Karnam *et al.* [23]

Specifically, these models are analyzed in the following two schemes

- Subject-wise analysis:- In this scheme, the EMGHandNet is trained and tested with the subject wise data. The average classification accuracy across the subjects is computed.

- Aggregated data analysis:- In this analysis, the EMGHandNet is trained and tested with aggregated data from the available subjects with split-up scheme mentioned in data preprocessing stage. The average accuracy is calculated as per (7).

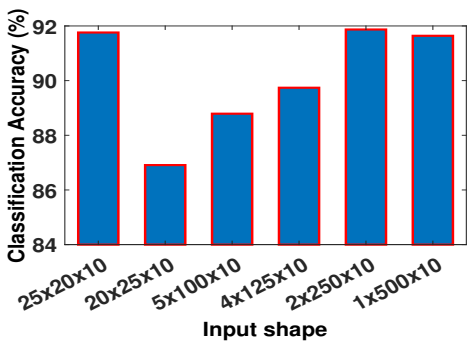
To validate the EMGHandNet, the following analyses are carried out: (1) analysis of the role of input shapes, (2) comparative analysis with the RNN layers, (3) analysis of the pre-processing methods, (4) loss curves for different datasets, (5) comparison with the state of the art models, and (6) time and space complexity analysis. For fair comparison, we have used the same dataset setup and input shape processing techniques both in the EMGHandNet and the other models.

5.1. Role of Input Shapes

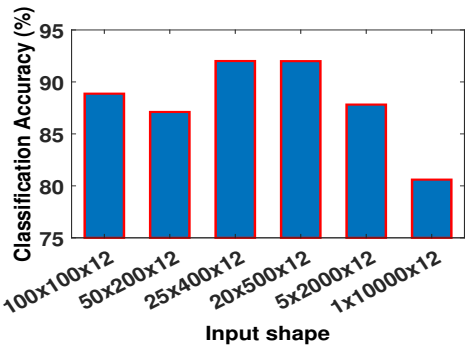
The EMGHandNet is also analysed with respect to different input shapes of the data as shown in Fig. 5 for the five datasets. It is observed that for some datasets with input shape consisting of samples with 200*ms* time segment (for NinaPro DB1, $T_S = 20$ samples, for NinaPro DB2, NinaPro DB4, and BioPatRec DB2, $T_S = 400$ samples) and 50*ms* time segment (for UCI Gesture, $T_S = 50$ samples), the performance is superior compared to when other time segments are used. For the BioPatRec dataset, the highest accuracy of 83.9% is achieved for an input shape of $[15, 400]$ (corresponds to 200ms time segment). This analysis suggests that the performance of the model varies with respect to different shapes and achieves an optimal average accuracy for the identified input shape. Finally, for the UCI Gestures, a time segment of 0.05s out of 3s trial data provides improved classification. It is observed that a similar time segment of 0.2s has provided better results for four datasets except UCI Gesture. Hence an optimal time segment is important for improved capture of temporal relations. The optimal time segment obtained is dependent on various factors such as sampling frequency (Ns), activity duration (T) and number of samples within a sub-sequence (Ts). The training and testing of datasets are done independently across the five datasets and observed that there is no direct linear relationship between no.of samples within a trial (N_T) and optimal time segment.

5.2. Performance Analysis with RNN Layers

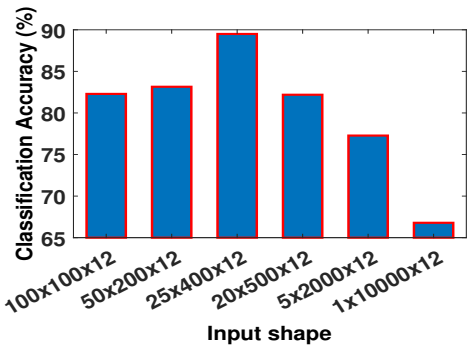
The performance of the EMGHandNet is also analysed by varying the number of stacked Bi-LSTM layers and results are shown in Fig. 6. It is observed that the EMGHandNet model with 4 Conv and 2 Bi-LSTM layers outperforms the EMGHandNet model with 4 Conv layers and other Bi-LSTM configurations. The model with no Bi-LSTM layer corresponds to the network with four Conv layers only. This analysis shows that the performance of the model with the Bi-LSTM layers is better than without Bi-LSTM layer (i.e., only Conv layers). Importantly, for the EMGHandNet, this analysis also supports the choice of using two Bi-LSTM layers following the CNN network.



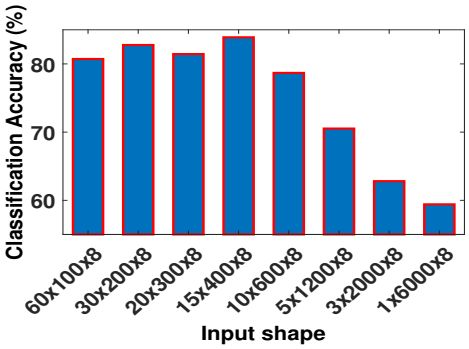
(a) NinaPro DB1



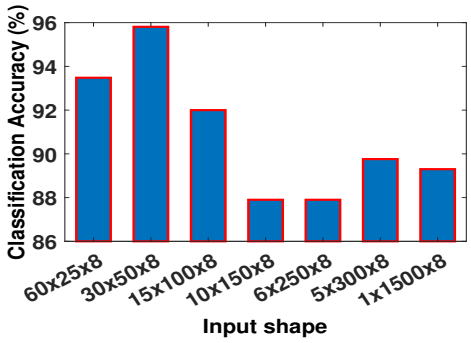
(b) NinaPro DB2



(c) NinaPro DB4



(d) BioPatRec DB2



(e) UCI Gesture

Figure 5: Performance analysis from Aggregate Data scheme with different shapes for NinaPro DB1, NinaPro DB2, NinaPro DB4, BioPatRec DB2 and UCI Gesture datasets. For NinaPro DB1, $T_S = 20$, for NinaPro DB2, NinaPro DB4 and BioPatRec DB2, $T_S = 400$ and for UCI Gesture, $T_S = 50$ (Time segment of 50ms)

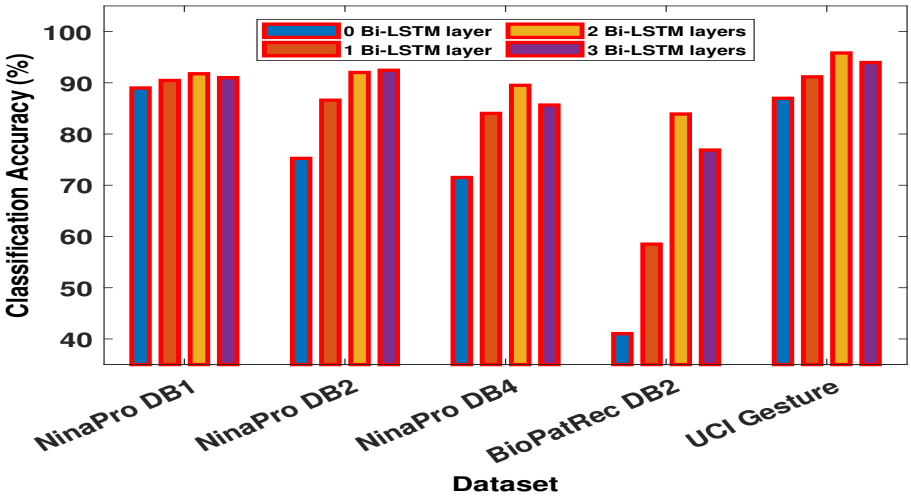


Figure 6: Performance analysis with respect to no. of Bi-LSTM layers in the proposed EMGHandNet model over all datasets - Aggregate data scheme. For NinaPro DB1, $T_S = 20$, for NinaPro DB2, NinaPro DB4 and BioPatRec DB2, $T_S = 400$ and for UCI Gesture, $T_S = 50$ (Time segment of 50ms)

The proposed model is also analysed with different type of RNN layers, such as LSTM, Gated Recurrent Unit (GRU), Bidirectional GRU (Bi-GRU), RNN, and Bidirectional RNN (Bi-RNN) on NinaPro DB1 dataset. The results in terms of the classification accuracy are shown in Fig. 7. From these results, it is evident that the Bi-LSTM is better suited in the proposed framework as it leads to the highest performance as compared to other type of RNN layers. The Bi-LSTM layer better captures the long-term temporal relations compared to other type of RNN layers as it learns both forward and backward temporal characteristics.

5.3. Analysis on Pre-processing Methods

The role of preprocessing for the improvement of classification performance is analyzed through following experiments, see Table 6. In one experiment, the preprocessing method in the EvCNN [29] is replaced with our preprocessing approach. This is compared with the combination consisting of the preprocessing method from the EvCNN followed by the EMGHandNet. The EMGHandNet with our preprocessed data exhibits better classification accuracy compared to other combinations. This analysis shows that the preprocessing technique used in this work is better suited for sEMG data based hand activity classification as compared to the preprocessing and architecture from [29]. Further experiments are carried

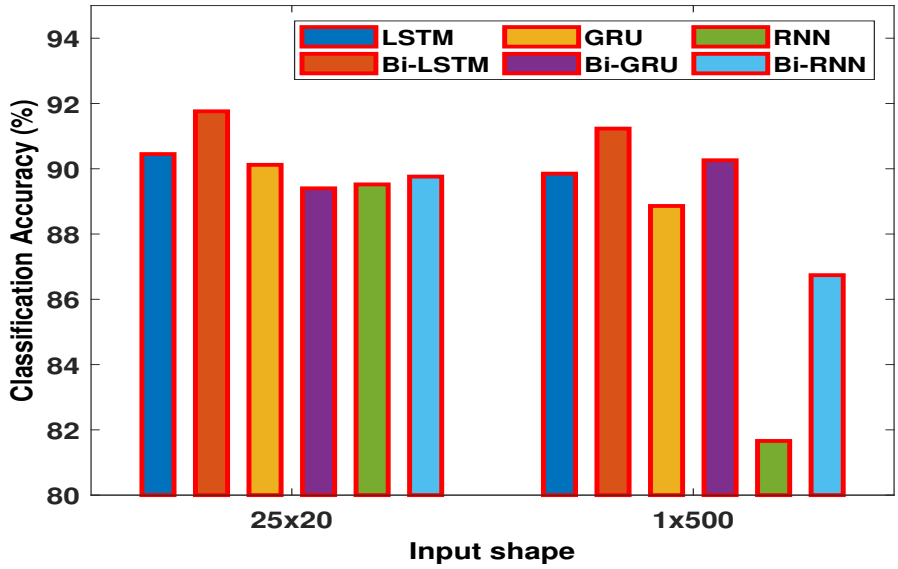


Figure 7: NinaPro DB1 performance analysis with different type of recurrent layers such as LSTM, Bi-LSTM, GRU, Bi-GRU, RNN and Bi-RNN layers in the proposed model

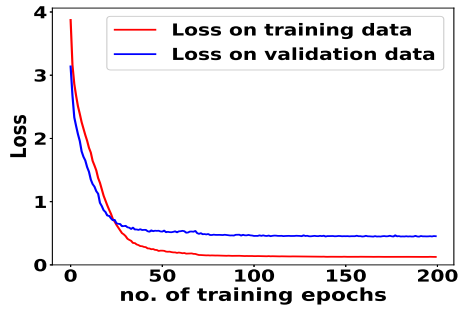
out by comparing the EMGHandNet model with and without any preprocessing of data. It is observed that, for BioPatRec DB2, there is an improvement of 17.69% in classification accuracy compared to that without preprocessing. Similarly, for NinaPro DB4, a comparable performance improvement of 10.58% is observed. Additionally, for the remaining datasets the improvement is at least 3%. This shows that there is an improvement in performance of the model when data is preprocessed compared to the case without preprocessing.

5.4. Loss Curves for Individual Datasets

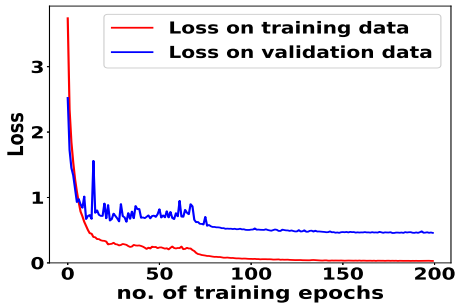
Fig. 8 shows the loss curves from the EMGHandNet corresponding to each of the five datasets. The input shapes chosen are as follows, for NinaPro DB1: $25 \times 20 \times 10$, for NinaPro DB2 and NinaPro DB4: $25 \times 400 \times 12$, for BioPatRec DB2: $15 \times 400 \times 8$ and for for UCI Gesture: $30 \times 50 \times 8$. The EMGHandNet obtains a stable response after 70 epochs for each of the five datasets.

5.5. Performance Comparison

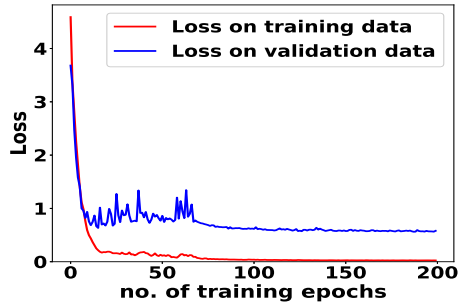
The EMGHandNet performance is compared with that of the MsCNN, EvCNN, CNNLM where the results are reproduced in this work and a few other models for which the results are reported from the literature (see Tables 7 and 8).



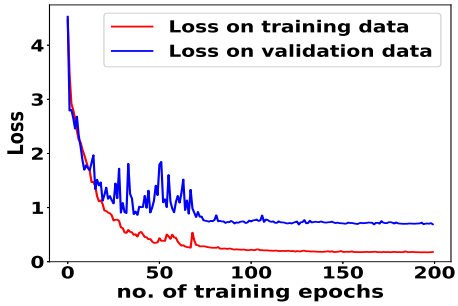
(a) NinaPro DB1



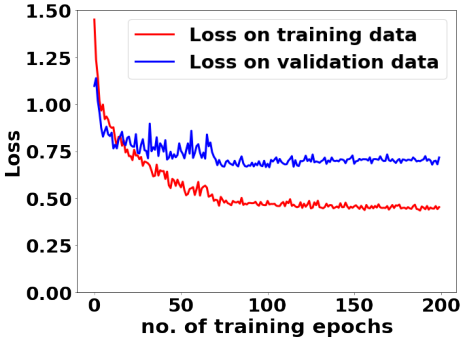
(b) NinaPro DB2



(c) NinaPro DB4



(d) BioPatRec DB2



(e) UCI Gesture

Figure 8: Loss curve observed during training of EMGHandNet over NinaPro DB1, NinaPro DB2, NinaPro DB4, BioPatRec DB2 and UCI Gesture datasets - Aggregate data scheme. For NinaPro DB1, $T_S = 20$, for NinaPro DB2, NinaPro DB4 and BioPatRec DB2, $T_S = 400$ and for UCI Gesture, $T_S = 50$ (Time segment of 50ms)

Table 6: Performance analysis using accuracy (%) of different preprocessing techniques with various architectures - Aggregate data scheme. For NinaPro DB1, $T_S = 20$, for NinaPro DB2, NinaPro DB4 and BioPatRec DB2, $T_S = 400$ and for UCI Gesture, $T_S = 50$ (Time segment of 50ms)

Dataset / Methodology	**NinaPro DB1**	**NinaPro DB2**	**NinaPro DB4**	**BioPatRec DB2**	**UCI Gesture**
Olsson Preprocessing - EvCNN [29]	81.57	66.64	13	77.71	54.41
Olsson Preprocessing - EMGHandNet	86.98	81.11	21.6	67.8	91.16
Proposed Preprocessing - EvCNN [29]	84.54	60.52	38	52.71	77.2
Proposed Preprocessing - EMGHandNet	**91.76**	**92.01**	**89.5**	**83.9**	**93.48**
Without Preprocessing - EMGHandNet	89.5	91.62	78.92	66.21	93.02

In the subject-wise analysis, as shown in Table 7, for the NinaPro datasets, the EMGHandNet shows higher average test accuracy compared to the state-of the art methods. The subject-wise average accuracy of the EMGHandNet model for NinaPro DB1 is 95.77%, which is an improvement of 7.57% over 88.2% from the Multi-view CNN [57]. For the NinaPro DB2 dataset, the EMGHandNet with an accuracy of 95.9% improved by 12.2% against 83.7% of the Multi-view CNN [57]. The EMGHandNet has an improvement of 8.73% over reproduced CNNLM [40]. For the Ninapro DB4 , the EMGHandNet with an average test accuracy of 91.65%, outperforms the Attention sEMG model [58] by 18.65%. For the UCI Gesture, there is a small improvement of 1.33% over Deep Neural architecture [59] by attaining a test accuracy of 98.33%. Based on the existing approaches, the BioPatRec DB2 dataset is used without any data augmentation, hence for the EMGHandNet model, the performance of 91.29% is approaching that of the state of the art.

In the aggregated scheme, as shown in the Table 8, for the NinaPro datasets, the accuracy of the EMGHandNet is again better compared to that of the existing models. Specifically, for NinaPro DB1, the EMGHandNet obtained an accuracy of 91.76%, which is an improvement of atleast 3.56% as compared to 88.2% based on Multi-view CNN [57]. For NinaPro DB2, an accuracy of 92.01% is observed using the EMGHandNet, which is an improvement of 8.31% as compared

Table 7: Classification accuracy (%) analysis with different architectures - Subject wise analysis. * are reproduced results. For NinaPro DB1, $T_S = 20$, for NinaPro DB2, NinaPro DB4 and BioPatRec DB2, $T_S = 400$ and for UCI Gesture, $T_S = 50$ (Time segment of 50ms)

Dataset / Architecture	**NinaPro DB1**	**NinaPro DB2**	**NinaPro DB4**	**BioPatRec DB2**	**UCI Gesture**
RMS, MAV, and DASDV by yang *et al.* [55] (Sub-wise)	91.35	-	-	-	-
Multi-sEMG-features image by Cheng *et al.* [56]	82.54	-	-	-	-
MsCNN [28] (Sub-wise)	85	-	-	-	-
MsCNN[28] (Sub-wise) *	74.25	50.99	34.1	66.18	95.58
EvCNN [29] (Sub-wise)	81.4	71.6	-	91.4	-
EvCNN [29] (Sub-wise) *	68.06	80.54	22.3	84.19	45.55
CNN-RNN by Hu *et al.* [36]	87	82.2	-	94.1	-
Multi-View CNN by Wei *et al.* [57]	88.2	83.7	58	94.0	-
Attention sEMG by Josephs *et al.* [58]	-	-	73	-	-
Deep Neural Network by Potekhin *et al.* [59]	-	-	-	-	97
CNNLM [40] (Sub-wise)*	92.99	87.17	87.37	89.17	86.51
EMGHandNet (Sub-wise)	**95.77**	**95.9**	**91.65**	**91.29**	**98.33**

to 83.7% of Multi-view CNN [57] but an improvement of 1.4% against the Energy features [23]. For the NinaPro DB4, the achieved accuracy is 89.5%, which is an 5.58% improvement over 83.92% of the CNNLM [40]. For the UCI Gesture, the achieved accuracy is 93.48%, which is an improvement of 3.98% over 89.5% of the MsCNN [28]. Finally, for the BioPatRec, the EMGHandnet improved the peformance by 6.19% against the accuracy of the EvCNN [29]. The EMGHandnet has out-perfomed the machine learning classifiers such as [23, 26]. Among the existing methods for the five datasets, the CNNLM [40] and Energy features [23] comes closest to the accuracy of the EMGHandNet. Additionally, for the 4 datasets other than UCI Gesture, the MsCNN [28] has the least performance among the competing methods.

The McNemar's test [62] is implemented to analyze the statistical significance of the observed improvement in classification performance. The terms in Table 9 are defined as follows: f_{cc} is the number of patterns for which both classifiers result in correct prediction, f_{ci} when EMGHandNet is correct and the state of

Table 8: Classification accuracy (%) analysis with different architectures - Aggregate data scheme. * are reproduced results. For NinaPro DB1, $T_S = 20$, for NinaPro DB2, NinaPro DB4 and BioPatRec DB2, $T_S = 400$ and for UCI Gesture, $T_S = 50$ (Time segment of 50ms)

Dataset / Architecture	**NinaPro DB1**	**NinaPro DB2**	**NinaPro DB4**	**BioPatRec DB2**	**UCI Gesture**
Benchmark classifier with handcrafted features [26] (Aggregate)	75.3	75.3	-	-	-
CNN by Atzori *et al.* [25] (Aggregate)	66.6	60.3	-	-	-
LDA by Nazemi *et al.* [60]	84.23	-	-	-	-
LS-SVM by Nazemi *et al.* [60]	85.19	-	-	-	-
Random Forest by Rubio *et al.* [61]	-	-	-	-	95.39
Energy features [23] (Aggregate)	87.07	90.61*	60.67*	89.36*	93.98*
MsCNN [28] (Aggregate) *	60	31.41	33.9	62.4	89.5
EvCNN [29] (Aggregate) *	81.57	66.64	13	77.71	54.41
CNN-RNN by Hu *et al.* [36]	87	82.2	-	94.1	-
Multi-View CNN by Wei *et al.* [57]	88.2	83.7	58	94.0	-
Attention sEMG by Josephs *et al.* [58]	-	-	73	-	-
CNNLM [40] (Aggregate)*	79.26	78.71	83.92	71.65	86.51
EMGHandNet (Aggregate)	**91.76**	**92.01**	**89.5**	**83.9**	**93.48**

the art classifier is incorrect, f_{ic} is Vice versa, and f_{ii} is the number of patterns for which both classifiers predictions are incorrect. From these metrics, the chi-square statistic is calculated [62] as $6.64 > 3.84$ (the threshold for one degree of freedom). Hence the improvement is significant at 95% confidence level. For the NinaPro DB1, the chi square value evaluated against the Energy features [23] is 47.2 and for the NinaPro DB4, the chi square value against CNNLM [40] is 10.07. For the UCI Gestures, the chi-square value against the Energy features [23] is 0.529, which indicates that both the classifiers provide similar results.

5.6. Time and Space Complexity Analysis

The time and space complexity of the ML methods are calculated based on the analysis provided in [29]. The time complexity of each Conv 1D, Bi-LSTM, and Fully Connected (FC) layer are computed based on the number of Floating Point Operations Per Second (FLOPS) and provided in Table 10. The time complexity for UCI Gesture can also be computed similar to the methods used for the first four

Table 9: Statistics from McNEMAR's test on Energy Features [23] and EMGHandNet for NinaPro DB2. Performance comparison based on correct proportions

		Energy Features [23]		
		Correct	Incorrect	Total
EMGHandNet	Correct	$f_{cc} = 3350$	$f_{ic} = 200$	3550
	Incorrect	$f_{ci} = 255$	$f_{ii} = 113$	368
	Total	3605	313	3918

Table 10: Time complexity of layers in the network (n = no.of filters, v = vertical stride, y = kernel height, N = no. of patterns, N_e = no. of epochs and N_A = no. of activities)

Layer Name	**Input shape**	**Theoretical values for layers (FLOPS)**	**Theoretical values for NinaPro DB1 (FLOPS)**	**Theoretical values for NinaPro DB2 and NinaPro DB4 (FLOPS)**	**Theoretical values for BioPatRec DB2 (FLOPS)**
$Conv1d$ 64@9	$T_S \times N_C$	$(T_S/v)n(2yN_C+1)$	115840	2777600	185600
$Conv1d$ 64@5	$T_2 \times F_1$	$(T_2/v)n(2yF_1+1)$	41024	1989664	1989664
$Conv1d$ 64@5	$T_3 \times F_1$	$(T_3/v)n(2yF_1+1)$	20512	1005088	1005088
$Conv1d$ 64@3	$T_4 \times F_1$	$(T_4/v)n(2yF_1+1)$	12320	308000	308000
$Bi-LSTM1$	$S_L \times F_2$	$2 \times 4 \times (F_2 + N_L + 1)N_L$	424000	1652800	1652800
$Bi-LSTM2$	$S_L \times 2 \times N_L$	$2 \times 4 \times (2N_L + N_L + 1)N_L$	1281600	1281600	1281600
$FC1$	$1 \times S_L \times 2 \times N_L$	$S_L \times 2 \times N_L \times 512$	10000×512	10000×512	6000×512
$FC2$	1×512	$512 \times N_A$	512×52	$512 \times 49/512 \times 52$	512×26
$Total$	$--$	$--$	5760320	$14159840/14161376$	6743264
$O(f)$	$--$	$Total \times N \times N_e$	1.6×10^{13}	$3.3 \times 10^{13}/8.8 \times 10^{12}$	1.7×10^{12}

datasets, see Table 10. The total training time, for NinaPro DB1, NinaPro DB2, NinaPro DB4, BioPatRec DB2 and UCI Gesture datasets are 48min, 48.3min, 16min, 6.6min and 6.6min respectively. The space complexity of Conv 1D, Bi-LSTM, FC and Batch Normalization (BN) layer are given as 4HC [29] based on the output shape $H \times C$ and given in Table 11. Additional memory is allocated

Table 11: Space complexity of layers in the network (n = no. of filters, v = vertical stride, y = kernel height, and N_A = no. of activities)

Layer Name	**Input shape**	**Output shape**	**Based on output shape (bytes)**	**Based on no. of learning parameters (bytes)**
$Conv1d$ 64@9	$T_S \times N_C$	$T_1 \times F_1$	$4T_1F_1$	$4n(yN_C+1)$
$Conv1d$ 64@5	$T_2 \times F_1$	$T_3 \times F_1$	$4T_3F_1$	$4n(yF_1+1)$
$Conv1d$ 64@5	$T_3 \times F_1$	$T_4 \times F_1$	$4T_4F_1$	$4n(yF_1+1)$
$Conv1d$ 64@3	$T_4 \times F_1$	$T_5 \times F_1$	$4T_5F_1$	$4n(yF_1+1)$
$Bi-LSTM1$	$S_L \times F_2$	$S_L \times (2 \times N_L)$	$4 \times 2S_LN_L$	$4 \times 2 \times 4 \times (F_2+N_L+1)N_L$
$Bi-LSTM2$	$S_L \times (2 \times N_L)$	$S_L \times (2 \times N_L)$	$4 \times 2S_LN_L$	$4 \times 2 \times 4 \times (2N_L+N_L+1)N_L$
$FC1$	$1 \times S_L \times 2 \times N_L$	1×512	4×512	$4 \times 512(S_L \times 2 \times N_L+1)$
$FC2$	1×512	$1 \times N_A$	$4 \times N_A$	$4 \times N_A(512+1)$
$BN1$	$T_1 \times F_1$	$T_1 \times F_1$	$4T_1F_1$	$16 \times F_1$
$BN2$	$T_3 \times F_1$	$T_3 \times F_1$	$4T_3F_1$	$16 \times F_1$
$BN3$	$T_4 \times F_1$	$T_4 \times F_1$	$4T_4F_1$	$16 \times F_1$
$BN4$	$T_5 \times F_1$	$T_5 \times F_1$	$4T_5F_1$	$16 \times F_1$
$BN5$	1×512	1×512	4×512	16×512

Table 12: Computational complexity comparison based on trainable parameters of various architectures - Aggregate data scheme. For NinaPro DB1, $T_S = 20$, for NinaPro DB2, NinaPro DB4 and BioPatRec DB2, $T_S = 400$ and for UCI Gesture, $T_S = 50$ (Time segment of 50ms)

Trainable parameters / Methodology	**NinaPro DB1**	**NinaPro DB2**	**NinaPro DB4**	**BioPatRec DB2**	**UCI Gesture**
MsCNN [28]	8.69×10^6	3.12×10^6	1.97×10^8	9.90×10^7	6.61×10^7
EvCNN [29]	3.77×10^5	1.31×10^7	2.80×10^6	2.92×10^6	1.66×10^6
CNNLM [40]	1.52×10^5	5.41×10^5	5.42×10^5	4.15×10^5	3.06×10^5
EMGHandNet	6.59×10^6	7.82×10^6	7.82×10^6	5.76×10^6	7.69×10^6

based on no. of learning parameters (weights and biases).

The time complexity and space complexity of Bi-LSTM is same [43]. The space complexity of Conv 1D [63], FC and BN layers are theoretically computed considering 32 bit operating system. The computational complexity depends on the number of trainable parameters. Based on this, the complexity of different architectures are compared as provided in Table 12. For most of the datasets, it is observed that the computational complexity of the EMGHandNet is higher compared to that of the EvCNN and CNNLM but less compared to the MsCNN.

5.7. Discussion

The performance of the proposed EMGHandNet model has improved due to the following reasons:

- The proposed hybrid CNN and Bi-LSTM architecture is able to extract both cross-channel and temporal features. The 1-D convolution encodes the cross-channel and short-term temporal information and the Bi-LSTM encodes the long-term temporal information in both forward and backward directions.

- The whole trial data of input samples is provided to the model as compared to segmented data in the existing methods. Instead of considering segmented data as an input pattern, the whole trial data, as a pattern, provides better sequential information for the model. This is because we do not know in which time segment the subject has performed the activity within a trial.

It is observed that subject wise performance analysis is better compared to aggregated data scheme because the model understands hand actions better due to low intra-subject signal covariance in the former case against the higher inter-subject signal covariance in the latter case. A trend or correlation is observed with respect to the duration of the segment being classified and the performance of the model. For example, a time segment of 0.2s has shown better performance for the datasets NinaPro DB1, NinaPro DB2, NinaPro DB4, and BioPatRec DB2 and a time segment of 0.05s has shown better performance for UCI Gesture. It is inferred that the performance of the model is affected by the input shape provided to the CNN. Some of the limitations of the proposed model are: (a) The model may need further innovation to improve the performance for the BioPatRec DB2 data. (b) For each dataset, the model requires separate training and testing. To reduce re-training requirements a transfer learning technique can be explored.

6. Conclusion & Future Scope

6.1. Conclusion

In this paper, we have proposed a hybrid CNN and Bi-LSTM architecture for the classification of human hand activities by using the sEMG signals. The EMGHandNet is analyzed for five benchmark sEMG datasets for the hand activity classification. The EMGHandNet outperforms (by at least 4% and up to

18.65%) the state-of-the-art models in terms of the average classification accuracy for the NinaPro DB1, NinaPro DB2 and NinaPro DB4 datasets. A superior performance is also observed in the aggregated data analysis scheme. It is also observed that the preprocessing performed in this paper is better than the existing ones for the said problem. Moreover, it is found that the performance of the EMGHandNet model can be tuned based on the shape of input data to the time distributed wrapper. Finally, the two layer Bi-LSTM is determined to be a better choice as compared to other RNN types.

6.2. Future Scope

As the sEMG signal is considered in time domain only, there is scope for performance improvement by converting the given signals to the wavelet domain or the Empirical Mode decomposition (EMD) domain before further processing by the deep learning models. The model can also be implemented on a hardware device to understand issues during practical implementation. When deploying on hardware, some of the issues are time latency and portability. The time latency to test a sample is 1.8μs in the best case and 518μs in the worst case which is a major factor to be considered for real time implementation. We further plan to build an sEMG signal dataset for Indian population to analyse geography related variations among the datasets. Finally, the model can be further improved to learn from the signals corresponding to highly dynamic and high speed movements involved in activities such as sports.

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