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A Novel SFDN+DNN Approach for Efficient Hand Movement Recognition Using Surface Electromyography Signals †

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Abstract: Surface electromyography (sEMG) signal classification is pivotal for evaluating neuromuscular function, especially in applications like rehabilitation and prosthetics. This paper introduces a novel Deep Neural Network (DNN) approach based on a Smooth, Filled outliers, Detrended, and Normalized (SFDN) dataset for SEMG signal classification in hand movement recognition. Through a comparative study with existing methods, our results highlight SFDN+DNN's remarkable classification accuracy—99.63%, 95.56%, and 96.14% on the UCI, Ninapro DB6, and Mendeley datasets, respectively. Notably, this approach offers online training capabilities at a low cost, presenting a significant advancement over traditional methods. Our findings suggest SFDN+DNN's potential in enhancing the efficiency of mechanical prosthetic hands, bridging the gap toward quasi-real-hand capabilities.

Keywords: sEMG signal; prosthetic hands; machine learning; deep learning; CNN; LSTM; time-wrapped DNN

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1. Introduction

Human mobility relies on a healthy nervous system for controlling movement. Deciphering the signals between the brain and muscles holds immense potential for improving the lives of individuals with disabilities [1]. These signals become crucial in the absence of a body part, guiding the design and implementation of appropriate prosthetics, artificial body parts like limbs, eyes, and hands that enable those with disabilities to lead normal lives [2]. This research concentrates on upper limb prostheses, specifically the hands, which play a vital role in daily activities such as grasping, manipulating, and sensing objects. The diverse range of functions performed by our hands underscores their profound impact on the quality of life of people with disabilities. Prosthetic organs, a developing solution for disabilities [3], have undergone significant advancements due to technology, particularly in artificial intelligence (AI) and related cognitive fields.

AI has facilitated the development of sophisticated bio-mimetic robotic systems, particularly in the field of prosthetic hands. While AI has simulated biological behaviors, enhancing the skills and grasping abilities of neuro-prosthetic hands remains a challenge. Surface electromyography (sEMG) signal processing plays a pivotal role in the design and implementation of neuro-prosthetic hands using AI. These signals, simple to record, contain valuable information related to the anatomy and physiology of the underlying active motor unit (MU) [4].

EMG, a diagnostic technique in medicine and human–machine interaction (HMI), records and analyzes electrical signals from muscle nerves [5]. These signals unveil individual intentions for specific actions, forming the foundation for an end-to-end prosthetic hand controlled by the user's brain. Achieving neuro-prosthetic hands that move and feel like real hands necessitates a robust neural interconnection between the human mind and the machine [6]. This pursuit of an optimum neuro-prosthesis stands as a pinnacle goal in the field of human–computer interaction.

Recent advancements in bio-signal acquisition and processing techniques have made it feasible to design robots controlled by bio-signals, particularly utilizing EMG in conjunction with AI. The recorded EMG is employed in tandem with AI to classify motor unit signals, contributing to the design of prosthetic hands with profound implications for individuals with disabilities. The sEMG-based control system framework generally encompasses four stages: (1) data acquisition, segmentation, and denoising; (2) feature extraction/dimension reduction; (3) classification; and (4) controller [3]. In the initial step, sEMG signals are collected from human muscles and denoised to eliminate extraneous signals. Subsequently, the signals are transformed into a feature vector in the second stage, followed by dimension reduction to eliminate redundant information. The third stage involves classification, where classes are discerned from the reduced feature vector using various machine learning (ML) or deep learning (DL) techniques. Finally, the controller stage interprets decisions from the classification stage as control commands [7].

Currently, AI-based prosthetic hands have limitations in decoding a specific set of actions based on muscle contractions. Consequently, if the required task deviates slightly from the trained action, the neuro-prosthetic hand may produce entirely different actions. This discrepancy arises from the classification algorithm lacking information about signal variations during diverse muscle contractions and body postures [8]. Recent efforts have been made to address these challenges, with scientists proposing various methods to enhance the algorithms and design of EMG pattern recognition systems. The upcoming section will delve into recent investigations, reviewing and highlighting the most promising advancements in this field.

2. Related Work

In the existing literature, researchers have employed both DL and ML algorithms to address the sEMG signal classification challenge. This section explores both approaches, delving into noteworthy advancements.

In recent studies employing DL techniques, Zou et al. utilized the Distribution Alignment Module (DAM) for data pre-processing and a Transfer Learning plus Multiscale Kernel Convolutional Neural Network (TL-MKCNN) as a classifier, achieving a classification accuracy of 73.72% on the Ninapro DB6 dataset [9]. However, this accuracy falls short of what is deemed trustworthy for prosthetic hand design, even with a relatively large dataset. Similarly, Zanghieri et al. employed a temporal convolutional neural network (CNN) without data pre-processing, achieving a classification accuracy of 65.2% on the Ninapro DB6 dataset, which is insufficient for precise prosthetic hand design [10]. Ali et al. used a similar approach on the Mendeley dataset, reaching a classification accuracy of 76.57%, still falling below the desired levels [11]. Chung et al. reported 85% accuracy using their small recorded dataset and a feed-forward ANN, but without detailed architecture information [12]. Alternative strategies include that of Côté-Allard et al., who used continuous wavelet transform (CWT) for preprocessing and a CNN classifier, achieving 68.98% accuracy on Ninapro DB6 [13], and that of Triwiyanto et al., who used filtering and a one-dimensional CNN on the Rami Khushaba bio-signals repository, attaining 77% accuracy—both considered insufficient [14]. Ozdemir et al. employed Short-Time Fourier Transform (STFT) for preprocessing, achieving an impressive 99.5% accuracy on a small sEMG dataset, albeit without clarifying the model architecture [15]. ERÖZEN et al. utilized slow fusion for feature extraction and a CNN to classify the UCI dataset, achieving accuracy of 83.97% [16]. Meanwhile, Nahid et al. utilized continuous wavelet transform (CWT) to generate images from an sEMG signal. They implemented a hybrid architecture combining a CNN and a Recurrent Neural Network (RNN) for classification on the UCI dataset. Despite achieving an impressive 99% accuracy, their paper lacks comprehensive insights into the architectural details of the CNN-RNN model [17], highlighting the effectiveness of Recurrent Neural Networks in capturing temporal dependencies in sequential data. Sikder et al. utilized Burg's method for feature extraction and a multi-channel CNN on the UCI dataset, achieving accuracy of 98.52% [18]. On the other hand, Burello et al., focusing on Ninapro DB6, did not apply any preprocessing, using a one-dimensional CNN layer with multiple self-attention layers but only achieving a maximum accuracy of 65.73% [19]. Nazari et al. implemented filtering as a pre-processing step and a Convolutional Neural network model on the Mendeley dataset, achieving a commendable maximum accuracy of 89.5% [20].

In recent articles employing ML classifiers for the sEMG classification problem, Sravani et al. utilized Flexible Analytic Wavelet Transform (FAWT) for data processing and an Extreme Learning Machine (ELM) classifier with a sigmoidal activation function [21]. Their study focused on classifying six features from the UCI Machine Learning Repository dataset, achieving training accuracy of 99% [22]. However, they did not provide information on testing accuracy or details regarding the architecture of their proposed method. Fatimah et al. employed the Fourier Decomposition Method (FDM) for denoising a dataset and the Ensemble Subspace Discriminant (ESD) for classifying two distinct feature sets—six features in the UCI dataset and seventeen features in Ninapro DB5 [23]. Their reported accuracies were 99% for the classification of the first set and 93.53% for the second set. Unfortunately, the architectural specifics and the step-by-step methodology leading to these high accuracies remain unclarified.

Senturk et al. implemented data normalization and the Naive Bayes method for the classification of six hand movements in the UCI dataset and claimed to reach a classification accuracy of 96.43% [24]. Subasi et al. combined the tunable-Q factor wavelet transform (TQWT) feature extraction method along with bagging and boosting of an SVM classifier and claimed to reach accuracy of 98% [2], however the dataset was relatively small and the features were limited. Hargrove et al. compared the leverage of four different feature sets in classification accuracy, the time domain statistics (TD) feature set, autoregressive (AR) model, combined TD and AR (TDAR), and root mean square (RMS), and used ANN and a linear discriminative analysis (LDA) classifier to discriminate ten classes of isometric contractions [25]. Their result from 12 healthy subjects showed the TDAR/LDA combination had the best performance, with accuracy of up to 97%. Guo et al. compared the classification accuracy of combinations of four TD features and support vector machine (SVM) classifiers to discriminate nine movements [26]. They recommended a muscular model (MM) and an ANN for real-time applications, while an MM with an SVM was more suitable when processing time was not a key requirement.

While the aforementioned offline studies have demonstrated the potential for nearly accurate decoding of gestures from sEMG signals, challenges persist in achieving optimal feature extraction and robust classification. These challenges are likely to impact the adoption and utilization of such systems by amputees for controlling prosthetic hands. Hence, enhancing classification accuracy stands as a crucial objective that could substantially elevate the functionality and usability of powered prostheses.

3. Datasets

In this research, the proposed SFDN+DNN method is applied and evaluated on three benchmark datasets, namely the UCI Repository sEMG dataset, the Ninapro DB6 sEMG dataset, and the Mendeley sEMG dataset. A comparative analysis is conducted with state-of-the-art literature articles.

The UCI Repository sEMG database is meticulously designed for studying essential hand movements related to grasping various objects [22]. Electrodes are strategically placed on the Flexor Capri Ulnaris, Extensor Capri Radialis, Peronious Longus, and Peronious Brevis, with a reference electrode positioned centrally between the Longus and Brevis. Data collection involved six healthy subjects, three males and three females aged approximately 20–22 years, replicating six specific movements (spherical, tip, palmar lateral, cylindrical, and hook). Each subject repeated each basic movement 30 times, with recordings lasting 6 s, facilitated by sEMG electrodes attached to the subject's body. The sEMG signals had a frequency range of [0;500] Hz, preventing aliasing during post-acquisition processing. The dataset underwent preprocessing to eliminate line interference artifacts.

The Ninapro DB6 [27] is an open-source sEMG dataset available on the Ninaweb website. It comprises data collected from ten intact subjects who performed 7 grasps 12 times using 14 different objects. The signals were recorded at a rate of 200 KHz across 14 channels, featuring 8 input features and 8 output classes for prediction.

The Mendeley sEMG dataset, also open-source [15], involves data collection from 40 intact subjects who performed 10 gestures five times. The signals were recorded at a rate of 2 KHz across 4 channels, focusing on the dominant forearm of all participants. The recording process involved participants observing gestures on a slide screen and simultaneously acting out their reactions. This dataset has 10 input features and 10 output classes for prediction.

4. Methodologies

As emphasized in the previous section, the recorded signals exhibit a minute scale measured in micro-volts, presenting a challenge for the classifier to effectively discern and classify the sEMG dataset. Consequently, a preprocessing stage becomes imperative before introducing the recorded sEMG dataset to the classifier. This thesis incorporates four pivotal preprocessing steps: denoising (smoothing), dimension reduction (filling outliers), feature selection (detrending), and normalization. Our proposed methodology, denoted as SFDN+DNN, integrates a preprocessed dataset—smoothed, outliers filled, detrended, and normalized—subsequently fed into a hybrid model featuring a Convolutional Neural Network (CNN) followed by a Long Short-Term Memory Network (LSTM), collectively forming a Deep Neural Network (DNN) architecture.

4.1. Preprocessing Approaches

Our preprocessing strategy unfolds in four distinct steps to enhance the effectiveness of the subsequent classification process. The initial step involves denoising the dataset, eliminating undesirable observations to facilitate a more robust analysis. In statistical terms, smoothing the dataset entails creating an approximate function to capture essential patterns, and we employ the widely recognized moving average smoothing method. This method calculates the moving average of a vector using a fixed window length determined heuristically, sliding the window down the vector's length to compute averages and effectively reduce overall noise (Equation (1)).

$$x_{denoised} = \frac{x_t + x_{t-1} + \cdots + x_{t-n-1}}{n} \quad (1)$$

Moving to the second preprocessing step, we address outliers—observations significantly deviating from the dataset's norm. Outliers can arise from various sources, such as human error or measurement inaccuracies. Our chosen method for handling outliers is the mean imputation method, where outliers are identified and replaced with the mean value of the entire feature column [11].

Detrending, our third step, involves manipulating the data to remove long-term trends, emphasizing short-term changes. This process is vital for eliminating potential distortions caused by overarching trends. Detrending enables clearer identification of subtrends, observed as fluctuations on a time-series graph.

Normalization, the final preprocessing step, is the adjustment of values measured on different scales to a common scale. This step enhances model performance, ensures training stability, and promotes network robustness to variable weight initialization (Equation (2)). Overall, our comprehensive preprocessing methodology sets the stage for a more accurate and reliable classification process.

$$x_{normalized} = \frac{x + x_{min}}{x_{max} + x_{min}} \quad (2)$$

4.2. Proposed DNN Architecture

The architectural configuration of the proposed model, illustrated in Figure 1, comprises two one-dimensional CNNs and one LSTM layer.

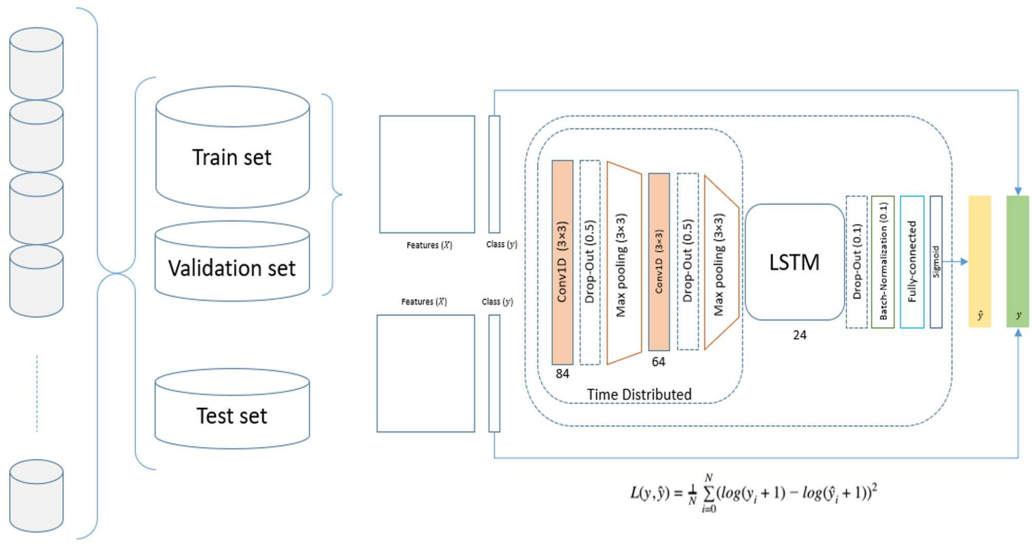

Figure 1. The architecture of the proposed model [28].

Convolutional Neural Networks (CNNs) constitute feed-forward fully connected Artificial Neural Networks (ANNs). While two-dimensional (2D) CNNs and three-dimensional (3D) CNNs find applications in image and video processing, one-dimensional (1D) CNNs are particularly suited for audio and text recognition, specifically for handling time-series data. Notably, 1D-CNNs have proven effective in time-series recognition and prediction, as evidenced by their applications in diverse fields such as early diagnosis, structural health monitoring, anomaly detection, and identification [29]. Given that the data utilized in this research comprise 1D voltage signals (time-series data), 1D-CNNs are employed.

To mitigate overfitting, a dropout layer is strategically placed after each CNN layer, effectively reducing the correlation between neurons. Following the CNN layers, max-pooling operations are employed through Pooling layers, contributing to invariance by down-sampling the resolution of the feature maps.

Long Short-Term Memory (LSTM) networks were specifically designed to model temporal sequences and capture long-range dependencies more effectively than conventional Recurrent Neural Networks (RNNs) [30]. While CNN-LSTMs are commonly employed in visual learning tasks, they also demonstrate efficacy in speech recognition and natural language processing [31]. Importantly, both CNNs and LSTMs serve as powerful tools for temporal sequence prediction [32]. In addressing large datasets or complex temporal/spatial sequence problems, CNN-LSTM enhances prediction accuracy and precision [33,34].

5. Results

In this section, we will present the classification accuracy results achieved by various conventional ML algorithms. Additionally, we will showcase the accuracy of the proposed method and conduct a comparative analysis with the performance of models discussed in Section II. This analysis aims to provide insights into how the proposed method performs in comparison to the relevant models discussed earlier.

5.1. Results of Conventional Machine Learning Algorithms

Prior to evaluating the efficacy of the proposed approach, we employed several traditional ML algorithms to assess their classification performance on the three benchmark datasets mentioned earlier. The conventional ML algorithms considered in this phase included K-Nearest-Neighbor (KNN), support vector machine (SVM), Decision Tree (DT), Random Forest (RF), Naïve Bayes (NB), Multi-Nominal Logistic Regression (LR), Extreme Gradient Boosting (XGBoost), and Multi-Layer Perceptron (MLP). Table 1 presents the classification accuracy of these conventional algorithms.

Table 1. Performance of conventional ML algorithms [28].

Algorithms	UCI	Ninapro DB6	Mendeley
KNN	0.6416	0.6714	0.4940
SVM	0.4333	0.4460	0.4853
DT	0.2958	0.3703	0.3777
RF	0.4042	0.4279	0.5212
NB	0.2542	0.4270	0.5286
LR	0.6875	0.4278	0.5257
XGBoost	0.7708	0.4362	0.5478
MLP	0.7625	0.4491	0.5544

5.2. Proposed Model Evaluation

After testing the performance of the conventional machine learning algorithms, we implemented the proposed algorithm and tested the classification performance on the three benchmark datasets. Meanwhile, we compared the results with those of some of the previously mentioned research. Table 2 shows the performance metrics of our proposed method and the algorithms in the previously mentioned studies.

Table 2. The performance comparison of our proposed method with other methods in the literature [28].

Dataset	Algorithm	Accuracy
UCI	Boosting of SVM [2]	0.98
	CNN [15]	0.8397
	NB [23]	0.9643
	LDA [25]	0.9796
	ELM [20]	0.99
	ESD [22]	0.9949
	CNN-RNN [16]	0.99
	CNN [17]	0.9852
	Proposed TCNN+LSTM	0.9963
Ninapro DB6	CNN [8]	0.7372
	1D-CNN+Self attention [18]	0.6573
	Temporal CNN [9]	0.937
	Proposed TCNN+LSTM	0.9556
Mendeley	Temporal CNN [11]	0.7657
	CNN [19]	0.895
	Proposed TCNN+LSTM	0.9614

6. Discussion

In Figure 2, the comparison reveals the superior performance of the proposed method over conventional ML algorithms. These results underscore the significantly superior of the proposed method across all three benchmark datasets.

The shift from simpler supervised learning models, like SVM and KNN, to more intricate ones, such as CNNs and RNNs, has been prompted by the inherent complexity of the data. Conventional ML algorithms tend to yield lower accuracies due to this complexity. Notably, this research introduces a novel approach by treating sEMG signals as time series and employing a sequential methodology for classification. Our proposed method, the integration of a time-wrapped CNN+LSTM, represents a robust model, particularly effective in handling temporal data.

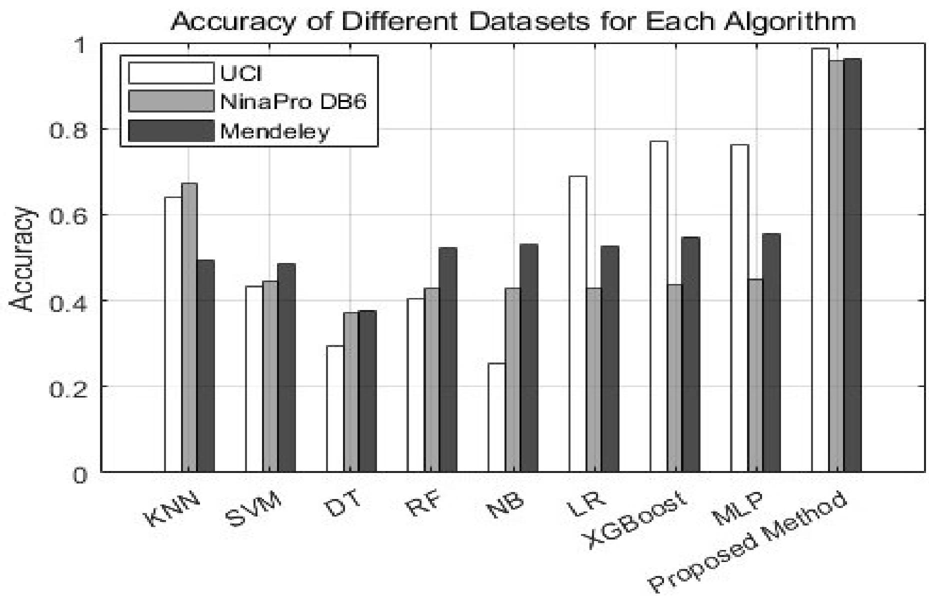

Figure 2. Comparison of results of SFDN+DNN with conventional ML algorithms [28].

Another crucial consideration is that, despite many studies reporting acceptable classification accuracy, their findings have frequently been confined to relatively small training and test datasets. In contrast, our approach utilizes a significantly larger data-frame of learning features compared to other literature, resulting in notably higher accuracy.

Furthermore, certain prior studies have achieved high accuracy without disclosing their proposed network's architecture or elucidating the methodological steps leading to their reported accuracies. In this research, we take a transparent approach, presenting the detailed network architecture that contributed to our high accuracy, along with a comprehensive account of the rationale behind selecting each element in the proposed network.

A common limitation in most of these studies lies in their computational cost, extended classification times, and reliance on offline training. In contrast, our proposed model boasts advantages such as low-cost computation, online learning capability, and commendable accuracy. These attributes make it a viable option for biomedical laboratories aiming to design thought-controlled prosthetic hands, offering a practical and efficient solution to the challenges posed by existing models.

7. Conclusions

In summary, numerous endeavors in the literature to classify sEMG signals, pivotal bio-signals directing muscle movements, for the design of lifelike prosthetic hands have often yielded suboptimal classification accuracies and high errors. This thesis introduces a pioneering deep learning approach, leveraging a time-wrapped CNN+LSTM classifier, surpassing existing benchmarks in the field. The classification was performed on three benchmark datasets: the UCI Machine Learning Repository sEMG dataset, the Ninapro DB6 dataset, and the Mendeley sEMG dataset.

Recognizing the inherent challenges of sEMG data—microvolt scale and high noise—a preprocessing strategy was employed, encompassing smoothing, filling outliers, detrending, and normalizing. This preprocessing paved the way for the proposed classifier, namely SFDN+DNN, which achieved remarkable training accuracies of 99.63%, 95.56%, and 96.14% for the UCI, Ninapro DB6, and Mendeley datasets, respectively—among the highest in the literature.

Our method's efficacy was further highlighted through comparisons with robust conventional learning algorithms, including KNN, SVM, Decision Tree, Random Forest, Naïve Bayes, Multi-Nominal Logistic Regression, XGBoost, and Multi-Layer Perceptron. The proposed approach outperformed all counterparts, affirming its superior classification power.

The noteworthy contributions of this research encompass achieving high classification accuracies, particularly suitable for designing functional prosthetic hands. The novel perspective of interpreting hand movements as sequential, time-series classifications further adds to the advancements. Additionally, our methodology stands out for its low computation cost and online learning capability, presenting a comprehensive and efficient solution in the realm of sEMG signal classification.

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