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Comparative analysis of machine learning algorithms on myoelectric signal from intact and transradial amputated limbs

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ABSTRACT

Control strategies of smart hand prosthesis-based myoelectric signals in recent years don't provide the patients with the sensation of biological control of prostheses hand fingers. Therefore, in current work hyperparameters optimization in machine learning algorithm and hand gesture recognition techniques were applied to the myoelectric signal-based on residual muscles contraction of the amputees corresponding to intact forearm limb movement to improve their biological control. In this paper, myoelectric signals are extracted using the MYO armband to recognize ten gestures from ten volunteers (healthy and transradial amputation) on the forearm, thereafter the noise of myoelectric signals using a notch filter (NF) is removed. The proposed classification system involved two machine learning algorithms: (1) the decision tree (DT), tri-layered neural network (TLNN), k-nearest-neighbor (KNN), support vector machine (SVM) and ensemble boosted tree (EBT) classifiers. (2) the optimized machine learning classifiers, i.e., OKNN, OSVM, OEBT with optical diffraction tomography (ODT) and ommatidia detecting algorithm (ODA). The experimental results of classifiers comparison pointed out an algorithm that outperformed with high accuracy is OEBT closely followed by OKNN achieves an accuracy of 97.8% and 97.1% for intact forearm limb, while for transradial amputation with an accuracy of 91.9% and 91.4%, respectively.

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1. INTRODUCTION

The bundles of specialized cells that constitute muscles are able to contract and relax. In the human body, a bioelectrical signal corresponding to muscle activity is produced during muscular contraction. The signal is known as Electromyography (EMG), and it is crucial for clinical diagnosis, treatment, rehabilitation, and automatic control of smart prosthetics and orthotics [1]. Therefore, it is important to study, analyze and classify the EMG signals then compared between them. Analysis of EMG signals using appropriate methods and algorithms can give efficient ways for understanding of their characteristics, and the EMG devices implementations can be made for various EMG signal related applications. The surgical resection of all or segments of an upper-lower limb, i.e., arm, hand, finger, leg, foot, or toe, is known as an amputation [2]. Amputations of the upper limbs range from losing only a finger part to losing an entire arm and part of the shoulder, furthermore, a transradial or below elbow amputation impacts hand function by losing part of the forearm below the elbow joint Morgan *et al.* [3]. EMG signals can be taken from the anterior and posterior muscles at Forearm. The anterior and posterior muscles of the forearm can generate EMG signals McCausland *et al.* [4]. Francesco Redi's reporting of the EMG dates back to 1666 [5], whereas Marey made the first recording of EMG electrical activity in 1890. Early in the 1980s, Cram and Steger developed a clinical technique for using an EMG measuring device to scan variety muscles [6]. Then, the scientific research in this field improved our knowledge of the characteristics of surface EMG recording. Depolarization produces an electromagnetic field called EMG, which is quantified as very low voltage. Motor neuron action potentials are propagated to the tendons after being transmitted to muscles by end-plates. Surface electrodes are used to detect these bioelectrical signals [7]. Disease and injury to the lower motoneuron or the muscle may result in muscular atrophy and partial paralysis of variable degrees [8]. There are two EMG types, (1) Clinical EMG, also known as "diagnostic EMG", and (2) "Nerve Conduction EMG," which is frequently performed by physiatrists and neurologists, while kinesiological EMG is used in movement analysis [9]. The MYO armband is a device that has eight sensors to measure the EMG signals of forearm muscles at a frequency of 200 Hz (sample rate) and are normalized to values in the range of 1 and -1 as a result of muscle activation, sending them to computer via Bluetooth [10]. The MYO armband is also equipped with several other sensors, such as accelerometer, gyroscope, and magnetometer which collect spatial data about the gesture and can facilitate gesture recognition [11]. MYO armband can be used to allow an amputee to control a prosthetic, robotic hand, a humanoid robot, interaction for the local surgeon by laparoscopic, in addition to other applications such as games, Maps, Myo music, and Keynotes. Feature extraction methods can be used to infer the efficacy information in EMG signal to study its characteristic and behavior in (time, frequency, or time-frequency domains). The time domain (TD) features are simple and efficient in EMG pattern recognition [12]. TD features are extracted from the variations of signal amplitude with time such as root mean square (RMS), mean absolute value (MAV) Zecca *et al.* [13], standard deviation (STD), integrated absolute value (IAV), maximum amplitude (MAX), minimum amplitude (MIN), and many other functions that are used in the time domain such as zero crossings (ZC), carrier operated relay (COR), Wide-area multilateration (WAM), and man-portable vector (MPV), the EMG signals can be employed to detection the dynamic activity of a muscle (contract and relax), whereas RMS or moving average (MA) values are used to gauge the muscle's level of activity or gauge how much force it generates Liu *et al.* [14]. The optimization the hyper-parameters of machine learning algorithm with several techniques for difference applications and the performances compared to develop, furthermore present the relationship among dataset, performance and hyperparameters [15]–[17]. There are six machine learning classifiers, i.e., support vector machine (SVM), random forest (RF) decision tree (DT), logistic regression (LR), naive bayes (NB) and ridge classifier (RC) are comparison and different hyperparameters methods tuning are employed Elgeldawi *et al.* [18]. Development the automatic machine learning to classification EMG signal that extracted with needle electrode based on hyper-parameters optimization for healthy and disease muscles Kefalas *et al.* [19]. The classification of EMG pick up from forearm using MYO armband and the training dataset's 5-fold cross-validation methods are used to choose the hyperparamet ers for classifiers [20].

In current study, the primary challenge is to employ the wireless MYO armband instead of cabled electrodes to collect myoelectric signal data from transradial amputation and a healthy forearm. This which increase the freedom and comfort of movement for the forearm-hand of the subject. Furthermore, the low cost of wearable MYO armband devices relative to other EMG equipment, thus, it may be an alternative to expensive devices.

The contribution of this paper is to propose tuning the parameters, functions and optimization hyper-parameters of the machine learning algorithms. Also, to recognize ten gestures (Clenched fist, fingers abduction, wrist extension, wrist flexion, and rest), which helps in reducing the difficulty of classification myoelectric signal data. Then the extracting during contraction muscles of transradial amputation resulting from weak or atrophic muscles and give high-rate performance to move hand prosthesis.

2. MATERIAL AND METHOD

A significant improvement in the dexterity of control in upper-limb prosthetics has been demonstrated by the intelligent classifier of EMG signal with the control method. In this study, the proposed methodology comprises several components as block diagram illustrated in Figure 1. The methodology procedures employ the MYO armband to pick up the myoelectric signal from transradial amputee and intact forearm with different hand movements intention at the wrist joint. The myoelectric signal preprocessing to reduce the noise associated with the myoelectric signal record, then windowing-overlapping data and features extracting to keep the most discerning hand movement-related information possible. The classification of data features collection using various machine learning algorithms with optimization to predict the best model of limb movements, and send as commands to control the movement that drives the prosthesis. These methodology stations are important in finding the total performance of the prosthetic system movement patterns. Therefore, the details components of the methodology are described.

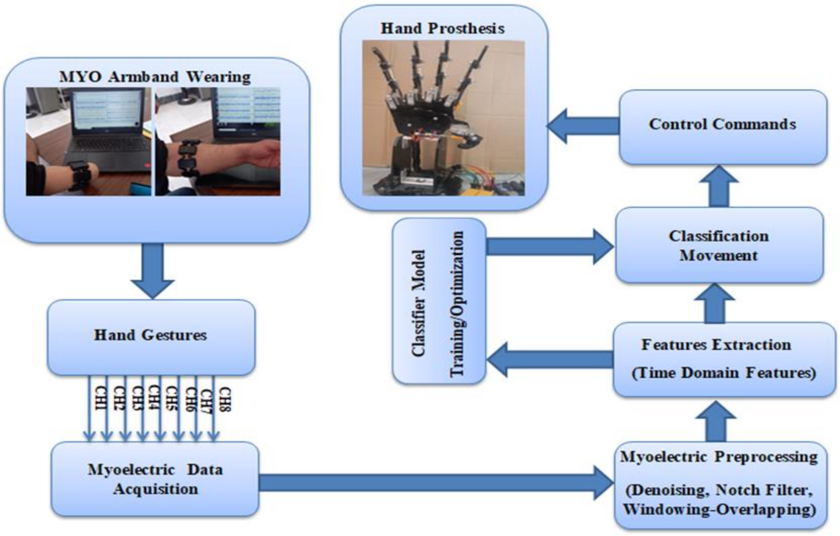

Figure 1. Proposed methodology

2.1. Myoelectric data acquisitions

The current investigation involves the MYO armband as shown in Figure 2 to capture the myoelectric signals Tavakoli *et al.* [21]. In this method, we use an external HM-10 Bluetooth module to connect the MYO armband to a controller board. These sensors use a sampling rate of 200 Hz and an 8-bit resolution for each of its eight myoelectric sensors to measure the electrical activity of the forearm muscles. The objectives of preprocessing are to minimize the noise in the collected myoelectric signal and make feature extraction easier. The raw signal has some additional noise, which might produce invalid features and cause classification problems, Therefore, the notch filter technique that collects low and high pass filters was implemented for removing the small area of bandwidth interference from the myoelectric signal [22]. The observed signals are first normalized to prepare for training, with each member of each matrix signal M=(M1, M2,...., M8) in the range [-1, 1]. An absolute value function is used to rectify the original signal in each eight-channel.

Figure 2. MYO armband for data acquisitions

The volunteers were requested to maintain a consistent behavior and record the whole myoelectric data signals as part of the study methodology. The myoelectric database often needs the participant to hold each motion for a brief period of time before repeating it multiple times. The movements were alternated with a resting stance to reduce fatigue. During frequent use, it is customary to keep a long posture. As a result, in order to design a bionic prosthesis that is more suitable for frequent use by amputees, each gesture necessitates the subject to sustain a relatively long duration, resulting in noise in the acquired signal owing to tiredness and recuperation. In this paper, the myoelectric signal was extracted from five male subjects participating in the experiments with transradial amputation (below the elbow) and intact forearm limb. Data sets of ten gestures (Clenched fist, fingers abduction, wrist extension, wrist flexion, and rest) were recorded for the amputated and healthy forearm of the same volunteer for this study, as illustrated in Figure 3(a) and

Figure 3(b). Each of the ten gestures was repeated three times and a myoelectric signal was recorded for a period of five seconds per gesture with a frequency of 200 Hz.

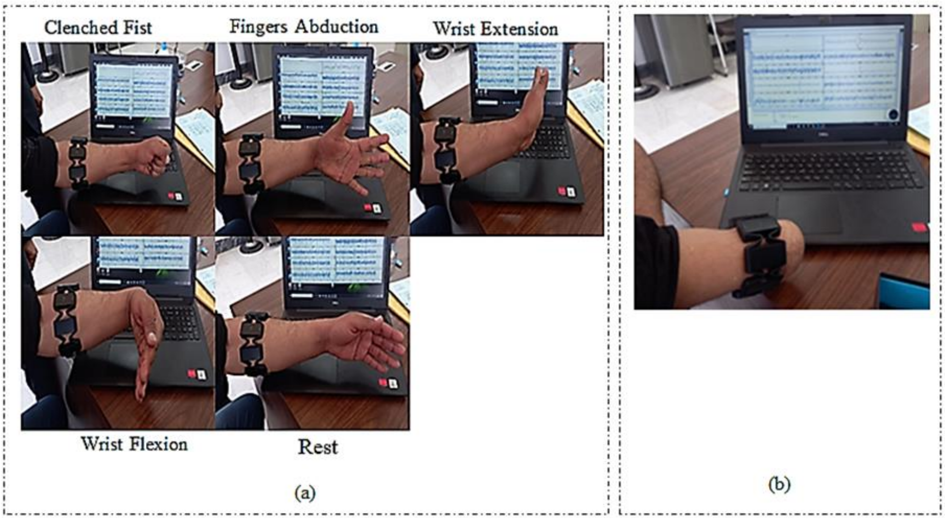

Figure 3. Experimental setup to record ten hand gestures: (a) intact forearm limb and (b) transradial amputation limb

These ten gestures: i.e., clenched fist, fingers abduction, wrist extension, wrist flexion, and rest are simulated with 1,000 elements per gesture as shown in Figure 4. Since the extracted myoelectric data was found have different length sizes for each gesture in the range 1,171-1,339 samples, the silence removal (SR) feature was used to delete extra data in order to obtain the same length size for all gesture data samples. One of the main criteria for improving the accuracy classification of the myoelectric data signal is the window-length based segmentation technique, therefore, the data sets signal is overlapped for feature extraction in this work. There are four features of the myoelectric signal after the segmentation window to equal size were extracted in the time domain and to reduce the time computational cost, the features selected are RMS, zero crossings (ZC), integrated ElectroMyography (IEMG), and waveform length (WL) for each window length and gesture [23]–[25].

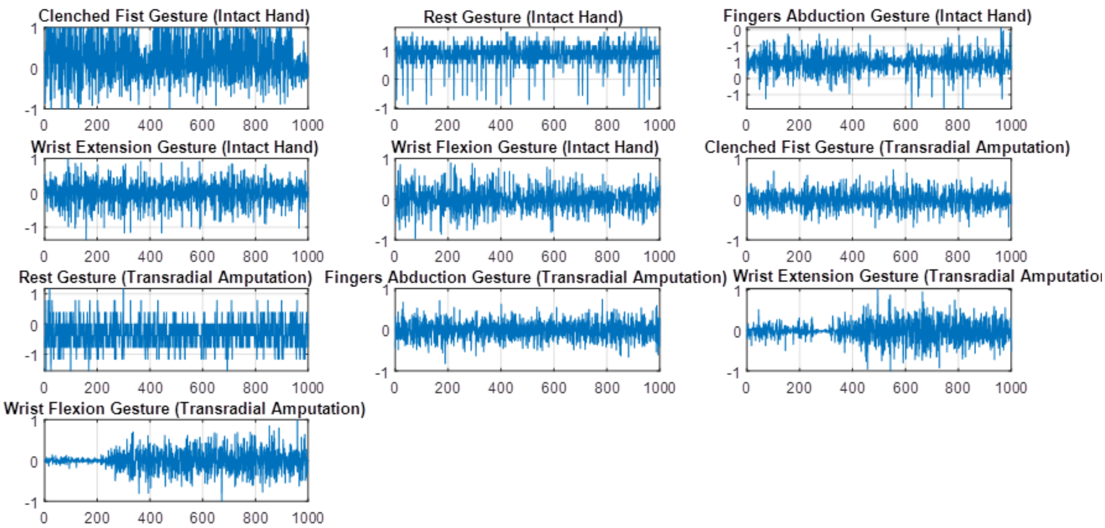

Figure 4. Myoelectric signals for ten gestures from both intact hand and transradial amputation

2.2. Gestures classifiers

In this work, two categories of the classifier are implemented: the first category consists of support vector machines (SVM) [26], [27], k-nearest neighbors (KNN) [28], decision tree (DT) [29], ensemble boosted tree (EBT) [30] and tri-layered neural network (TLNN) [31], Ye *et al.* [32]. These supervised machine learning classifiers trained the features of myoelectric data. The second category involved optimized classifiers i.e., optimal support vector machine (OSVM), optimal k-nearest neighbors (OKNN), optical diffraction tomography (ODT) and ensemble optimal electronic benefits transfer (OEBT) by optimization of the internal parameters of classifiers using the hyper-parameters model. Evaluation of the classification to obtain a robust classifier model is adopted by implementing cross-validation value i.e. K-Fold=10.

3. EXPERIMENTAL RESULTS AND DISCUSSION

This paper implemented three different protocol of experiments procedure: the first is pre-setting the parameters of the fine gaussian SVM, TLNN, fine KNN, fine DT and EBT classifiers before training with different parameters and functions: i.e., kernel functions (Gaussian, linear, quadratic), The structure of TLNN classifier included 32 neurons in input layer, three fully-connected layers have with three activation-functions rectified linear unit (ReLU), Tanh, Sigmoid connected with each fully-connected layer and softmax function is connected to the last fully-connected layer. Finally, the output layer that corresponds to the five gestures labels. The non-optimized EBT classifier trained with three ensemble methods (AdaBoost, Bag, RUSBoost), while the for fine KNN classifier used three metrics (Chebyshev, Euclidean, Cosine) to find the distance to points. In fine DT classifier the split criterion measure (maximum deviance reduction, Gini’s diversity index, twoing rule) are specified to deciding when to split nodes.

The second is setting the hyperparameters after training the machine learning classifiers, SVM, KNN, EBT, and DT. It will obtaine automated machine-learning classifiers, which are: OSVM, OKNN, ODT and OEBT. There are various parameters and functions for optimization used as present in Table 1. The third experiment protocol represents the evaluation classifiers performance.

Table 1. Optimized hyper-parameters details of the SVM, KNN, EBT AND DT classifiers

Optimized classifier	Selected parameters for optimization	Optimized hyperparameters		
OKNN	Number of neighbors	[1-8,000]		
	Distance metric	Chebyshev	Cosine	Ecuildean
	Distance weight	Equal	Inverse	Squared inverse
	standardize data	TRUE		FALSE
OSVM	Kernel function	Gaussian	Cubic	Linear
	Box constraint level	[0.001-1]		
	Kernel scale	Auto		
	Multiclass method	standardize data		
OEBT	Ensemble method	AdaBoost	Bag	RUSBoost
	Learner type	Decision Tree		
	Maximum number of split	[1-8,000]		
	Number of learners	[5-1,000]		
	Learning rate	[0.01-1]		
	Number of predictors to sample	[1-10]		
	Optimizer type	Bayesian optimization	Grid search	Random search
ODT	Maximum number of splits	[1-8,000]		
	Split criterion	Maximum deviance reduction	Gini’s diversity index	Twoing rule

Initially, the evaluation performance of the fine gaussian SVM, TLNN, fine KNN, fine DT and EBT classifiers function are examined by measure the accuracy as shown in Table 2, respectively. From results the performance of the Gaussian Kernel Function of Fine Gaussian SVM classifier is better than the others function. Its accuracy is 84.1% for transradial amputation and 91.4% for intact forearm limb.

The results conducted that TLNN based Tanh activation function high accuracy than other function for amputee and intact volunteers with an accuracy 84.2% and 94.6%, respectively. Overall, the results indicated that the EBT classifier outperformed other classifiers with an average accuracy 95.4% for intact and 84.1% for amputee by using ensemble method Bootstrap Aggregation (Bagging) followed by classifier KNN with an accuracy equals to 95.4% and 88.1%. On other hand, The DT classifier performance was the worst with an accuracy rate of 90.3% for intact and SVM classifier based Quadratic Kernel Function for amputee with an accuracy equal to 70.9%.

The results of classification accuracy, MCE and AUROC (area under the curve of convergence receiver operating characteristic (ROC)), that examined by the proposed classifiers for intact and amputee myoelectric signal are listed in Table 3. From Table 3 it is obvious that OEBT performed better than other classifiers (OKNN, OSVM, ODT) for amputee with an accuracy of 91.9%, followed by OKNN with 91.4% and with high rate AUROC, and MCE performances of 0.99 and 0.081, respectively. While, the ODT classifier, whose accuracy is 89.41% has the worst performance. Based on the results, the optimized classifiers can satisfactorily perform better than those specified parameter classifiers.

Table 2. Comparison performance accuracy results-based functions and parameters classifiers models

Classifier	Classifier Functions and Parameters						
	Kernel functions	Gaussian		Linear		Quadratic	
Fine Gaussian SVM	Volunteer	Intact	Amputee	Intact	Amputee	Intact	Amputee
	Accuracy (%)	91.4	84.1	87	71.9	82.3	70.9
	Activation functions	ReLU		Tanh		Sigmoid	
TLNN	Volunteer	Intact	Amputee	Intact	Amputee	Intact	Amputee
	Accuracy (%)	90.7	83.4	94.6	84.2	91.9	83.6
	Distance metric	Chebyshev		Euclidean		Cosine	
Fine KNN	Volunteer	Intact	Amputee	Intact	Amputee	Intact	Amputee
	Accuracy (%)	94.6	84.4	95.4	88.1	91.9	83.3
	Split criterion	Maximum deviance reduction		Gini's diversity index		Twoing rule	
Fine DT	Volunteer	Intact	Amputee	Intact	Amputee	Intact	Amputee
	Accuracy (%)	90.3	81.5	90.7	81.7	91.5	83.9
	Ensemble methods	AdaBoost		Bag		RUSBoost	
EBT	Volunteer	Intact	Amputee	Intact	Amputee	Intact	Amputee
	Accuracy (%)	92.4	82.6	95.4	84.1	93.1	79.1

Table 3. Comparative performance of different optimized classifiers-based accuracy, MCE AND AUROC

Optimized Classifier	Classification accuracy (%)		MCE		AUROC	
	Intact	Amputee	Intact	Amputee	Intact	Amputee
OKNN	97.1	91.4	0.029	0.086	0.99	0.99
OSVM	93.4	89.9	0.066	0.101	0.98	0.98
OEBT	97.8	91.9	0.022	0.081	0.99	0.99
ODT	92.1	89.4	0.079	0.106	0.97	0.96

According to an evaluation of the results in Tables 2 and 3 can be it can be deduced that the best classifiers are OEBT and OKNN for transradial amputation and intact forearm cases. Therefore, both classifiers: OEBT and OKNN are adopted in the rest of the results. The comparison of the minimum classification error (MCE) convergence graph of selected optimization methods based on the OKNN and OEBT as the best classifiers for transradial amputation are shown in Figure 5(a) and Figure 5(b) and for intact forearm limbs are displayed in Figure 5(c) and Figure 5(d).

The MCE plot consists of two convergence graphs, the first represents the estimated MCE that is indicated in light blue points color calculated by the optimization process taking into account all of the hyperparameter value sets that have been tried up to this point, including the present iteration. While the second convergence graph represents the observed MCE that is indicated in dark blue points color calculated thus far through the optimization procedure. From Figure 5(b) it is observed that reaching the best point hyperparameters at fourth iteration that less than iteration number in Figure 5(a), while in Figure 5(d) at the eighth iteration. It is seen that attaining the best point hyperparameters that less than iteration number in Figure 5(c).

Figure 6 shows the confusion matrix for both groups (transradial amputation and intact forearm limb). The recognition rate of five different hand gestures reaches 90.3% for clenched fist, 86.1% for finger abduction, 98% for rest, 98.2% for wrist extension and 87.2% for wrist flexion gesture in transradial amputation case as illustrated in Figure 6(a) based OEBT classifier. While after classification using the OKNN classifier the result of the confusion matrix for transradial amputation, the recognition rate for each gesture gives 89.3% for clenched fist,86.3% for finger abduction, 97.8% for rest, 98% for wrist extension and 85.9% for wrist flexion as shown in Figure 6(b). As for the outcomesof recognition rate related to intact volunteers are shown in Figure 6(c) based OEBT classifier for five various hand movement, i.e., 100% for clenched fist, 95.5% for finger abduction, 99.4% for rest, 97.1% for wrist extension and 97.1% for wrist flexion gesture. Whereas the recognition accuracy using OKNN classifier for clenched fist is 100%, for finger abduction is 93.9%, for rest is 99.6%, for wrist extension is 96.6% and 95% for wrist flexion movement as shown in Figure 6(d).

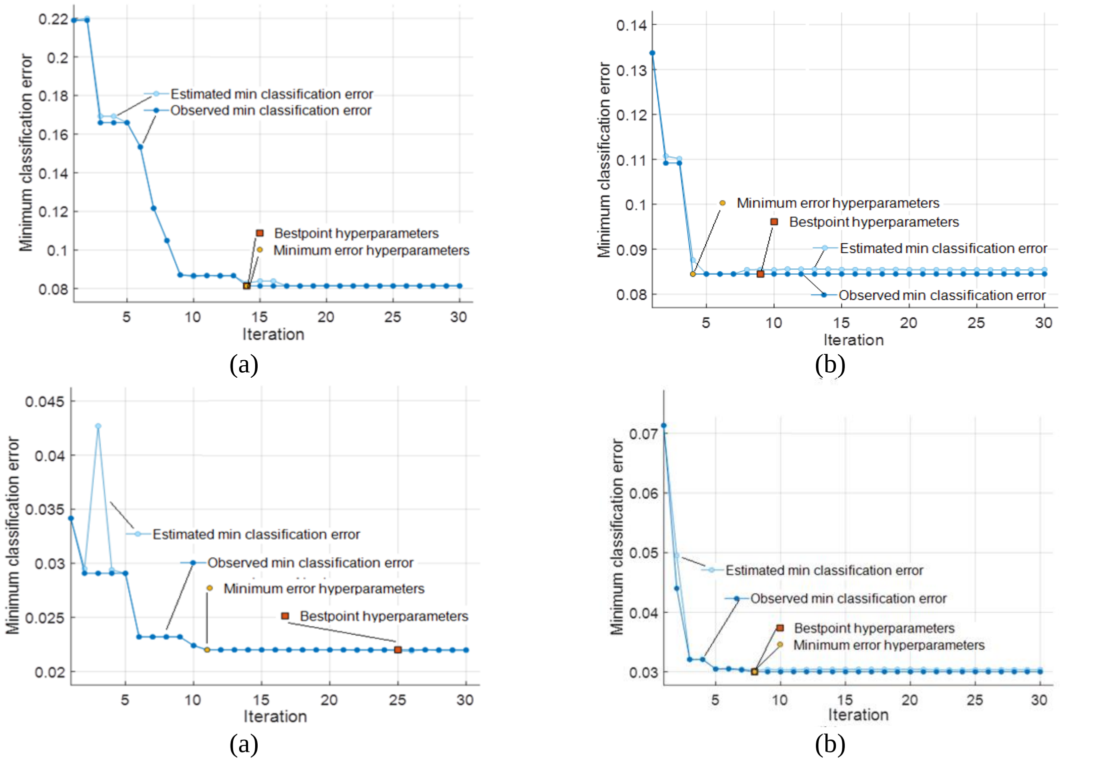

Figure 5. Minimum classification error graph: (a) OEBT classifier for transradial amputation limb, (b) OKNN classifier for transradial amputation limb, (c) OEBT classifier for intact forearm limb, and (d) OKNN classifier for intact forearm limb

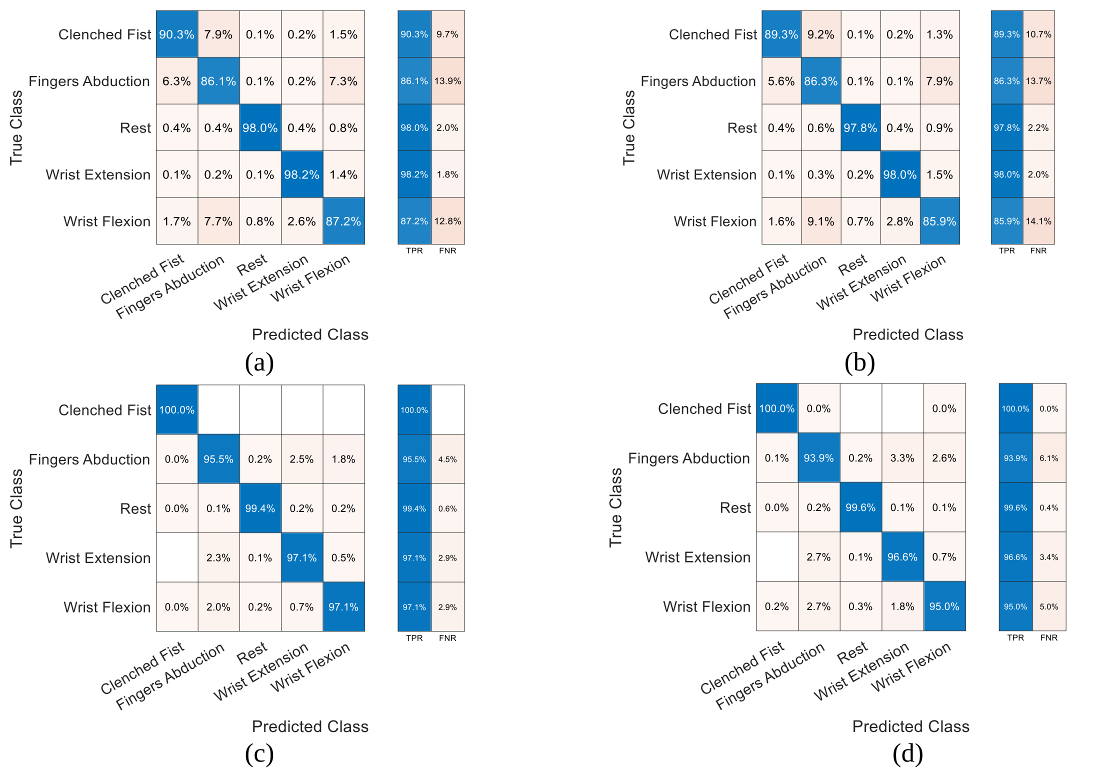

Figure 6. Confusion matrix for five gestures: (a) OEBT classifier for transradial amputation limb, (b) OKNN classifier for transradial amputation limb, (c) OEBT classifier for intact forearm limb, and (d) OKNN classifier for intact forearm limb

4. CONCLUSION

In the cases of most transradial amputees, it is difficult to extract features and performed classify myoelectric signals due to weak muscle activities, causing complexity to control wearable hand prostheses. The myoelectric data was collected using the MYO armband device, where the employed MYO armband increased the system mobility and flexibility while effectively processing the myoelectric signals. The proposed preprocessing and overlap-segmentation techniques improved the results recognition of five hand gestures using myoelectric data signals and in extracting four time-domain features RMS, ZC, IEMG, and WL for each segment and the classifier. In this paper, the SVM, KNN, DT, TLNN and EBT classification algorithms were proposed, developed, examined and optimized using the hyperparameters optimization technique, i.e., OSVM, OKNN, ODT and OEBT on myoelectric data of five gestures for both transradial amputees and intact forearm limb. The results showed that the classification utilizing OEBT and OKNN that were more accurate and robustness than those from other classifiers and had a higher rate of recognition for different hand movements for volunteers either with transradial amputation or healthy forearm limb, respectively. A recommendation for future study in this field can be combined the MYO armband device Neuro-headsets device that extracted Electroencephalography signal (EEG) to design couple brain-computer interface (BCI) system in recognizing patterns for different forearm anatomical movements to obtain high rate accuracy. Furthermore, connected this system to low-cost field programmable gate arrays (FPGA) platform to improve machine learning classifier performance.

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