

Enhancing Upper Limb Prosthetic Control in Amputees Using Non-invasive EEG and EMG Signals with Machine Learning Techniques

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Abstract—Amputation of the upper limb significantly hinders the ability of patients to perform activities of daily living. To address this challenge, this paper introduces a novel approach that combines non-invasive methods, specifically electroencephalography (EEG) and electromyography (EMG) signals, with advanced machine learning techniques to recognize upper limb movements. The objective is to improve the control and functionality of prosthetic upper limbs through effective pattern recognition. The proposed methodology involves the fusion of EMG and EEG signals, which are processed using time-frequency domain feature extraction techniques. This enables the classification of seven distinct hand and wrist movements. The experiments conducted in this study utilized the binary grey wolf optimization algorithm to select optimal features for the proposed classification model. The results demonstrate promising outcomes, with an average classification accuracy of 93.6% for three amputees and five individuals with intact limbs. The accuracy achieved in classifying the seven types of hand and wrist movements further validates the effectiveness of the proposed approach. By offering a non-invasive and reliable means of recognizing upper limb movements, this research represents a significant step forward in biotechnical engineering for upper limb amputees. The findings hold considerable potential for enhancing the control and usability of prosthetic devices, ultimately contributing to

the overall quality of life for individuals with upper limb amputations.

Index Terms—Upper limb amputees, Prosthetic control, EEG and EMG signals, Machine learning, Movement recognition.

I. INTRODUCTION

Upper limb amputation is a condition that severely limits the capacity of amputees to do daily duties. The myoelectric prosthesis aims to help restore the function of these lost limbs using signals from the remaining muscles. Unfortunately, there are multiple difficulties facing patients with missing upper limbs in terms of the challenge of collecting this signal, and the percentage of upper limb amputation, as much research in this sector is now focused on helping amputees live as normal a life as feasible (Kumar, Singh and Mukaherjee, 2021). The development of fusion bio-signals-based rehabilitation devices has become now very interesting to many biomedical researchers. However, the development of electroencephalography (EEG) and electromyography (EMG)-controlled prostheses remains a challenging issue in developing countries (Khan, Khan and Farooq, 2019). Multiple-source signal fusion is one way to solve the problem of not having enough information to control a prosthesis (Hooda, Das and Kumar, 2020; Radha, Abdul Hassan and Al-Timemy 2023).

In the previous studies, most researchers applied advanced signal processing, robust feature extraction, machine learning, and feature selection algorithms to improve the performance of the biosignal pattern recognition (PR) system (Dey et al., 2018; Udhaya Kumar and Hannah Inbarani, 2017). Signal processing, in general, transforms the signal to obtain useful signal information. The goal of feature extraction is to extract useful information from a signal. The feature selection algorithm attempts to identify the best features from the initial set of features. Finally, machine

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learning functions as a classifier, categorizing features to recognize hand movements (Krishnan and Athavale, 2018). Many EEG and EMG features have recently been proposed and used in fusion PR (Al-Quraishi, et al., 2021; Fang, et al., 2020; Radha, Abdul Hassan and Al-Timemy, 2022; Verma and Tiwary, 2014). Increasing in the number of EEG, EMG features not only increase the classifier's complexity but also have a negative impact on the classification process (Cai, et al., 2020). Following this line of thought, feature selection is an important step in removing irrelevant and redundant information, which reduces the number of features and unnecessary complexity (Alelyani, Tang and Liu, 2018). Feature selection methods classify selection approaches based on the participation of the learning algorithm. Filter method (Information Gain) (Singer, Anuar and Ben-Gal, 2020), Gain Ratio (Voelzke, 2015), and Chi-square (Ahakonye, et al., 2023) rely on some data properties without engaging a specific learning process. Wrapper approaches, on the other hand, rely on a specialized learning algorithm (e.g., classifier) to evaluate the specified subset of features (Shahana and Preeja, 2016; Jović, Brkić and Bogunović, 2015). When comparing these families, wrappers are more accurate since they take into account the relationships between the traits themselves. They are, however, more computationally expensive than filters, and their performance is heavily dependent on the learning technique used (Thabtah, et al., 2020). Another important consideration when creating a feature selection algorithm is looking for the (near) optimal subset of features. To choose the best feature subset, wrapper-based feature selection uses a meta-heuristic optimization technique, such as binary grey wolf optimization (BGWO), binary particle swarm optimization, ant colony optimization, and genetic algorithm (Beheshti, 2022). This study proposes an algorithm for classifying the upper limb motions of below-elbow amputees by fusing EMG and EEG data as parallel input. The following is a summary of the main contributions of the current work:

1. Build a dataset for hand and wrist motion detection for two biosignals (EEG, EMG).
2. Binary gray wolf optimization-based feature selection is utilized to select the proper set of features, which improved outcomes for selecting effective features for signal segment classification to categorize seven classes of hand and wrist motion, which are (wrist flexion [WF], flexion of outer part of the wrist, hand close [HC], hand open [HO], pronation [PRO], supination [SUP], and rest [RST]).

II. METHODOLOGY

A. Subjects and Data Acquisition

Data were collected from eight subjects, five subjects are intact-limbed, and three are amputees and were recorded in the laboratory of the Department of Biomedical Engineering. Al-Khwarizmi College of Engineering, University of Baghdad. To classify hand movements, a set of seven movements was selected: WF, outward part of the wrist

(WE), HO, HC, PRO, SUP, and RST see Fig. 1. When recording the signal, the following was observed:

- Subjects have given their consent to participate in the study.
- The experimental protocol was done according to the Declaration of Helsinki and its later amendments.

This study was focused on these motions according to their relationship with low-level amputation. Table I displays the demographic data of the amputees. In addition, Fig. 2 provides illustration pictures of amputees in the registration of this dataset. Eight EMG channels were recorded in the data. Moreover, four frontal EEG channels were provided as shown in Fig. 3. Subjects received a thorough explanation of the events, and they received some brief training to get them acclimated to the process. Each participant in the experiment was instructed to do the exercise in turn for a duration of 10 s, after which the motions were recorded three more times. In this setting, two trails were used to train the classifier and the remaining trail was used to test the classifier to calculate the classification error rate. EMG and EEG were recorded simultaneously while performing the movement. EMG signals were collected. They used a high-density EMG system where the signal frequency was 200 Hz for eight channels; Electrodes were placed on the surface of the skin to check for residues arm for each subject. On the other hand, EEG Muse data were collected on 252 Fs, and with 4 channels Raw. At a sampling rate of 1 kHz, raw data are gathered from which

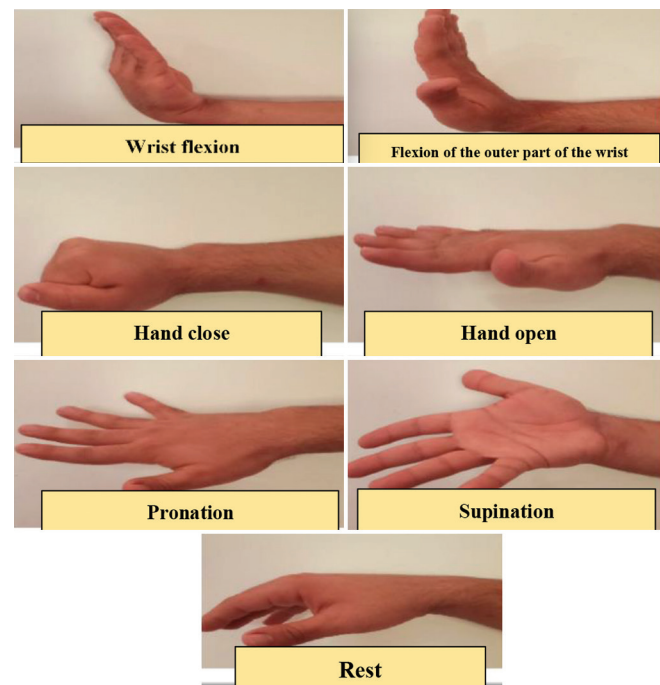


Fig. 1. Hand and wrist motion classes.

TABLE I
DEMOGRAPHIC DATA FOR AMPUTEE SUBJECTS

Amputee ID	Age (years)	Missing arm	Time since amputation (years)
Amputee 1	67	Left	30
Amputee 2	48	Right	31
Amputee 3	35	Left	7

useful features can be extracted. Fig. 4 depicts a visualization plot comparing both the EEG and EMG signals for an



Fig. 2. Amputee’s participants during the acquisition of the proposed dataset. (a) Amputee subject 1, (b) Amputee subject 2, and (c) Amputee subject 3.



Fig. 3. Electroencephalography Muse four channels and electromyography Armband placement eight channels devices.

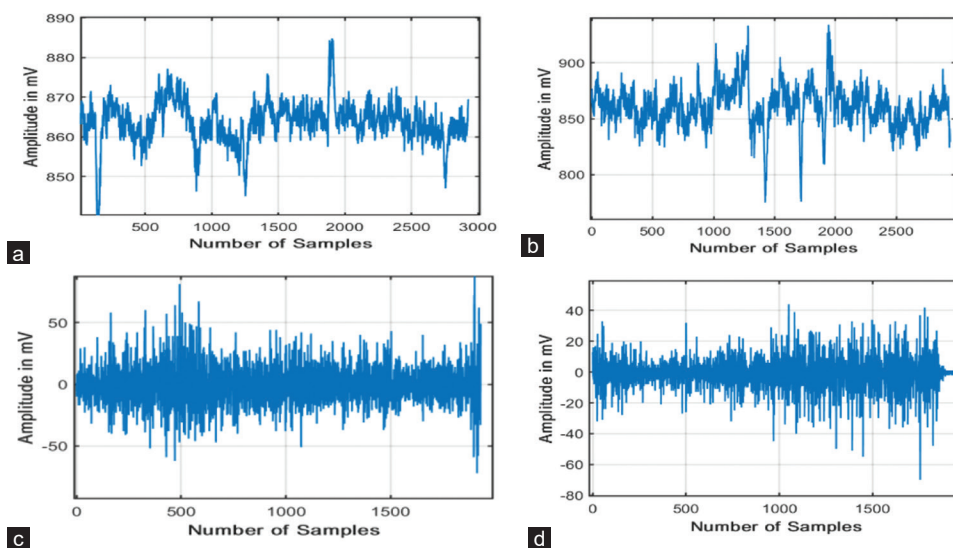


Fig. 4. Waveforms obtained from electroencephalography (EEG) and electromyography (EMG). (a) EEG signal for non-amputee subject, (b) EEG signal for amputee subject, (c) EMG signal for non-amputee subject, and (d) EMG signal for amputee subject.

amputee and intact-limb subject. Because the EMG is based on the acquisition of bioelectrical signals associated with muscular contraction, it appears to acquire more information per motion. The accuracy of the classification was calculated according to the following equation:

$$\text{Classification accuracy(\%)} = \frac{\text{Number of correctly classified motion samples}}{\text{Total number of motion samples}} \quad (1)$$

B. Data Windowing

The data were segmented using an overlapped segmentation approach with a window size of 150 ms and an increment of 50 ms, applied on the eight channels for EMG signals and four channels for EEG. Using Bluetooth, the data were transferred from Myo armband and Muse to the computer.

C. Feature Extraction

After windowing the EEG and EMG signals, they were included in separate matrices. This was done before extracting the time-frequency domain (TFD) features. One matrix has four columns, one for each channel of EEG, and the other has eight columns, one for each channel of EMG recorded signal, and gets the class for each segment. TFD involves the extraction of fourteen features from EEG signal and six features from EMG signal. Tables II and III provide extracted features equations using in EEG and EMG signals, respectively (Al-Quraishi, et al., 2021, Krishnan and Athavale, 2018).

D. Dimensionality Reduction

A significant question in the area of PR is how to extract fewer but more useful features. Dimensionality reduction is a common method employed to resolve this problem. In this

TABLE II
FEATURES BASED ON THE EEG SIGNAL

Feature Name	Equation
Hjorth Complexity	$Complexity = \frac{Mobility(y'(t))}{Mobility(y(t))}$
Hjorth Mobility	$Mobility = \sqrt{\frac{var(y'(t))}{var(y(t))}}$
Tsallis Entropy	$Ts = \left(\frac{1}{\alpha - 1}\right) * (1 - \sum En(x))$ Where x denotes the signal segment, and $\alpha = 2$
Shannon Entropy	$Shan En = - \sum_i p_i \log p_i$ Where p_i stands for EEG signal likelihood having a value of a_i , at some certain location, i , within general signal
Band Power Alpha	$BPA = bandpower(x, fs, [f_{low} f_{high}])$ Where $fs = 252$, $flow = 8$, and $f_{high} = 12$
Band Power Beta	$BPB = bandpower(x, fs, [f_{low} f_{high}])$ Which ranges from 12 to 30 Hz
Band Power Gamma	$BPG = bandpower(x, fs, [f_{low} f_{high}])$ Which ranges from 30 to 64 Hz
Band Power Theta	$BPT = bandpower(x, fs, [f_{low} f_{high}])$ Which ranges from 4 to 8 Hz
Band Power Delta	$bandpower(x, fs, [f_{low} f_{high}])$ which ranges from 1 to 4 Hz
Ratio of Band Power Alpha to Beta	$RBA = \left(\frac{BPB}{BPA}\right)$
Mean energy	ME = mean (x^2)
Median value	MED = medium (x)
Maximum value	Max = max (x)
Minimum value	Min = min (x)

TABLE III
FEATURES BASED ON THE EMG SIGNAL

Feature Name	Equation
Wavelength feature Mean absolute value	$MAV = \frac{1}{N} \sum_{i=1}^N x_i $
Slope sigh changes	$SSC = \sum_{i=2}^{n-1} [f[(x_i - x_{i-1}) \times (x_i - x_{i+1})]]$
Cardinality	$n(A \cup B) = n(A) + n(B) - n(A \cap B)$
Wilson amplitude	$WAMP = \sum_{i=1}^{N-1} f(x_i + 1 - x_i)$
Simple square integral	$SSI = \int_0^1 \int_0^1 x - y ^n dx dy$

study, through the experiments, we used principal components analysis (PCA) as a feature reduction to reduce the features; we found that it is better to reduce the features to 35 features.

PCA provides an orthogonal transformation that converts data with correlated variables into samples with linearly associated features. The main components are new features that have fewer or equivalent variables to the ones that were present at the start. Because PCA is an unsupervised method, data label information is not included. Normally, dispersed data have self-contained primary components (Nanga et al., 2021).

E. Dimension Reduction Results

The dimension reduction method chosen is determined by the nature of the input data. For example, different strategies apply to continuous, category, count, or distance data. We must also consider our intuition and domain expertise about aggregated measurements. Consider the amount of variance described by each primary component when determining the number of dimensions to keep. We know that the variance of the data is equal to the diagonal sum of matrix D, that is, the sum of the eigenvalues $Var(X) = \sum |\lambda|$ (García, Luengo and Herrera, 2015).

Recognizing different motions using a single set of features is the most challenging task in biosignal-based motion recognition systems. The feature reduction-based PCA technique has been introduced in this work, with the aim of narrowing down the set of potentially unimportant expert features describing a dataset to a few key features. Fig. 5 displays the classification test error for a different number of features in the proposed dataset.

The testing error obtained for each subject (i.e., intact-limb and amputee) for classification-based PCA feature reduction to EEG signal only (colored red) and EMG signal only (colored yellow) is presented in Fig. 6, by varying the number of features (10, 15, 20, 25, 30, 35), respectively. That the testing error for EEG signal for intact-limb subjects ranges from (36–48%), and for amputee subjects ranges from (32–50%), whereas the testing error for EMG signal for intact-limb subjects ranges from (5–15%), and the testing error for EMG signal for amputee subjects ranges from (20–25%). The results of intact-limb subjects were different from the amputee’s subject. This may be due to that the intact-limb have the whole arm that make them apply the motions as required for HO, HC, or other motions. However, the amputees are not having hand that cause them not do the movement as required. This paper presents the BGWO algorithm, which select effective sets of features for each biosignal classification to optimize the results obtained. The following sections explain the fundamental concepts of the BGWO algorithm.

F. Feature Selection based Binary Grey Wolf Optimization

Through given the nature of each signal acquired in this work and the importance of the characteristics extracted from it to improve the prosthetic limb movement recognition system for upper limb amputees, consideration has been given to suggest the best method of feature selection algorithms to achieve three objective in this proposal. First, enhance the performance of a data-mining module by delivering a faster and more cost-effective learning process as well as a better grasp of the underlying data selection process. The algorithm for BGWO in this work was chosen to since its nature is in line

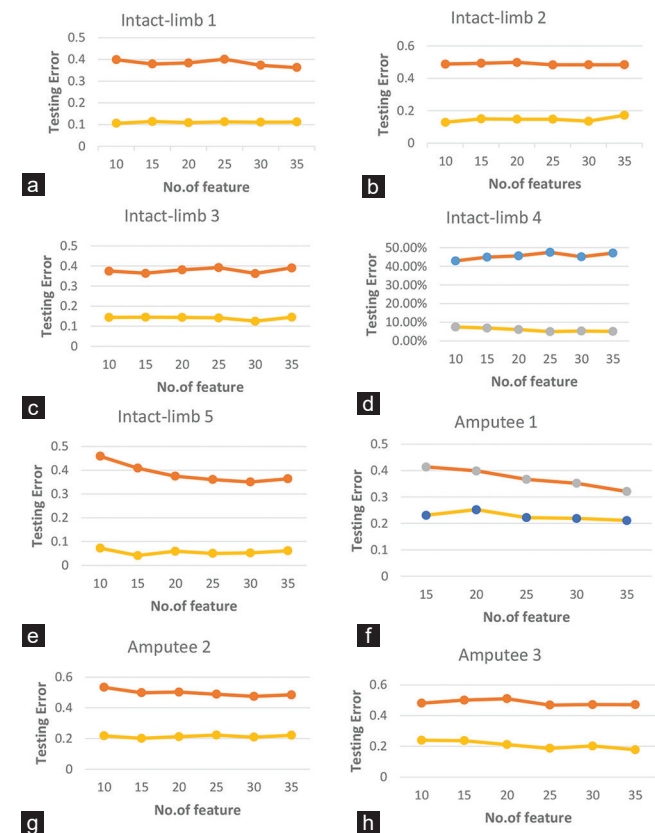


Fig. 5. Testing error for classification using PCA feature reduction for all subjects in proposed dataset, (a) intact-limb 1, (b) intact-limb 2, (c) intact-limb 3, (d) intact-limb 4, (e) intact-limb 5, (f) amputee 1, (g) amputee 2, and (h) amputee 3.

with the set of features extracted from the biological signals used in this work. This algorithm uses the three best levels such as (*alpha*, *beta*, and *delta*), in addition to the secondary (i.e., *omega*, and so on) priority levels. This is consistent with the desire to achieve higher gradient levels to select the best features extracted from the signals recorded in this work. The details of the proposed system are illustrated in Fig. 6. First, wolves' initial populations are randomly initialized (either bit 1 or 0). The fitness of gray wolves is assessed next. The fitness is used to select the three leaders, alpha, beta, and delta, whose positions are denoted by X_1 , X_2 , and X_3 . After that, update the gray wolf's new location. Following that, the wolves' fitness is evaluated, and alpha, beta, and delta positions are updated (Udhaya Kumar and Hannah Inbarani, 2017).

All the solutions are guided through such three solutions (i.e., $[\alpha]$, $[\beta]$, and $[\delta]$) for discovering the search space to find the optimal solution. The mathematical modeling of the encircling behavior is done using the next equations. The algorithm kept running until the termination criterion was met. The best feature subset ultimately determined to be the alpha solution. Algorithm 1 demonstrates the steps taken during BGWO feature selection.

$$\vec{X}(t+1) = \vec{X}p(t) + \vec{A} \times \vec{D} \quad (2)$$

$$\vec{D} = \left| \vec{C} \times \vec{X}p(t) - \vec{X}(t) \right| \quad (3)$$

ALGORITHM I
THE PROPOSED BGWO BASED FEATURE SELECTION

Input: Extracted EEG , EMG Features matrix (Training file)
Output: Sfeat1(): selected features of EEG matrix
 SF1(): (index of best selected feature columns from EEG matrix)
 Sfeat2(): selected features of EMG matrix
 SF2(): (index of best selected feature columns from EMG matrix)

Begin

Step 1: Initialized BGWO parameters (Population of grey wolves, $X=15$).
 (Number of iteration, $T=100$), (Weight of cross-validation value $cv=0.5$)

Step 2: Initialize the parameter a , A and C

Step 3: Compute the fitness of wolves, $F(X)$.

Step 4: Set X_α = the position of best wolf.
 Set X_β = the position of second best wolf.
 Set X_δ = the position of third best wolf.

Step5: for $t = 1$ to maximum number of iteration , T

Step6: for $i = 1$ to number of wolf, N

Step7: Compute X_1 , X_2 , ,& X_3 using Equation (6)

Step 8: Generate X_i^{new} by applying the Equation (7)

Step 9: next i

Step 10: Compute the fitness of all grey wolves, $F(X^{new})$

Step 11: Update the position of alpha, beta and delta.

Step 12: Update the Parameter a , A and C

Step 13: next t

Step 14: //Select the best features from (EEG, EMG) Testing file according of //Index vector SF1 () and SF2 (), respectively. For testing evaluation,
Return Sfeat1 (), SF1 (), Sfeat2 (), SF2 ().

Step 15: End

Where \vec{D} is as defined in equation (3), t is the number of iterations, $\vec{X}p(t)$ is the position of the prey, \vec{A} , \vec{C} are coefficient vectors, and \vec{X} is the gray wolf position.

$$\vec{C} = 2 \times \vec{r}_2 \quad (4)$$

$$\vec{A} = 2 \times \vec{a} \times \vec{r}_1 - \vec{a} \quad (5)$$

The vectors \vec{A} , and \vec{C} have been estimated using equations (4) and (5). Components of \vec{a} are reduced linearly from (2 to 0) over the course of the iterations and r_1 , r_2 represent random vectors in [0, 1].

Typically, the alpha drives the hunting. In some cases, the beta and delta may be involved in the hunt. For mathematically simulating gray wolf hunting behavior, beta, alpha, and delta (i.e., the highest solutions) are expected to have a better understanding of prey location. Other search agents follow the first three optimal solutions found thus far in the hunting processes to update their position to the search agent's optimal position. The equations below show the wolves' updated positions.

$$\left. \begin{aligned} \vec{D}_\alpha &= \left| \vec{C}_1 \times \vec{X}_\alpha - \vec{X} \right| \\ \vec{D}_\beta &= \left| \vec{C}_2 \times \vec{X}_\beta - \vec{X} \right| \\ \vec{D}_\delta &= \left| \vec{C}_3 \times \vec{X}_\delta - \vec{X} \right| \quad \vec{X}_1 = \left| \vec{X}_\alpha - \vec{A}_1 \times \vec{D}_\alpha \right| \\ \vec{X}_2 &= \left| \vec{X}_\beta - \vec{A}_2 \times \vec{D}_\beta \right| \\ \vec{X}_3 &= \left| \vec{X}_\delta - \vec{A}_3 \times \vec{D}_\delta \right| \end{aligned} \right\} \quad (6)$$

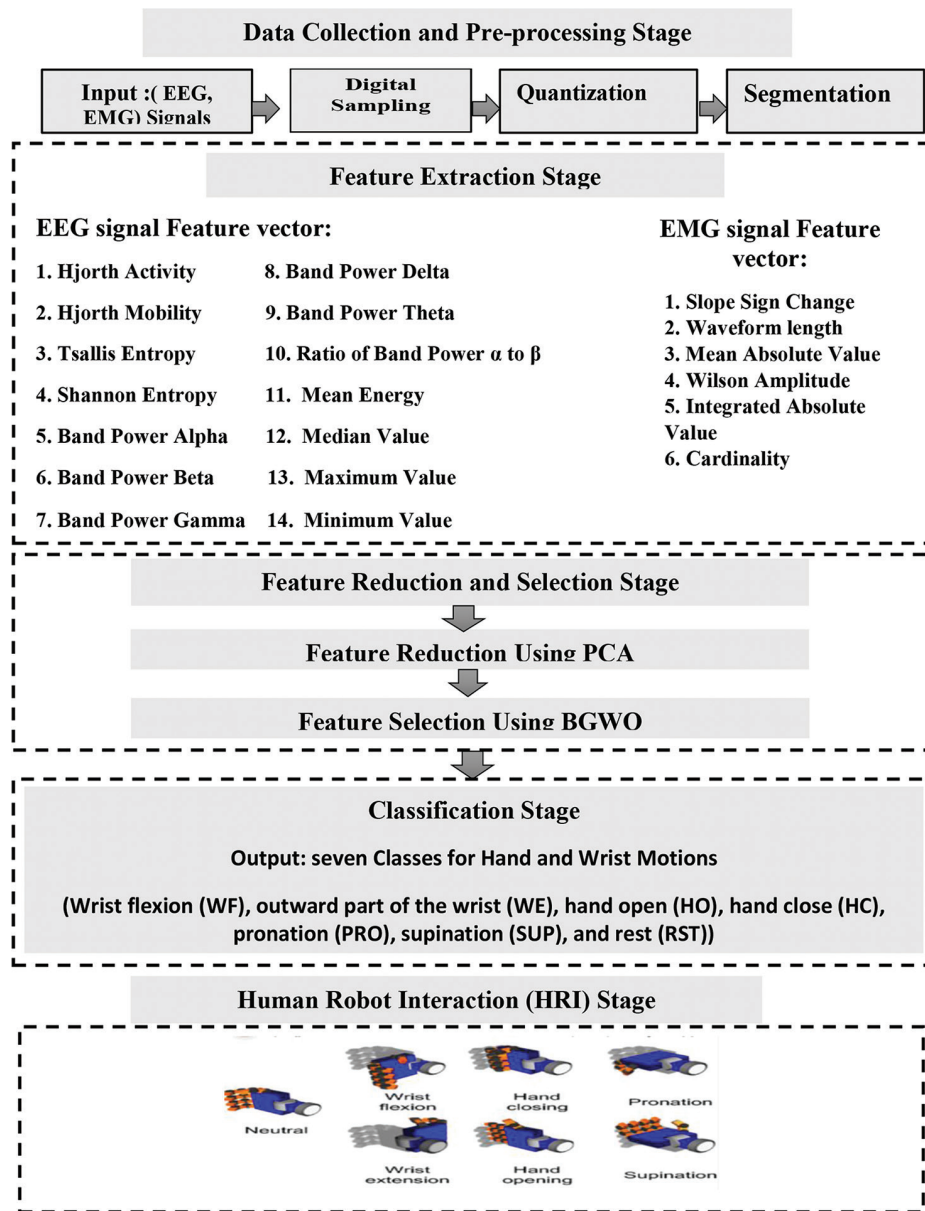


Fig. 6. The proposed system detailed structure.

$$\bar{X}(t+1) = \frac{\bar{X}_1 + \bar{X}_2 + \bar{X}_3}{3} \quad (7)$$

This study proposes a GWO modification. As a binary GWO (BGWO) for modifying binary variables in the search region (i.e., the nature of the Feature Selection problem). The generation function of the solutions and equation of new position (i.e., $\bar{X}(t+1)$) Equation (7) are adjusted for identifying practical solutions throughout BGWO execution, as follows:

$$Sig(\bar{X}(t+1)) = \frac{1}{1 + e^{-\bar{x}(t+1)}} \quad (8)$$

The X solution's decision variables are updated by Equation (8), where $Sig(\bar{X}(t+1))$ denotes the possibility that they will be set to "0" or "1" in the X solution.

$$\bar{X}(t+1) = \begin{cases} 1 & \text{if } r < Sig(\bar{X}(t+1)) \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

where the sigmoid function is used in Equation (8) to translate the value of $\bar{X}(t+1)$ in Equation (9) in the range [0, 1], r denotes random numbers between (0, 1).

Tables IV and V show the final selected feature subset for intact-limbl as an example, using BGWO-based EEG and EMG signals, respectively, whereas Table VI lists the total number of feature subsets that were chosen for the proposed dataset for all subjects.

G. Classification

Liner discriminant classifier (LDC) was utilized to perform the classification. LDC's primary task is to look

TABLE IV
FINAL SELECTED FEATURE SUBSET FOR INTACT-LIMB 1 OF CLASSIFICATION FOR IN THE PROPOSED DATASET-BASED ON THE EEG SIGNAL

Feature No.	Feature Name	CH 1	CH 2	CH 3	CH 4
F1	Band Power Alpha			✓	
F2	Band Power Beta			✓	
F3	Band Power Delta				
F4	Band Power Gama	✓	✓		✓
F5	Band Power Theta				
F6	Ratio Band Power Alpha Beta		✓		
F7	Shannon Entropy			✓	
F8	Mean Energy		✓	✓	✓
F9	Median	✓		✓	✓
F10	Maximum		✓	✓	
F11	Minimum	✓	✓	✓	✓
F12	Hjorth Mobility		✓	✓	
F13	Hjorth Complexity			✓	✓
F14	Tsallis Entropy		✓		

No. of selected features=24

TABLE V
FINAL SELECTED FEATURE SUBSET FOR INTACT-LIMB 1 OF CLASSIFICATION FOR IN THE PROPOSED DATASET BASED ON THE EMG SIGNAL

Feature No.	Feature Name	CH 1	CH 2	CH 3	CH 4	CH 5	CH 6	CH 7	CH 8
F1	Wavelength		✓	✓			✓	✓	
F2	Mean Absolute Value		✓				✓	✓	✓
F3	Slope Sign Change			✓	✓				✓
F4	Cardinality	✓				✓		✓	
F5	Wilson Amplitude	✓		✓	✓				
F6	Integrated Absolute Value	✓		✓		✓		✓	

No. of selected features=21

TABLE VI
NUMBER OF SELECTED FEATURES FOR ALL SUBJECTS OF CLASSIFICATION FOR PROPOSED HYBRID EEG-EMG DATASET

Signal Type	Intact-limb1	Intact-limb 2	Intact-limb 3	Intact-limb 4	Intact-limb 5	Amputee 1	Amputee 2	Amputee 3	Total number of selected features for all subjects
EEG	24	24	22	29	27	15	26	24	191
EMG	21	24	26	23	23	21	20	26	184

TABLE VII
COMPARISON WITH PREVIOUS RELATED WORKS

Authors	Type of signal	Methodology	Dataset	Accuracy
Gordleva et al. (2020)	EEG, EMG	CSP features extraction from a combination of EEG+EMG and then classification of the LDA.	Dataset consist of 8 healthy subjects	80% for LDA classifier
Nsugbe et al. (2020)	EMG, EEG	TD time-domain Feature Extraction such as (MAV, WL, ZC, and SSC), PCA dimension reduction with two-classifier K-mean and Gaussian mixture model (GMM).	Case Study for one amputee	88% for GMM classifier 82% for K-mean classifier
Nsugbe and A. H. Al-Timemy (2021)	EMG, Accelerometers (Acc.)	MAV, WL, ZC, and RMS are examples of features extracted from two signals in the time domain. Cepstrum, Auto-regression (AR) coefficients, Sample entropy (SampEN), Maximum fractal length (MFL), Higuchi fractal dimension (HFD), and Detrended fluctuation analysis (DFA) are examples of features extracted from two signals in the frequency domain. With the LDA, SRDA, and SVM three classifiers.	Dataset consists of 10 subjects for four Amputees and six intact-limb	70% for LDA classifier 70% for SRDA classifier 88% for SVM classifier
Colli and Trejos (2022)	EMG, Accelerometers Acc.	Features vector extracted from two signals such as (MAV, MAVS, WL, 4 th order auto-regressive coefficients (AR), and ZC) with Adaptive Least-Squares Support Vector Machine	Dataset consists of 22 healthy subjects	92.9% for adaptive SVM classifier
The proposed system	EEG, EMG	Time-Domain with feature for EMG, Frequency-domain with feature for EEG)	Dataset: Proposed Dataset for hand and wrist motion, which consists of 8 subjects (3 amputees and 5 intact limbs).	93.26% For LDA classifier

for any vectors in the vector space that can better separate the different classes of data. The original data points could be projected onto such vectors (s) for evaluating the class separability. Therefore, LDC seeks to better differentiate the classes in the case when they overlap for a given set of data points using a few sorts of transformation method (Alzubi, Nayyar and Kumar, 2018).

In classification stage, the result of extracted EEG and EMG features is separated into training and testing sets. The training data are fed into the feature selection stage which uses BGWO algorithm to select the best features. The output of this algorithm is the set of optimum extracted features known as (Sfeat) see algorithm 1, as well as the index of this optimum column known as (SF), which is utilized to choose the column from the testing set. These steps are also used to obtain EMG training set features. The following phase sends the class labels from the training and testing sets into the LDC classifier, which predicts the class by completing performance measures. The final step is to concatenate the EEG and EMG training and testing sets, as well as their class labels, to feed into the LDC classifier, which will predicate class by performing performance evaluation satisfying fusion concepts.

H. Comparison with the Previous Studies

Table VII shows a comparison of the proposed system’s findings with the state-of-the-art works. The comparison table shows that the proposed system outperformed the current standard in the following:

1. The achieved accuracy is increased by approximately 31.24% and 6.35%, respectively, when only EEG and EMG signals are used.
2. The proposed system has been evaluated utilizing the seven basic hand and wrist motions, including the RST (no movement) class.
3. The proposed system has been tested on a dataset containing people of various ages and conditions. This is a reflection of the suggested system's flexibility and the dependability of the extracted EEG and EMG features, which can distinguish motion regardless of control intensity or presence. This research aimed to combine EEG and EMG to identify upper limb voluntary movement.
4. In general, a method for improving the detection of upper limb voluntary movement intention by combining EEG and EMG patterns was provided, which is important for the interactive control of the upper limb exoskeleton robot.

III. RESULTS AND DISCUSSION

The proposed algorithm was tested and evaluated with the following step. Testing error and classification accuracy based on EEG, EMG, and fusion EEG, and EMG were calculated. Once more, the 1st experiment is conducted using the collection of features known as TFD, including 14 features extracted from EEG signal and five features extracted from EMG signal. For intact-limb 1 value-based BGWO (feature selection), the acquired classification accuracy is calculated using the LDC classifier, as shown in Fig. 7.

The classification performance confusion matrix for intact-limb 1 is shown in this figure as example for the single-

signal approaches of (4-ch EEG) which is 60.5%, (8-ch EMG) which is 91.1%, respectively.

Table VIII shows the average testing errors for the single-signal approaches of 8-ch only EMG, 4-ch only EEG, for all subjects.

As shown from Table VIII, the average testing error for all subjects-based EEG signal only is 38.48% and for EMG only is 9.55%. This gives the impression that it is possible to benefit from the EMG signal in terms of taking the characteristics that it is better than the EEG signal; however, due to the difficulty in obtaining the characteristics from the EEG signal, we employed 14 features in this work to benefit from the characteristics of this signal.

IV. EEG – EMG FUSION RESULTS

This section presents the fusion stage results. The accuracy achieved by the fusion method was presented first, followed by a comparison of the results obtained by the fusion method, EEG, and EMG alone.

The fusion of EEG and EMG results is performed at the decision level. LDA classifier is tried to fuse the outputs for seven classes which are (WF, Flexion of the outer part of the wrist, HC, HO, PRO, SUP, and RST), and the achieved results for the proposed dataset are shown in Table IX.

Fig. 8 illustrates the graphical representation of comparison of the achieved results for the proposed dataset using EEG only, EMG only, and Fusion (EEG+EMG). As shown, EMG data often have a higher classification accuracy than EEG data. Therefore, using EMG signals in combination with EEG signals rather than EMG signals alone will always increase accuracy.

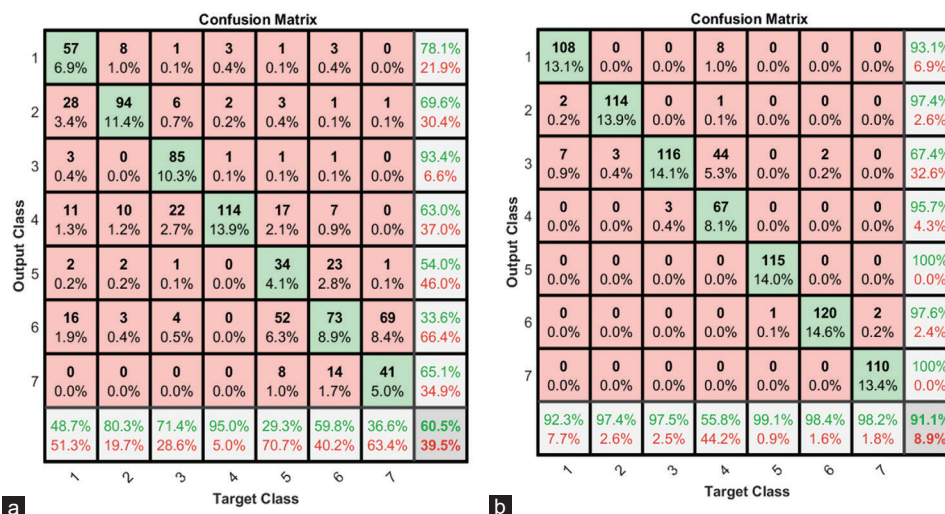


Fig. 7. (a) Confusion matrices for Intact-limb 1 (EEG only). (b) Confusion matrices for Intact-limb 1 (EMG only).

TABLE VIII
TESTING ERRORS FOR THE SINGLE-SIGNAL APPROACHES FOR ALL SUBJECTS

Signal Type	Intact-limb1	Intact-limb 2	Intact-limb 3	Intact-limb 4	Intact-limb 5	Amputee 1	Amputee 2	Amputee 3	Average Testing Error
EEG only	39.5%	34.8%	34.9%	39.5%	34.2%	43.3%	45.8%	35.9%	38.48%
EMG only	8.9%	2.5%	3.4%	8.0%	8.4%	16.3%	15.7%	13.2%	9.55%

EEG: Electroencephalography, EMG: Electromyography

TABLE IX
CLASSIFICATION ACCURACY ACHIEVED FOR ALL SUBJECTS WITH THE PROPOSED DATASET

Signal type	Intact-limb1	Intact-limb 2	Intact-limb 3	Intact-limb 4	Intact-limb 5	Amputee 1	Amputee 2	Amputee 3	Average Accuracy for all subjects
Fusion (EEG, EMG)	96.2%	98.3%	98.1%	97.6%	95.6%	86.8%	84.6%	88.9%	93.26%

EEG: Electroencephalography, EMG: Electromyography

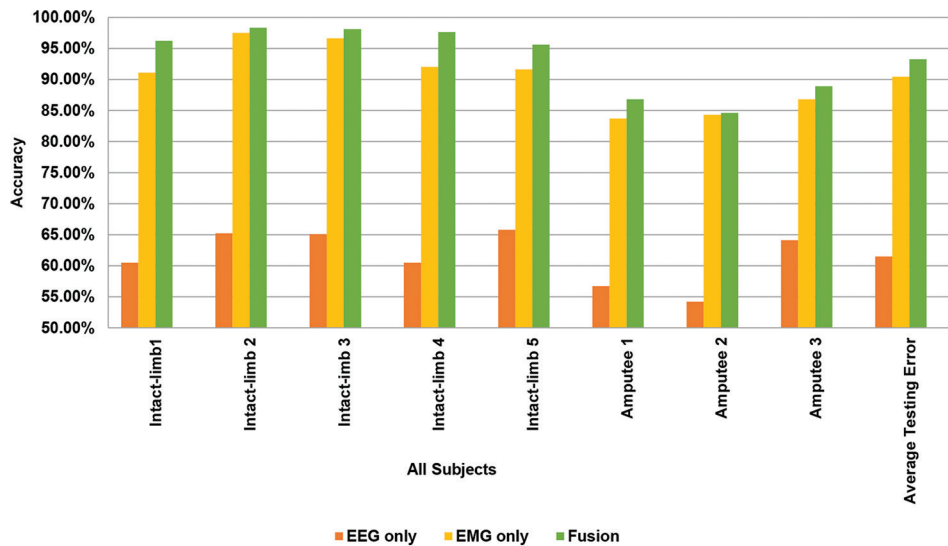


Fig. 8. Comparison of the achieved results for the proposed dataset using electroencephalography (EEG) only, electromyography (EMG) only, and Fusion (EEG+EMG).

As a result, users of the most recent prosthetic devices based on EMG data alone encounter numerous drawbacks.

From the foregoing, we conclude that EEG signals, in conjunction with EMG signals, should be used to determine the direction of development of the prosthesis for movement classification. This work mainly focused on the use of PR algorithms in transfer learning by combining EEG and EMG signals.

As shown to Fig. 8, the fusion of EMG and EEG data can be more accurate, allowing upper-limb amputees to use hand movements as non-invasive and intuitive control cues for prosthetic replacement. The experiment showed that BGWO algorithm for feature selection using an LDC classifier was facilitated by extracting regular patterns of vital signs. With an average classification, accuracy of 97.16% for five intact-limb subjects and of 86.76% for three amputee's subjects. The average classification achieved for all subjects in the proposed dataset is 93.26%.

The proposed PR system was successful in recognizing seven hand-grinding movements based on the obtained results and effective solutions from conducting experiments using the methods approved in this thesis. The findings of the study could be utilized to improve the functionality of electrosurgical prosthetics for persons who have lost lower limbs. To improve control instructions, control speed, and application, future work will focus on building a portable, low-cost, completely synchronous EEG/Electrooculogram/EMG-based multimodal human-machine interface and a synchronous multi-information acquisition system. In the meanwhile, the Multimodal Human-Machine Interface

(mHMI) should be used to help severely injured stroke patients regain hand motor function.

IV. CONCLUSION

This study proposed system that was tested and modified to handle a dataset of various hand and wrist movements for low-level upper limb amputees for recording actual dataset. Using different types of biosignals extracted from the human body and pre-processing each one in accordance with the method of acquisition. In the proposed system, TFD features were used for feature extraction, BGWO feature selection was used to improve results for selecting effective features for signal segment classification to categorize seven classes of hand motion, and LDA was used as a classifier with a 75ms window size segment. A novel EEG-EMG fusion method was presented in this study to improve the performance of bioelectrical signal-controlled robotic devices used for assistance and rehabilitation. The PR system was able to identify seven classes for hand and wrist motions with classification accuracy of 86.7% for three amputee subjects and 97.1% for five intact-limb subjects when utilizing EEG and EMG channels.

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REFERENCES

- Ahakonye, L.A.C., Nwakanma, C.I., Lee, J.M., and Kim, D.S., 2023. SCADA intrusion detection scheme exploiting the fusion of modified decision tree and Chi-square feature selection. *Internet of Things*, 21, p.100676.
- Alelyani, S., Tang, J., and Liu, H., 2018. Feature selection for clustering: A review. In: *Data Clustering*. CRC Press, United States, p.29-60. Available from: <https://www.taylorfrancis.com/chapters/edit/10.1201/9781315373515-2/feature-selection-clustering-review-salem-alelyani-jiliang-tang-huan-liu> [Last accessed on 2023 Jul 01].
- Al-Quraishi, M.S., Elamvazuthi, I., Tang, T.B., Al-Qurishi, M., Parasuraman, S., and Borboni, A., 2021. Multimodal fusion approach based on EEG and EMG signals for lower limb movement recognition. *IEEE Sensors Journal*, 21(24), p.27640-27650.
- Alzubi, J., Nayyar, A., and Kumar, A., 2018. Machine learning from theory to algorithms: An overview. *Journal of physics: Conference series*, 1142, p.012012.
- Beheshti, Z., 2022. BMPA-TVSinV: A binary marine predators algorithm using time-varying sine and V-shaped transfer functions for wrapper-based feature selection. *Knowledge-Based Systems*, 252, p.109446
- Cai, H., Qu, Z., Li, Z., Zhang, Y., Hu, X., and Hu, B., 2020. Feature-level fusion approaches based on multimodal EEG data for depression recognition. *Information Fusion*, 59, pp.127-138.
- Dey, N., Borra, S., Ashour, A., and Shi, F., 2018. *Machine Learning in Bio-Signal Analysis and Diagnostic Imaging*. Academic Press, United States. Available from: https://books.google.iq/books?id=3OR8DwAAQBAJ&dq=Machine+learning+in+bio-signal+analysis+and+diagnostic+imaging:+academic+press.&lr=&hl=r&source=gbs_navlinks_s [Last accessed on 2023 Jul 01].
- Fang, C., He, B., Wang, Y., Cao, J., and Gao, S., 2020. EMG-centered multisensory based technologies for pattern recognition in rehabilitation: State of the art and challenges. *Biosensors (Basel)*, 10(8), p.85.
- García, S., Luengo, J., and Herrera, F., 2015. *Data Preprocessing in Data Mining*. Vol. 72. Springer, Germany.
- Hooda, N., Das, R., and Kumar, N., 2020. Fusion of EEG and EMG signals for classification of unilateral foot movements. *Biomedical Signal Processing and Control*, 60, p.101990.
- Jović, A., Brkić, K., and Bogunović, N., 2015. A review of feature selection methods with applications. In: *Paper Presented at the 2015 38th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*.
- Khan, S.M., Khan, A.A., and Farooq, O., 2019. Selection of features and classifiers for EMG-EEG-based upper limb assistive devices-a review. *IEEE Reviews in Biomedical Engineering*, 13, pp.248-260.
- Krishnan, S., and Athavale, Y., 2018. Trends in biomedical signal feature extraction. *Biomedical Signal Processing and Control*, 43, pp.41-63.
- Kumar, R., Singh, A.K., and Mukherjee, S., 2021. Review of An EMG-Controlled Prosthetic Arm. In: *Computational Methodologies for Electrical and Electronics Engineers*. IGI Global, United States. pp. 85-92.
- Nanga, S., Bawah, A.T., Acquaye, B.A., Billa, M.I., Baeta, F.D., Odai, N.A., and Nsiah, A.D., 2021. Review of dimension reduction methods. *Journal of Data Analysis and Information Processing*, 9(3), pp.189-231.
- Radha, H.M., Abdul Hassan, A.K., and Al-Timemy, A.H., 2023. Enhanced prosthesis control through improved shoulder girdle motion recognition using time-dependent power spectrum descriptors and long short-term memory. *Mathematical Modelling of Engineering Problems*, 10(3), pp.861-870.
- Radha, H.M., Abdul Hassan, A.K., and H Al-Timemy, A., 2022. Classification of different shoulder girdle motions for prosthesis control using a time-domain feature extraction technique. *Aro-the Scientific Journal of Koya University*, 10(2), pp.73-81.
- Shahana, A., and Preeja, V., 2016, Survey on feature subset selection for high dimensional data. In: Paper Presented at the 2016 International Conference on Circuit, Power and Computing Technologies (ICCPCT).
- Singer, G., Anuar, R., and Ben-Gal, I., 2020. A weighted information-gain measure for ordinal classification trees. *Expert Systems with Applications*, 152, p.113375.
- Thabtah, F., Kamalov, F., Hammoud, S., and Shahamiri, S.R., 2020. Least Loss: A simplified filter method for feature selection. *Information Sciences*, 534, p.1-15.
- Udhaya Kumar, S., and Hannah Inbarani, H., 2017. PSO-based feature selection and neighborhood rough set-based classification for BCI multiclass motor imagery task. *Neural Computing and Applications*, 28, p.3239-3258.
- Verma, G.K., and Tiwary, U.S., 2014. Multimodal fusion framework: A multiresolution approach for emotion classification and recognition from physiological signals. *Neuroimage*, 102, p.162-172.
- Voelzke, J., 2015. Weakening the gain-loss-ratio measure to make it stronger. *Finance Research Letters*, 12, p.58-66.