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Utilization of Electromyographic Signal Classification for Predicting Hand Gestures and Grasping Forces Through Artificial Neural Networks

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Keywords

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Abstract

Electromyographic (EMG) signals have gained significant recognition for their potential applications in various fields, particularly in the classification of hand gestures and grasping force prediction. These signals provide critical information that can be utilized to develop systems capable of interpreting human intentions, making them indispensable in areas such as assistive technology and human-computer interaction. The primary objective of this study was to assess the effectiveness of different time-domain features extracted from EMG signals in predicting hand gestures and grasping force simultaneously. The study specifically tested features such as Root Mean Square (RMS), Variance of EMG (VAR), Waveform Length (WL), Integrated EMG (IEMG), Difference Absolute Standard Deviation Value (DASDV), and Difference Absolute Mean Value (DAMV), employing an artificial neural network (ANN) to evaluate their ability to predict hand movements and grasping force. EMG data were collected from the flexor carpi radialis muscle, which plays a significant role in hand movement control. After extracting the relevant time-domain features from the EMG signals, these were input into an ANN for further analysis. The results demonstrated that the RMS feature provided the highest accuracy for both prediction of hand gesture (success rate 90.0% for resting position, 93.3% for wrist flexion, and 86.7% for hand pronation) and grasping force (0.09 RMSD and 0.89 PCC values for resting position, 0.15 RMSD and 0.85 PCC for wrist position). These findings underscore the potential application of these EMG-derived features in practical systems, particularly in the development of myoelectric-controlled prostheses. Such advancements hold promise for enhancing the functionality and intuitiveness of prosthetic devices, offering users more efficient and effective control, and thus improving their overall quality of life in assistive technology contexts.

Cite

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1. INTRODUCTION

The human hand is a highly functional part of the body, integral to nearly all daily activities. Upper limb amputation significantly impacts the quality of life of amputees (Sims et al., 2020). The loss of an upper limb severely affects work ability and overall well-being, prompting numerous studies on the control of hand gestures and grasping movements for prosthetic hands (Zecca et al., 2002; Jahani Fariman et al., 2016; Kundu et al., 2018; Noce et al., 2019; Parajuli et al., 2019). Consequently, electromyographic (EMG) signals have been commonly employed in the control of upper limb prosthetics (Oskoei & Hu, 2007; Micera et al., 2010; Atzori et al., 2014; Al-Timemy et al.; 2015; Onay & Mert, 2020).

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EMG, which reflects the electrical activation of contracting muscles (Basmajian & De Luca, 1985), has been utilized in diagnosing muscle diseases (Haig et al., 1996), in rehabilitation engineering (Oskoei & Hu, 2007), and for operating various human-machine interfaces (Zecca et al., 2002; Wu et al., 2022). Surface EMG (sEMG) is a well-established method due to its non-invasive nature and ease of application, allowing for the recording of muscle activity from superficial muscles and providing insights into neuromuscular activities (Micera et al., 2010; Ni et al., 2024). sEMG holds promise for reliable hand movement recognition and the provision of detailed movement information (Zhang et al., 2019). However, the classification of EMG signals for prosthetic control remains a challenging task due to their nonlinear characteristics and the dependencies between individuals (Gu et al., 2018). The success of EMG classification relies heavily on two key factors: an appropriate feature extraction method and an effective classifier.

Time-domain feature extraction is commonly used to reduce the dimensionality of EMG data without significantly altering the signal’s amplitude-time characteristics (Tkach et al., 2010; Phinyomark et al., 2018). Compared to frequency-domain approaches, time-domain methods offer efficient computation and ease of implementation, making them suitable for myoelectric-controlled prosthetics (Hudgins et al., 1993; Geethanjali, 2016). Extracted EMG features are classified using various machine learning models to capture the nonlinear relationship between EMG signals and hand gestures or grasping forces (Phinyomark et al., 2018; Joshi et al., 2024). To enhance the performance of myoelectric-based upper-limb prosthetics, particularly in achieving accurate execution of force and position, several researchers have explored different feature patterns alongside classification techniques (Choi et al., 2009; Phinyomark et al., 2012; Vásconez et al., 2023). Among these techniques, artificial neural networks (ANNs) are the most widely employed and versatile classifiers for EMG signal feature classification (Veer & Sharma, 2016; Waris et al., 2018). Researchers (Farina et al., 2014) compared the accuracy of ANN, non-negative matrix factorization, and linear regression in mapping kinematics from EMG in offline tests. Their findings indicated that ANN exhibited a higher correlation between measured and estimated kinematics than the other methods.

Most existing studies have focused on either hand (or wrist) position/gesture recognition or grasping force prediction using EMG signals (Prakash et al., 2019; Zhang et al., 2019; Saikia et al., 2022). However, the main limitation of these studies is that force and position are estimated separately, which is not directly relevant to the nature of human movement. It is essential to predict both motion (kinematics) and force (kinetics) simultaneously to develop a functional and effective hand prosthetic capable of realistically mimicking human hand behavior in daily activities. Thus, the aim of our research was to predict both hand grasping force and gestures simultaneously using EMG signals. For this purpose, EMG signals were recorded during various hand gestures, while the grasping force was concurrently measured using a hand dynamometer. Time-domain features from the EMG signals were extracted and classified using an ANN to simultaneously predict grasping force and recognize hand gestures. To the best of our knowledge, this is the first study to simultaneously predict both grasping force and hand gesture patterns for the upper limb.

2. MATERIAL AND METHOD

2.1. Experimental Protocol

Ten healthy participants (3 females, 7 males; age: 20.9 ± 1.21 years, height: 174.1 ± 8.19 cm, weight: 79.5 ± 19.45 kg) with no musculoskeletal or neurological disorders participated in this study. All were right-handed and instructed to avoid upper extremity exertion prior to the experiment. Prior to the signal recording process, participants were provided with adequate information about the experiments and their informed consent was obtained. The workflow of the study is presented in Figure 1.

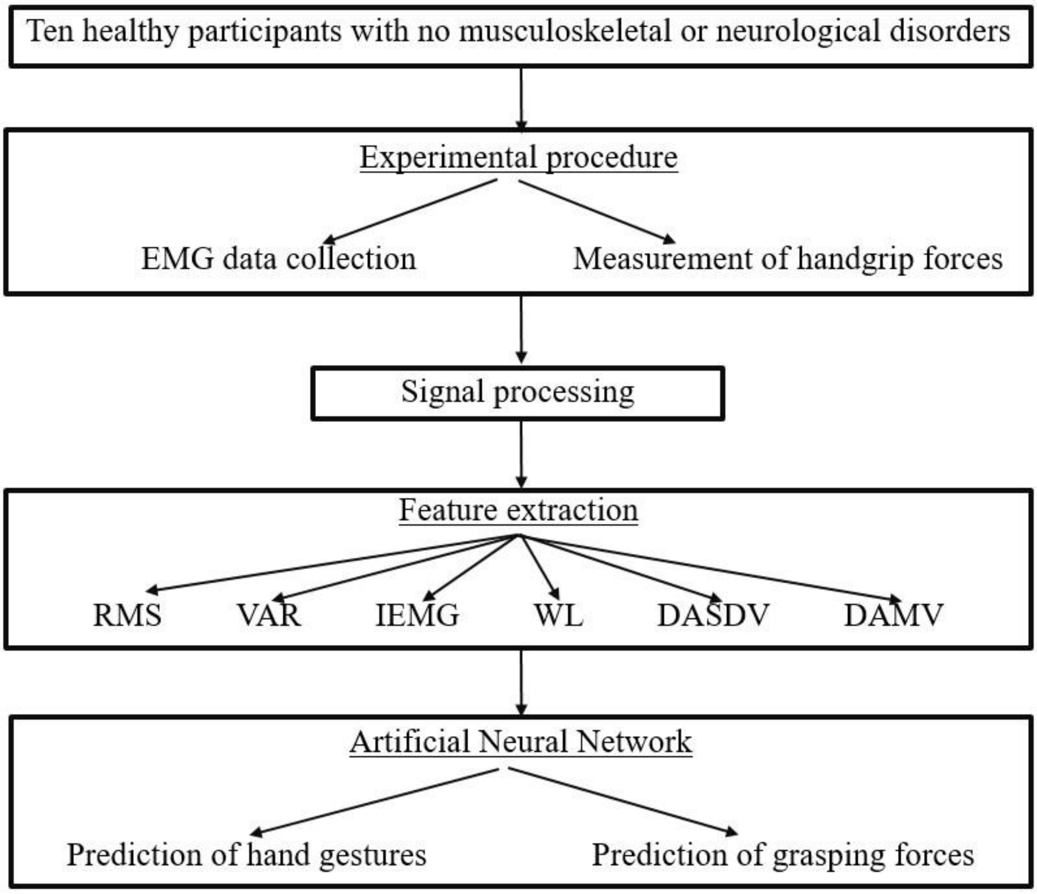
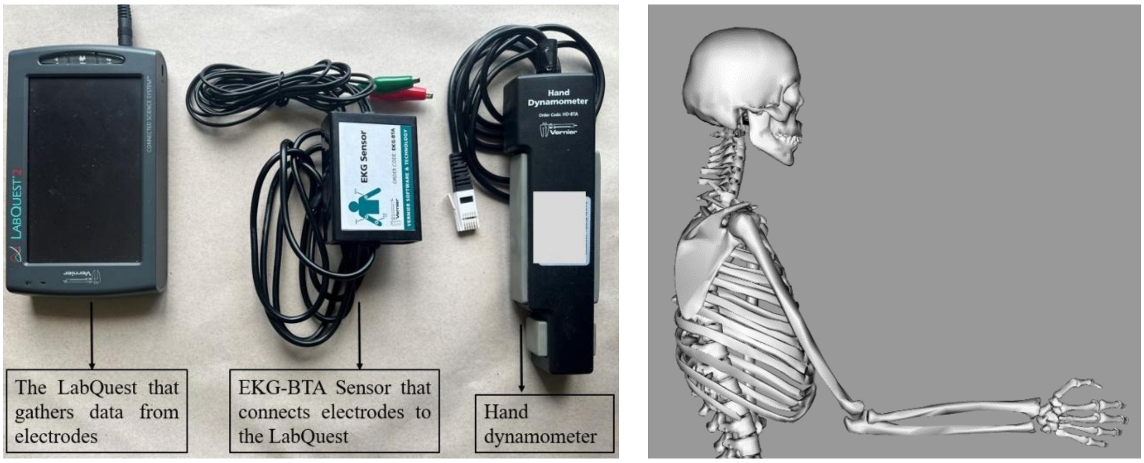


Figure 1. *Flowchart of the study. RMS: Root mean square, VAR: Variance of EMG, IEMG: Integrated EMG, WL: Waveform length, DASDV: Difference absolute standard deviation value, DAMV: Difference absolute mean value.*

sEMG signals were recorded from the flexor carpi radialis (FCR) muscle. The EMG signals were recorded using a Vernier EKG Sensor (EKG-BTA) and LabQuest 2 (Vernier Software and Technology, USA) with a 100 Hz sampling rate (Figure 2a). Electrode placement and skin preparation followed the SENIAM Project guidelines (Hermens et al., 1999). Pre-gelled, self-adhesive disposable surface electrodes were used. The electrodes contained an electrolytic gel interface. The skin at electrode sites was shaved and cleaned with alcohol. Muscle belly was identified and marked using a pen for accurate electrode placement. Electrodes were then attached to the marked site and the EMG receivers were connected to the electrodes.

Handgrip forces were measured using a strain-gauge-based isometric hand dynamometer (accuracy: ±0.6 N, resolution: 0.2141 N, sampling rate: 100 Hz) (Vernier, Beaverton, USA). During the EMG and handgrip force recording, the participants sat upright in a neutral posture (Figure 2b). Each trial during the measurements had a duration of 3 seconds.



(a) **(b)**

Figure 2. a) *Details of the experimental rig.* ***b)*** *The subjects' positioning during the EMG and handgrip force assessments involved the shoulder being placed in 30° abduction and the elbow in 90° flexion.*

The participants were instructed to firmly grasp the dynamometer and apply handgrip forces during three distinct wrist motion patterns: i) The wrist was positioned neutrally and remained motionless (resting position), ii) the wrist was in flexion with the fingers oriented upwards (wrist flexion), and iii) the hand was in pronation. They performed three trials for each wrist position, with a minimum rest period of ten seconds in neutral position with the hand open and flat on the table, free of muscle contraction between each repetition. After completing each set, the participants rested in a neutral position for at least two minutes before starting the next motion pattern.

For EMG signal normalization, participants were asked to perform a maximum voluntary contraction three times to maximize their grasping force, and thereby the amplitudes of the corresponding EMG signals. The participants maintained the same posture throughout all protocols. A three-minute rest period was provided between trials to prevent muscle fatigue (Kamavuako et al., 2009).

2.2. Signal Processing and Feature Extraction

The raw EMG signals underwent processing through a 6th-order band-pass filter, with cut-off frequencies of 15 Hz on the lower end and 450 Hz on the upper end, followed by full-wave rectification (Tkach et al., 2010). The rectified signals were divided into segments using sliding windows, with each window having a time span of 500 ms. The time gap between consecutive windows was set to 25 ms (Chen et al., 2013). All EMG signals were normalized based on those recorded during maximal voluntary contraction.

Various signal features can be applied to quantitatively describe EMG signals and reduce the size of the data (Zecca et al., 2002; Shin et al., 2024). In our research, since our goal was to correlate EMG signals with different hand gestures and handgrip forces of varying amplitudes, we employed the following time-domain signal features, which are commonly used to establish the nonlinear relationship between EMG signals and hand gestures (Phinyomark et al., 2012; Shin et al., 2024).

2.2.1. Root Mean Square (RMS)

Root mean square (RMS) is a well-accepted feature in the time domain analysis of EMG signal (Boostani & Moradi, 2003; Phinyomark et al., 2012). The mathematical expression of RMS can be defined as:

$$RMS = \sqrt{\frac{1}{N}\sum_{k=1}^{N} x_k^2} \tag{1}$$

where x_k represents the k^{th} sample and N is the total number of samples in each segment. These abbreviations are also applicable in the subsequent formulations.

2.2.2. Variance of EMG (VAR)

Variance (VAR) of EMG is expressed as a measure of EMG signal power (Zecca et al., 2002; Phinyomark et al., 2012). The mathematical expression of VAR can be defined as:

$$VAR = \frac{1}{N-1}\sum_{k=1}^{N} x_k^2 \tag{2}$$

2.2.3. Integrated EMG (IEMG)

Integrated EMG (IEMG) is a cumulative absolute value of EMG signal (Phinyomark et al., 2012). The calculation of IEMG feature is defined as:

$$IEMG = \sum_{k=1}^{N} \left| x_k \right| \tag{3}$$

2.2.4. Waveform Length (WL)

Waveform length (WL) is an estimation of the cumulative length of EMG waveform in a segment (Kamavuako et al., 2013). The waveform length of EMG is defined as:

$$WL = \sum_{k=1}^{N-1} \left| x_{k+1} - x_k \right| \tag{4}$$

2.2.5. Difference Absolute Standard Deviation Value (DASDV)

The difference absolute standard deviation value (DASDV) is the absolute deviation of the standard deviation between adjacent samples. It is calculated by taking the first-order differential value of the RMS feature (Phinyomark et al., 2014) and defined as follows:

$$DASDV = \sqrt{\frac{1}{N-1}\sum_{k=1}^{N-1}(x_{k+1}-x_k)^2} \quad (5)$$

2.2.6. Difference Absolute Mean Value (DAMV)

The difference absolute mean value (DAMV) is calculated for each data window using the following equation (Phinyomark et al., 2012).

$$DAMV = \frac{1}{N-1}\sum_{k=1}^{N-1}\left|x_{k+1}-x_k\right| \quad (6)$$

2.3. Artificial Neural Networks (ANN)

ANN is commonly utilized for classifying EMG signals due to its ability to manage the nonlinear nature of muscle activations (Waris et al., 2018; Saikia et al., 2022). In our research, we used ANN to predict hand gestures and handgrip force simultaneously. The neural network architecture consisted of one input layer, two hidden layers, and one output layer. The model used for training features had layers with 100, 60, 30, and 501 neuron. A log-sigmoid transfer function was used as the activation function. The number of epochs for the training phase was set to 1000. Additionally, the force values in the target set were normalized to a range between 0 and 1 to enhance the classification performance of the network. Furthermore, the training and testing datasets were carefully adjusted to ensure the optimal pairing of train-test data for the specific case under investigation. To achieve this, data from all trials were incorporated into the analysis. Leave-one-out cross-validation (LOOCV), a special type of k-fold cross-validation, was employed to train the network and assess the accuracy of its predictions (Arlot & Celisse, 2010). In this method, the network was trained using all data except for one trial, and the prediction (or test) was made for that specific trial. The LOOCV process was repeated until all trials had been used for both training and testing. As a result, the average error was calculated by taking the arithmetic mean of the errors from each test trial. The extracted EMG signal features, which served as inputs to the neural network, were also normalized with respect to the corresponding EMG signals recorded during the maximal voluntary contraction test (Soylu & Arpinar-Avsar, 2010).

2.4. Data Analysis

Hand gesture recognition was quantified by calculating the ratio of correct predictions to the total number of predictions (i.e., true and false predictions). To quantitatively assess the relationship between the predicted and experimental force-time histories, root mean square differences (RMSD) and Pearson cross-correlation coefficients (PCC) were computed. An RMSD value of 0.1 indicates that the mean error in magnitude between the predicted and actual forces is 10%. PCC serves as a measure of similarity between two curves; a PCC value of 1 between two force-time histories suggests a 100% agreement between the predicted and experimental handgrip force profiles.

Statistical significance was analyzed using SPSS software (Version 21.0; SPSS; Chicago, IL, USA), with a significance threshold set at 0.05 ($p < 0.05$). The Shapiro-Wilk test was conducted to assess the normality of the average prediction values for hand gestures, as well as the average RMSD and PCC values. All data were statistically evaluated using Friedman's ANOVA, and the Mann-Whitney U test was applied to determine significant differences between groups. Bonferroni correction was used to adjust the p-value for multiple comparisons ($p < 0.016$).

3. RESULTS AND DISCUSSION

The results of hand gesture recognition and handgrip force prediction for all features were presented in Table 1. As shown in Table 1, the highest success rates for hand gesture prediction were achieved using RMS (90%) and WL (88%) (p=0.013). For the resting position, the best recognition rate was achieved using WL, while RMS provided the best performance for wrist flexion. Both RMS and WL produced the same detection rate for hand pronation. No statistically significant difference was observed between RMS and WL. As it can be seen from Table 2, the minimum average RMSD (0.09) and maximum PCC (0.89) values between the actual and predicted force-time histories were obtained from RMS (p=0.014).

Table 1. *Hand gestures Recognition Rates for all Signal Features*

	Resting position	**Wrist flexion**	**Hand pronation**	**Total**
RMS	27/30 (90.0%)	28/30 (93.3%)	26/30 (86.7%)	81/90 (90.0%)
VAR	27/30 (90.0%)	27/30 (90.0%)	22/30 (73.3%)	76/90 (84.4%)
WL	28/30 (93.3%)	26/30 (86.7%)	26/30 (86.7%)	80/90 (88.0%)
IEMG	27/30 (90.0%)	26/30 (86.7%)	21/30 (70.0%)	74/90 (82.2%)
DASDV	21/30 (70.0%)	17/30 (56.7%)	20/30 (66.7%)	58/90 (64.4%)
DAMV	25/30 (83.3%)	24/30 (80.0%)	17/30 (56.7%)	66/90 (73.3%)

RMS: Root mean square, VAR: Variance of EMG, WL: Waveform length, IEMG: Integrated EMG, DASDV: Difference absolute standard deviation value, DAMV: Difference absolute mean value.

Table 2. *The Mean RMSD and PCC Results Obtained from all Subjects for all Features*

	Resting position		**Wrist flexion**		**Hand pronation**	
	RMSD	**PCC**	**RMSD**	**PCC**	**RMSD**	**PCC**
RMS	0.09	0.89	0.15	0.85	0.20	0.84
VAR	0.12	0.81	0.16	0.83	0.26	0.75
WL	0.23	0.84	0.24	0.82	0.26	0.74
IEMG	0.14	0.88	0.17	0.81	0.21	0.85
DASDV	0.26	0.77	0.24	0.71	0.28	0.72
DAMV	0.24	0.79	0.22	0.75	0.31	0.73

RMS: Root mean square, VAR: Variance of EMG, WL: Waveform length, IEMG: Integrated EMG, DASDV: Difference absolute standard deviation value, DAMV: Difference absolute mean value, RMSD: Root mean square differences, PCC: Pearson cross-correlation coefficients.

In this study, the objective was to map the EMG signals from the forearm muscles to hand gestures and handgrip forces using an artificial neural network (ANN) combined with time-domain feature extraction techniques. To better simulate real-world conditions, we designed the current protocol, in which both hand gesture and applied force were predicted simultaneously. To our knowledge, this is the first study that attempts to predict both force and position concurrently. The analysis of hand gesture prediction results revealed that RMS and WL outperformed other features (Table 1) ($p = 0.013$). Contrary to the findings of the related study (Phinyomark et al., 2014), features derived from the first difference of the EMG time series, such as DASDV and DAMV, did not yield more accurate prediction results compared to their original feature counterparts. The inferior performance of DASDV and DAMV can be attributed to the classifier employed in our study, as the effectiveness of ANN classification is greatly influenced by network structure parameters (Phinyomark et al., 2012). When evaluating each hand gesture individually, it was noted that the resting position was predicted with the highest accuracy, while the prediction rate for hand pronation was significantly lower compared to other positions ($p = 0.011$) (Table 1). This outcome may be explained by the role of the associated muscles, as the FCR functions as radial abductors in addition to their primary roles. As a result, the EMG data from this muscle might not be sufficient to accurately represent the hand pronation pattern.

Based on the RMSD, PCC, and gesture prediction outcomes, RMS and WL consistently provided superior prediction performance for most positions compared to other features ($p = 0.014$).

Although the classification of certain hand motion patterns and the estimation of handgrip force using EMG signals from a single muscle yielded reasonable predictions in some instances, using EMG data from multiple muscles could result in significantly improved accuracy. This aligns with the findings of the researchers (Zhang et al., 2016), who observed a reduction in root mean square error when the FCR and ECRL muscles were included together in the prediction model. Similarly, researchers emphasized the need to account for co-activation when estimating the forces of forearm muscles (Brown et al., 2010).

Given that prediction accuracy is heavily dependent on the ANN structure, identifying an optimal ANN configuration remains a challenge (Demir et al., 2016). While the ANN provided promising results, varying the network structure parameters would yield different outcomes. The inherent instability and inconsistency of the ANN are significant drawbacks of this machine learning approach. Consequently, future research will focus on evaluating classifiers whose performance is less dependent on the optimization of structure and parameters, such as linear and quadratic discriminant analysis and k-nearest neighbors.

Several limitations of this study should be acknowledged. Firstly, only EMG data from one muscle were used. Although incorporating additional forearm muscles could improve prediction performance, this would likely introduce higher computational costs and greater nonlinearity. Secondly, our study focused on three hand gestures and isometric handgrip forces. To increase the generalizability of the methods used, future studies should include a broader range of hand/wrist motion patterns and dynamic muscle contractions.

4. CONCLUSION

This study comparatively assessed several time-domain EMG feature extraction techniques, including RMS, VAR, WL, IEMG, DASDV, and DAMV, for the concurrent estimation of hand gestures and handgrip force using ANN. The results demonstrated that RMS and WL provided effective outcomes for hand gesture recognition, while RMS and IEMG were the most accurate for predicting handgrip forces. The insights gained from this study are expected to contribute to the development of control systems for EMG-based applications, such as myoelectric-controlled prostheses. These findings highlight the importance of feature extraction methods in the classification performance of EMG-based control models for prosthetics. Future studies can be conducted to investigate factors such as expanding the dataset, considering different movement patterns, recording EMG signals from more muscles, and using different machine learning methods to improve the success rate and real-world applicability.

AUTHOR CONTRIBUTIONS

Conceptualization, D.K. and S.C.D.; methodology, D.K. and S.C.D.; software, D.K.; title, D.K. and S.C.D.; validation, D.K. and S.C.D.; laboratory work, D.K. and S.C.D.; research, D.K. and S.C.D.; sources, D.K. and S.C.D.; manuscript-original draft, D.K. and S.C.D.; manuscript-review and editing, D.K. and S.C.D.; visualization, D.K.; supervision, S..; funding, the authors have no received any financial support for the

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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