https://www.scirp.org/journal/jbise

J. Biomedical Science and Engineering, 2021, Vol. 14, (No. 12), pp: 426-434

Implementation of an Assortment of Machine Learning Classification Algorithms Regarding Diadochokinesia for Hemiparesis with Quantification from Conformal Wearable and Wireless System

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Keywords: Diadochokinesia, Conformal Wearable, Wireless, Inertial Sensor, Gyroscope, Machine Learning, Hemiparesis

Received: November 1, 2021 **Accepted:** December 20, 2021 **Published:** December 23, 2021

ABSTRACT

Diadochokinesia pertains to a standard aspect of the conventional neurological examination, which involves the oscillation between muscle groups with an agonist and antagonist relationship. A representative example is the pronation and supination of the forearm. Hemiparesis visibly demonstrates disparity of diadochokinesia, and clinical quantification is achieved through the use of an ordinal scale, which is inherently subjective. A conformal wearable and wireless inertial sensor equipped with a gyroscope mounted about the dorsum of the hand can objectively quantify diadochokinesia respective of forearm pronation and supination. The objective of the research endeavor was to apply an assortment of machine learning algorithms to distinguish between a hemiplegic affected and unaffected upper limb pair based on diadochokinesia with respect to pronation and supination of the forearm. Performance of the machine learning algorithms, such as the multilayer perceptron neural network, J48 decision tree, random forest, K-nearest neighbors, logistic regression, and naïve Bayes, were evaluated in consideration of classification accuracy and time to develop the machine learning model. The machine learning feature set was derived from the acquired gyroscope signal data. Using the gyroscope signal data from the conformal wearable and wireless inertial sensor the logistic regression and naïve Bayes machine learning algorithms achieved considerable performance capability with respect to both time to converge the machine learning model and classification accuracy for distinguishing between a hemiplegic upper limb pair for diadochokinesia in consideration of pronation and supination.

1. INTRODUCTION

The application of wearable and wireless systems has provided substantial diagnostic acuity for the evaluation of neurological status [1-5]. In particular, the gyroscope sensor of the wearable and wireless system provides a clinically relevant signal data for evaluating kinematic features pertaining to observational disparities manifested by hemiparesis. The wearable and wireless system can convey gyroscope signal data with wireless connectivity to the Internet. With the consolidation of the gyroscope signal data to a feature set considerable classification accuracy has been achieved to distinguish between a hemiplegic affected and unaffected limb pair [6-8].

In particular, diadochokinesia, which involves the variation between agonist and antagonist muscle activation, such as pronation and supination of the forearm, provides valuable insight regarding the integrity of neurological status. A hemiplegic upper limb pair can reveal observationally perceptive disparity of diadochokinesia with disfunction pertaining to the affected side [9-11]. As a significant extension beyond the domain of expert yet subjective interpretation of a skilled clinician exists the application of wearable and wireless systems that are equipped with an inertial sensor package [1-5]. Originally, the smartphone as a wearable and wireless inertial sensor platform has been successfully applied regarding the upper limb for identifying subject status and therapy intervention technique [7, 12-17]. In particular, the gyroscope sensor provides a clinically recognizable signal regarding subject status [18].

Recent technology evolutions have considerably transcended the capabilities of the smartphone. For example, the BioStamp nPoint constitutes a conformal wearable and wireless inertial sensor system with a profile on the order of a bandage. The BioStamp nPoint utilizes the wireless attributes of a tablet and smartphone with connectivity to a secure Cloud computing environment [19]. The objective of the research endeavor was to distinguish disparity of diadochokinesia with respect to a hemiplegic upper limb pair from the perspective of machine learning classification through the BioStamp nPoint as a conformal wearable and wireless inertial sensor system. An assortment of machine learning algorithms was evaluated, such as the multilayer perceptron neural network, J48 decision tree, random forest, K-nearest neighbors, logistic regression, and naïve Bayes. The performance of these machine learning algorithms was established based on classification accuracy attained to differentiate diadochokinesia with respect to a hemiplegic upper limb pair and the time to develop the machine learning model.

2. BACKGROUND

2.1. Fundamentals of Diadochokinesia

The evaluation of diadochokinesia is a standard aspect of a neurological examination [9]. Diadochokinesia pertains to the alternation between agonist and antagonist muscle groups, such as alternation between forearm pronation and supination [9, 10]. Disfunction of diadochokinesia is manifested with disturbance to the nervous system, such as from hemiparesis [9-11].

2.2. Techniques for Quantifying Diadochokinesia Using Instrumentation

The characteristics of diadochokinesia involve the application of ordinal scales based on the observation of a clinical expert. Emphasis is placed upon the determination of angular rotation rate. However, Hermsdörfer *et al.* also recommend other kinematic parameters, such as amplitude and consistency [9]. However, the clinical interpretation is inherently subjective in nature [1-5, 9]. Objectively quantified and instrumented systems would be beneficial for the quantification of diadochokinesia [9].

Okada and Okada applied an instrumented device for acquiring a quantified representation of diadochokinesia. The subject would have their hands secured to the protruding handles supported by elastic bandages. The pronation and supination of the forearms would generate a quantified voltage signal for pending analysis through a local computer. The device is effectively portable and supported by a tripod to accommodate a sitting subject. The quantified data demonstrated the capacity to identify statistically significant disparity for healthy subjects and subjects with neurological disorders [20]. Although this device is capable of evaluating diadochokinesia, the device is more suitable for a clinical environment, and it is relatively large by comparison to wearable and wireless systems that are conformal.

Further attempts have been applied for the quantification of forearm rotation. Hermsdörfer *et al.* applied ultrasound with specific markers to evaluate the characteristics of diadochokinesia [9, 11]. Other three-dimensional techniques, such as an electromagnetic tracking system, have been successfully applied [21]. Matsuki *et al.* 2010 developed a relevant application utilizing radiography to evaluate forearm kinematics during dynamic rotation [22]. Although these techniques consist of considerable accuracy, these applications are not suitable for personalized use in the context of wearable and wireless systems, especially conformal wearable devices.

2.3. Conformal Wearable and Wireless Systems, Such as the BioStamp nPoint, Quantifying Upper Limb Health Status

Preliminary applications of wearable and wireless systems were demonstrated through the smartphone that is equipped with both an accelerometer and gyroscope, which can constitute a wearable and wireless inertial sensor system through the proper software application. The inertial sensor signal has been recorded by the smartphone functioning as a wearable and wireless system, which has then been transmitted wirelessly to the Internet as an email attachment. The email resource represents a functional semblance of a Cloud computing resource, for which experimental location and post-processing resources can be logistically separated anywhere in the world. Post-processing can encompass machine learning classification, such as the differentiation of a hemiplegic limb pair and efficacy of movement disorder therapy intervention [7, 12-17].

Further evolutions involve the advent of conformal wearable and wireless inertial sensor systems, such as the BioStamp nPoint. The BioStamp nPoint is specifically intended for the acquisition of medical grade inertial sensor data (gyroscope and accelerometer), and it is certified as an FDA 510(k) medical device. The BioStamp nPoint is flexible, which enables the device to be conformal to the contours of the body. With a mass less than ten grams, BioStamp nPoint mounts to an aspect of the body through adhesive medium. The BioStamp nPoint utilizes the wireless capabilities of the smartphone and tablet, achieving wireless connectivity to a secure Cloud computing environment for subsequent post-processing [19]. The BioStamp nPoint has been successfully applied for differentiating health status with considerable classification accuracy, such as through the multilayer perceptron neural network [23].

2.4. Machine Learning for Diagnostics of Wearable and Wireless System Applications

Machine learning has been successfully applied for distinguishing between disparate movement characteristics with the use of wearable and wireless inertial sensor systems [7, 12-17, 23]. The Waikato Environment for Knowledge Analysis (WEKA) provided an assortment of machine learning algorithms. The machine learning algorithms considered for the research objective available through WEKA were:

- multilayer perceptron neural network
- J48 decision tree
- random forest
- K-nearest neighbors
- logistic regression
- naïve Bayes [24-26]

3. MATERIALS AND METHODS

The research objective was achieved through an engineering proof of concept perspective by one subject with chronic hemiparesis. The BioStamp nPoint representing a conformal wearable and wireless inertial sensor device acquired gyroscope signal data of diadochokinesia for hemiparesis with data storage through a Cloud computing environment. The signal data was recorded at a sampling rate of 250 Hz. In order to properly record the inherent features of pronation and supination, the conformal BioStamp nPoint was secured about the dorsum of the hand for both the hemiplegic affected arm and unaffected arm through an adhesive medium. **Figure 1** illustrates the mounting technique for the BioStamp nPoint as a conformal wearable and wireless inertial sensor system to quantify diadochokinesia in the context of pronation and supination for a hemiplegic affected and unaffected arm pair.

The hemiplegic affected arm and unaffected arm trial data were acquired by the following experimental protocol:

1) Secure the BioStamp nPoint to the dorsum of both hands (hemiplegic affected and unaffected).

2) Commence the BioStamp nPoint application to record the gyroscope signal data for approximately two minutes and thirty seconds for thirty time slices of five seconds.

3) Instruct the subject to begin pronation and supination until the recording is completed.

4) Wirelessly transmit the inertial signal data, such as the gyroscope signal, to the secure Cloud computing environment for subsequent post-processing.

Machine learning classification was enabled through Waikato Environment for Knowledge Analysis (WEKA). Tenfold cross-validation was incorporated [24-26]. The signal data was consolidated to a feature set through software automation using Python.

4. RESULTS AND DISCUSSION

The gyroscope signal data acquired by the BioStamp nPoint illustrates considerable observable disparity regarding diadochokinesia with respect to the hemiplegic affected forearm by comparison to the unaffected forearm. Based on the orientation of the BioStamp nPoint mounting strategy of the hand and the pronation and supination, the X-direction of the gyroscope signal was the focal for the post-processing. **Figure 2** illustrates the gyroscope signal for the affected hemiplegic arm, and **Figure 3** represents the gyroscope signal for the unaffected arm for the assessment of diadochokinesia with respect to pronation and supination.

In order to conduct machine learning classification using WEKA, the gyroscope signal data requires consolidation into a feature set. The feature set was composed of five numeric attributes inclusive of descriptive statistics:

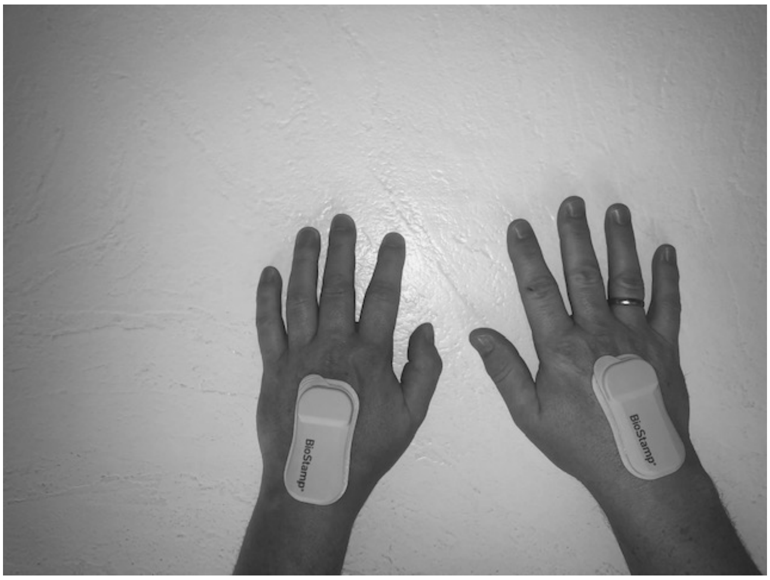

Figure 1. Mounting the BioStamp nPoint as a conformal wearable and wireless gyroscope platform for the quantification of diadochokinesia with respect to pronation and supination.

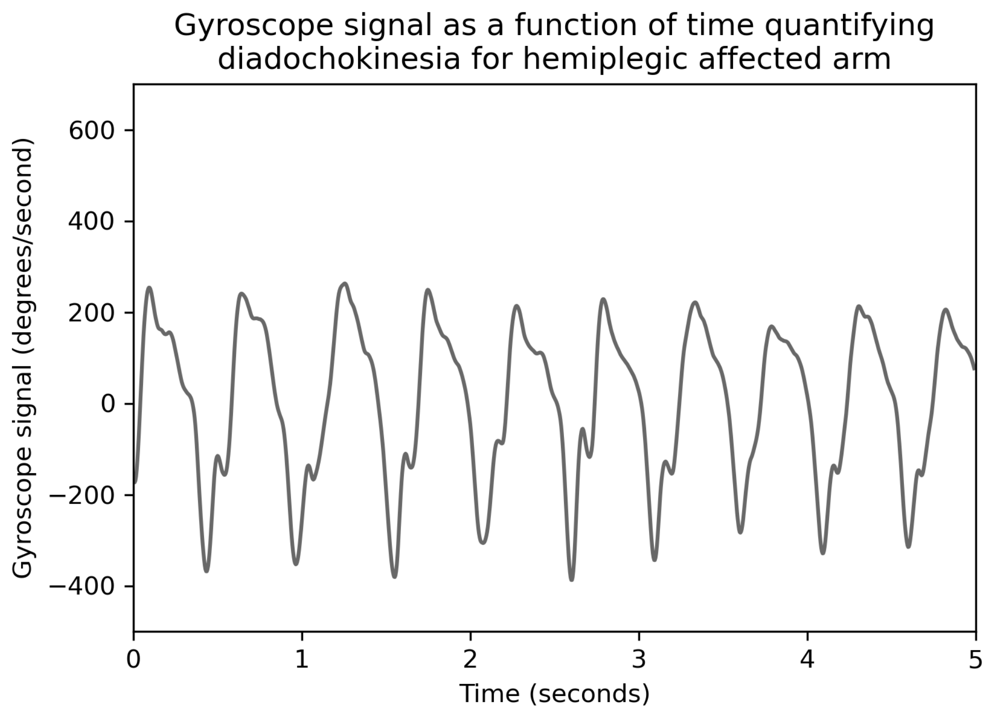

Figure 2. **The gyroscope signal acquired by the BioStamp nPoint as a conformal wearable and wireless inertial sensor system for measuring diadochokinesia pronation and supination of the hemiplegic affected arm.**

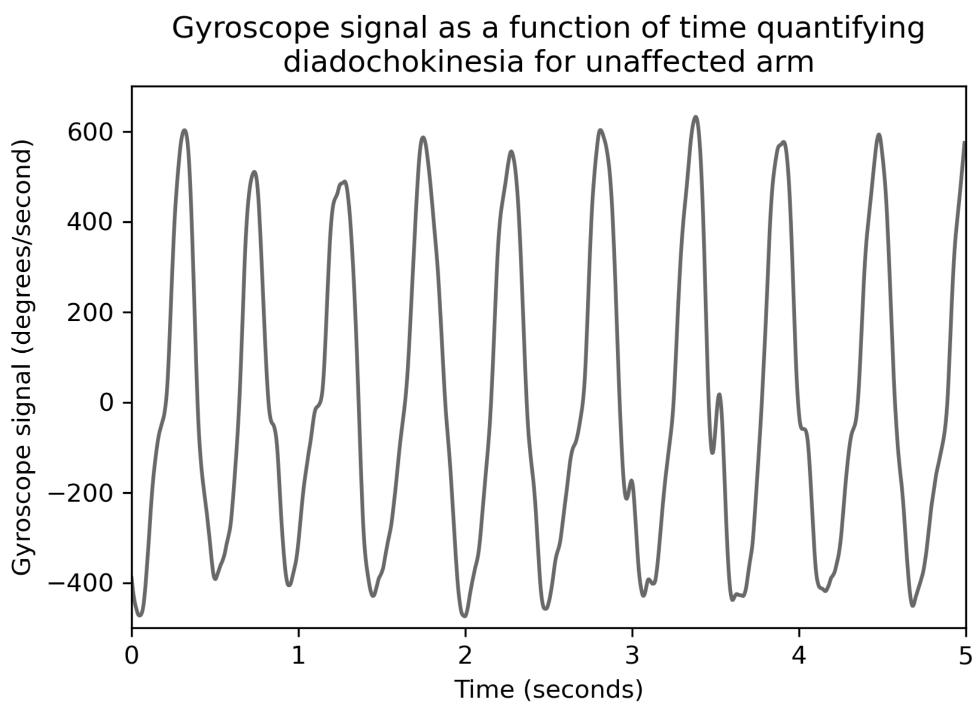

Figure 3. **The gyroscope signal acquired by the BioStamp nPoint as a conformal wearable and wireless inertial sensor system for measuring diadochokinesia pronation and supination of the unaffected arm.**

- Maximum
- Minimum
- Mean
- Standard deviation
- Coefficient of variation

The attributes have been successfully applied to other arm and hand mounted scenarios incorporating machine learning classification based on wearable and wireless inertial sensor systems [7, 12-17, 23].

The operation of WEKA generated a multilayer perceptron neural network that consisted of five input layer nodes, three hidden layer nodes, and two output layer nodes as illustrated in **Figure 4**. The multilayer perceptron neural network attained 100% classification accuracy. The machine learning model was converged within the bound of 0.05 seconds. Hemiplegic asymmetry regarding diadochokinesia through pronation and supination of the forearm was successfully quantified through the BioStamp nPoint as a conformal wearable and wireless inertial sensor system, and machine learning through a multilayer perceptron neural network successfully distinguishes the hemiplegic affected and unaffected arm pair for the evaluation of diadochokinesia.

The J48 decision tree was visualized in **Figure 5**. The J48 decision tree presented in **Figure 5** implies the significance of the maximum of the gyroscope signal as the most prevalent numeric attribute for discerning the classes of the feature set. A classification accuracy of 98.3% was achieved with one instance of the affected arm misclassified as an instance of the unaffected arm. The machine learning model was converged within less than 0.01 seconds.

The other four machine learning classification algorithms (random forest, K-nearest neighbors, logistic regression, and naïve Bayes) attained 100% classification accuracy for differentiating between the hemiplegic affected arm and unaffected arm in the context of diadochokinesia. The random forest required 0.07 seconds to develop. The machine learning model for K-nearest neighbors was derived within 0.02 seconds. The logistic regression and naïve Bayes machine learning models demonstrated the fastest convergence

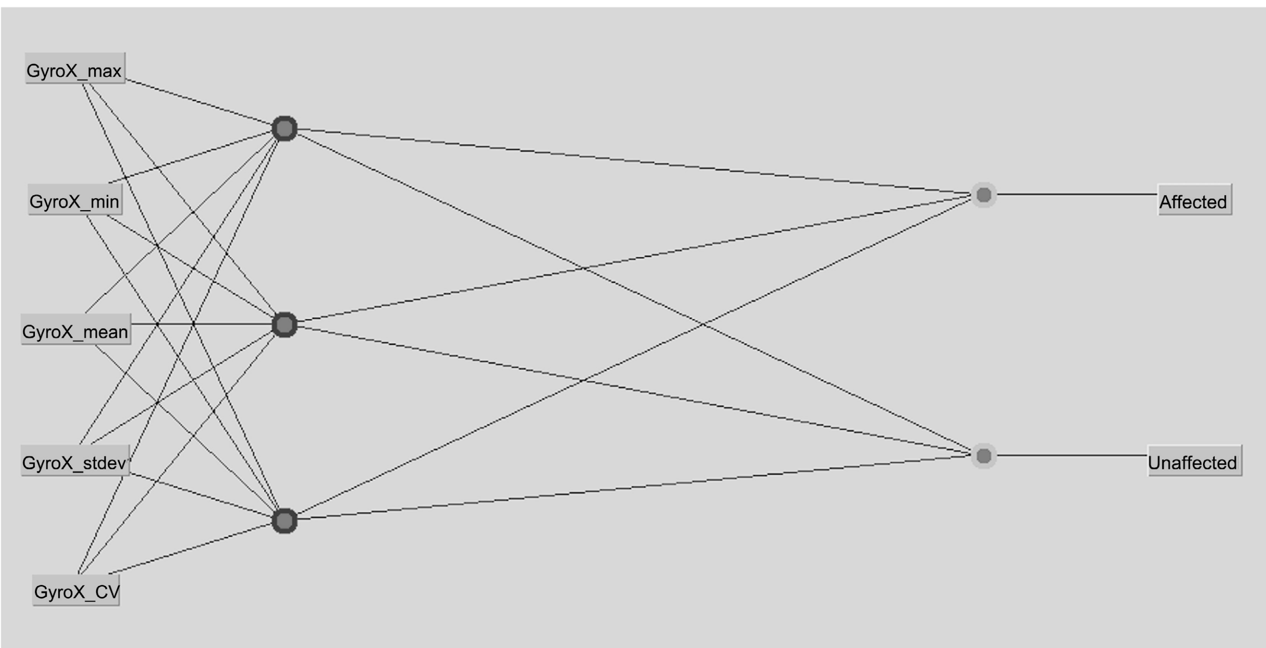

Figure 4. Multilayer perceptron neural network for attaining machine learning classification to distinguish between a hemiplegic affected and unaffected arm pair for diadochokinesia based on pronation and supination through the application of the BioStamp nPoint as a conformal wearable and wireless inertial sensor system.

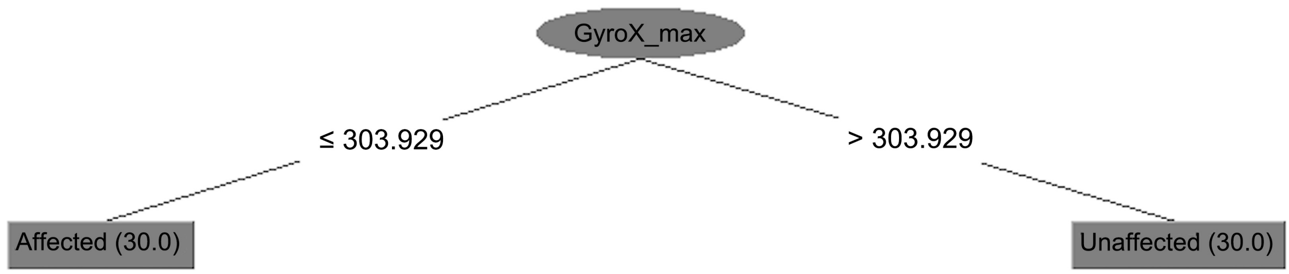

Figure 5. The J48 decision tree for distinguishing between a hemiplegic affected arm and unaffected arm for diadochokinesia based on pronation and supination using the BioStamp nPoint as a conformal wearable and wireless inertial sensor system.

with less than 0.01 seconds. Therefore, the logistic regression and naïve Bayes machine learning algorithms demonstrated the best performance in consideration of 100% classification accuracy for distinguishing between the hemiplegic affected arm and unaffected arm with respect to diadochokinesia and machine learning model development within the span of less than 0.01 seconds.

In particular, the BioStamp nPoint as a conformal wearable and wireless inertial sensor system demonstrates the utility of Network Centric Therapy, which involves the separation of the experimental site and post-processing location through wireless connectivity to the Internet, such as a secure Cloud computing environment. Rather than addressing the challenges of a prescribed medical appointment with a clinician, a patient can literally conduct an evaluation of diadochokinesia from the vantage of a homebound setting. The inertial sensor signal data package can be conveyed by wireless connectivity to the secure Cloud computing environment for remotely situated post-processing. This capability enables highly interactive and quantified evaluation of a therapy strategy [1, 23].

Additionally, the utility of the machine learning application can be further evolved. Further research can develop the refined distinction for the severity of hemiplegia based on the quantification of diadochokinesia through the use of conformal wearable and wireless inertial sensor systems with machine learning. Alternative numeric attributes warrant investigation to enhance the machine learning classification accuracy and the time to develop the model.

5. CONCLUSION

Considerable classification accuracy has been attained through the application of an assortment of machine learning algorithms to distinguish between a hemiplegic affected and unaffected upper limb pair for diadochokinesia involving pronation and supination. In particular, the logistic regression and naïve Bayes machine learning algorithms achieved the optimal performance in consideration of both classification accuracy and the time to develop the machine learning model. The gyroscope signal data was provided by the BioStamp nPoint as a conformal wearable and wireless inertial sensor system mounted about the hand through an adhesive medium. The significance of this preliminary demonstration was the observation that a subject can perform an evaluation of the status of diadochokinesia from a homebound setting with wireless Internet connectivity through access to a secure cloud computing resource to clinical resources anywhere in the world. The clinical team can proactively interact with the subject and provide optimal rehabilitation.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest regarding the publication of this paper.

REFERENCES

1. LeMoyne, R. and Mastroianni, T. (2018) Wearable and Wireless Systems for Healthcare I: Gait and Reflex Re-

sponse Quantification. Springer, Singapore.

2. LeMoyne, R. and Mastroianni, T. (2015) Use of Smartphones and Portable Media Devices for Quantifying Human Movement Characteristics of Gait, Tendon Reflex Response, and Parkinson's Disease Hand Tremor. In: Rasooly, A. and Herold, K.E., Eds., *Mobile Health Technologies*: *Methods and Protocols*, Springer, New York, 335-358. https://doi.org/10.1007/978-1-4939-2172-0_23
3. LeMoyne, R. and Mastroianni, T. (2017) Wearable and Wireless Gait Analysis Platforms: Smartphones and Portable Media Devices. In: Uttamchandani, D., Ed., *Wireless MEMS Networks and Applications*, Elsevier, New York, 129-152. https://doi.org/10.1016/B978-0-08-100449-4.00006-3
4. LeMoyne, R. and Mastroianni, T. (2016) Telemedicine Perspectives for Wearable and Wireless Applications Serving the Domain of Neurorehabilitation and Movement Disorder Treatment. In: LeMoyne, R. and Mastroianni, T., Eds., *Telemedicine*, SMGroup, Dover, 1-10.
5. LeMoyne, R. and Mastroianni, T. (2017) Smartphone and Portable Media Device: A Novel Pathway toward the Diagnostic Characterization of Human Movement. In: Mohamudally, N., Ed., *Smartphones from an Applied Research Perspective*, InTech, Rijeka, 1-24. https://doi.org/10.5772/intechopen.69961
6. LeMoyne, R. and Mastroianni, T. (2016) Smartphone Wireless Gyroscope Platform for Machine Learning Classification of Hemiplegic Patellar Tendon Reflex Pair Disparity through a Multilayer Perceptron Neural Network. *Proceedings of the IEEE Wireless Health* (*WH*), Bethesda, 25-27 October 2016, 103-108. https://doi.org/10.1109/WH.2016.7764563
7. LeMoyne, R. and Mastroianni, T. (2016) Implementation of a Smartphone as a Wireless Gyroscope Platform for Quantifying Reduced Arm Swing in Hemiplegic Gait with Machine Learning Classification by Multilayer Perceptron Neural Network. *Proceedings of the* 38th *Annual International Conference of the IEEE EMBS*, Orlando, 16-20 August 2016, 2626-2630. https://doi.org/10.1109/EMBC.2016.7591269
8. LeMoyne, R. and Mastroianni, T. (2017) Implementation of a Smartphone Wireless Gyroscope Platform with Machine Learning for Classifying Disparity of a Hemiplegic Patellar Tendon Reflex Pair. *Journal of Mechanics in Medicine and Biology*, **17**, Article ID: 1750083. https://doi.org/10.1142/S021951941750083X
9. Hermsdörfer, J., Marquardt, C., Wack, S. and Mai, N. (1999) Comparative Analysis of Diadochokinetic Movements. *Journal of Electromyography and Kinesiology*, **9**, 283-295. https://doi.org/10.1016/S1050-6411(98)00050-9
10. Klotz, P. and Kraus, P.H. (1995) Measurement of Diadochokinesia, In: Przuntek, H., Kraus, P.H., Klotz, P. and Korczyn, A.D., Eds., *Instrumental Methods and Scoring in Extrapyramidal Disorders*, Springer, Berlin, 221-226. https://doi.org/10.1007/978-3-642-78914-4_23
11. Hermsdörfer, J. and Goldenberg, G. (2002) Ipsilesional Deficits during Fast Diadochokinetic Hand Movements Following Unilateral Brain Damage. *Neuropsychologia*, **40**, 2100-2115. https://doi.org/10.1016/S0028-3932(02)00048-9
12. LeMoyne, R., Tomycz, N., Mastroianni, T., McCandless, C., Cozza, M. and Peduto, D. (2015) Implementation of a Smartphone Wireless Accelerometer Platform for Establishing Deep Brain Stimulation Treatment Efficacy of Essential Tremor with Machine Learning. *Proceedings of the* 37*th Annual International Conference of the IEEE EMBS*, Milan, 25-29 August 2015, 6772-6775. https://doi.org/10.1109/EMBC.2015.7319948
13. LeMoyne, R. and Mastroianni, T. (2017) Virtual Proprioception for Eccentric Training. *Proceedings of the* 39th *Annual International Conference of the IEEE EMBS*, Jeju, 11-15 July 2017, 4557-4561. https://doi.org/10.1109/EMBC.2017.8037870
14. LeMoyne, R., Mastroianni, T., Tomycz, N., Whiting, D., Oh, M., McCandless, C., Currivan, C. and Peduto, D. (2017) Implementation of a Multilayer Perceptron Neural Network for Classifying Deep Brain Stimulation in "On" and "Off" Modes through a Smartphone Representing a Wearable and Wireless Sensor Application. *Pro-*

ceedings of the 47*th Annual Society for Neuroscience*, Washington DC, 11-15 November 2017.

15. LeMoyne, R., Mastroianni, T., McCandless, C., Currivan, C., Whiting, D. and Tomycz, N. (2018) Implementation of a Smartphone as a Wearable and Wireless Accelerometer and Gyroscope Platform for Ascertaining Deep Brain Stimulation Treatment Efficacy of Parkinson's Disease through Machine Learning Classification. *Advances in Parkinson's Disease*, **7**, 19-30. https://www.scirp.org/journal/paperinformation.aspx?paperid=84978
16. LeMoyne, R., Mastroianni, T., McCandless, C., Currivan, C., Whiting, D. and Tomycz, N. (2018) Implementation of a Smartphone as a Wearable and Wireless Inertial Sensor Platform for Determining Efficacy of Deep Brain Stimulation for Parkinson's Disease Tremor through Machine Learning. *Proceedings of the* 48th *Annual Society for Neuroscience* (*Nanosymposium*), San Diego, 3-7 November 2018.
17. LeMoyne, R., Mastroianni, T., McCandless, C., Whiting, D. and Tomycz, N. (2019) Evaluation of Machine Learning Algorithms for Classifying Deep Brain Stimulation Respective of "On" and "Off" Status. *Proceedings of the* 9*th Int. IEEE/EMBS Conf. Neural Engineering* (*NER*), San Francisco, 20-23 March 2019, 483-488. https://doi.org/10.1109/NER.2019.8717095
18. LeMoyne, R. and Mastroianni, T. (2014) Implementation of a Smartphone as a Wireless Gyroscope Application for the Quantification of Reflex Response. *Proceedings of the* 36th *Annual International Conference of the IEEE EMBS*, Chicago, 26-30 August 2014, 3654-3657. https://doi.org/10.1109/EMBC.2014.6944415
19. MC10 Inc. https://www.mc10inc.com/our-products#biostamp-npoint
20. Okada, M. and Okada, M. (1983) A Method for Quantification of Alternate Pronation and Supination of Forearms. *Computers and Biomedical Research*, **16**, 59-78. https://doi.org/10.1016/0010-4809(83)90007-1
21. Lang, C.E. and Beebe, J.A. (2007) Relating Movement Control at 9 Upper Extremity Segments to Loss of Hand Function in People with Chronic Hemiparesis. *Neurorehabilitation and Neural Repair*, **21**, 279-291. https://doi.org/10.1177/1545968306296964
22. Matsuki, K.O., Matsuki, K., Mu, S., Sasho, T., Nakagawa, K., Ochiai, N., Takahashi, K. and Banks, S.A. (2010) *In Vivo* 3D kinematics of Normal Forearms: Analysis of Dynamic Forearm Rotation. *Clinical Biomechanics*, **25**, 979-983. https://doi.org/10.1016/j.clinbiomech.2010.07.006
23. R LeMoyne, R. and Mastroianni, T. (2020) Machine Learning Classification for Network Centric Therapy Utilizing the Multilayer Perceptron Neural Network. In: Vang-Mata, R., Ed., *Multilayer Perceptrons: Theory and Applications*, Nova Science Publishers, Hauppauge, 39-76.
24. Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P. and Witten, I.H. (2009) The WEKA Data Mining Software: An Update. *ACM SIGKDD Explorations Newsletter*, **11**, 10-18. https://doi.org/10.1145/1656274.1656278
25. Witten, I.H., Frank, E. and Hall, M.A. (2011) Data Mining: Practical Machine Learning Tools and Techniques. Morgan Kaufmann, Burlington.
26. WEKA. http://www.cs.waikato.ac.nz/~ml/weka