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Editorial

Wearable Sensors for Supporting Diagnosis, Prognosis, and Monitoring of Neurodegenerative Diseases

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1. Introduction

The incidence of neurodegenerative disorders (NDs) is increasing in an aging population. NDs encompass a wide range of disorders characterized by the progressive deterioration of the central or peripheral nervous system, affecting millions of individuals worldwide. Despite the clinical significance of monitoring ND's symptoms, this can be challenging in current practice due to the difficulty of accurately remembering and describing symptoms and the infrequency of clinical appointments. Moreover, individuals with NDs may experience difficulties in objectively assessing their symptoms, and these may be perceived differently by their care partners. Thus, there is an unmet need for more objective and continuous monitoring of symptoms in NDs.

To address this challenge, new technological solutions are required for computerized diagnosis, evaluation of the effectiveness of therapy, and continuous monitoring of disease progression. In such a context, wearable technology has emerged as a revolutionary approach to healthcare, offering a more personalized approach to diagnosis and disease management. For example, in the field of neurological diseases, wearable technology has the potential to improve diagnosis, provide inexpensive and non-invasive assessment tools, monitor disease progression, and inform ongoing disease management. Recent advances in wearable and portable sensors, information, and communication technologies have enabled continuous monitoring of NDs. The use of wearable technology allows the collection of high-dimensional data from different domains during daily activities. In addition, signal processing and machine learning (ML) approaches have provided powerful methods for analyzing large amounts of multimodal data, facilitating the obtaining of detailed, objective, and accurate information on disease manifestations.

Wearable technology offers several advantages in monitoring NDs, such as continuous monitoring, objective measurements, and remote monitoring, which can lead to earlier diagnosis, more accurate treatment decisions, and improved outcomes. Wearable technology can also be used to measure various parameters, such as heart rate, blood pressure, movement, sleep patterns, and brain activity, providing insights into cognitive function and facilitating the diagnosis of NDs. In addition, the data collected from wearable technology can be analyzed using ML algorithms to identify patterns and develop predictive models, supporting clinicians in making informed decisions about treatment and care. In conclusion, wearable technology has excellent potential in NDs, providing continuous and objective monitoring and enabling ML analysis of high-dimensional data. As wearable technology continues to advance, it is likely to play an increasingly important role in diagnosing and managing NDs.

2. The Present Special Issue

The present Special Issue comprises eleven research and review articles that propose wearable solutions and explore signal processing, ML, and deep learning (DL) approaches

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for the computerized diagnosis and monitoring of NDs. The following is a brief summary of each of the articles.

Masi et al. [1] provided an overview of non-intrusive approaches to sleep monitoring for NDs. The authors reviewed twenty-six articles to gather information on the proposed solutions in terms of technologies, methods, and fields of application. The results showed that wearable sensors were mainly used for automatic sleep staging and movement analysis, while non-wearable solutions were used for home monitoring. In addition, inertial sensors were the most commonly used technology, followed by environmental cameras and bedside sensors. The authors concluded that, despite the wide variety of proposed solutions, these need further validation before being applied in clinical practice and in patients' daily lives.

Sigcha et al. [2] proposed a wearable system to estimate the severity of bradykinesia (i.e., slowness of movement) in Parkinson's disease (PD). Six subjects with PD and seven age-matched healthy controls (HCs) were equipped with a consumer smartwatch and asked to perform a series of motor exercises for 6 weeks. Inertial data were processed using different data representations, data augmentation techniques, feature sets, and ML models. The combination of convolutional neural network (CNN) and random forest (RF) classifier provided the best performance, with an accuracy of 0.86. Furthermore, a Pearson's correlation coefficient (r) of 0.94 and a mean square error of 0.46 were obtained between the system output and the clinical severity score.

Carvajal-Castaño et al. [3] collected inertial data from forty-five subjects with PD and eighty-nine HCs, including forty-four young and forty-five elderly people. Participants were asked to perform various gait tasks while wearing inertial measurement units attached to their shoes. Different data representations and DL models were used to process the data. The CNN fed with the short-time Fourier transform provided comparable results to the gated recurrent unit fed with raw data. The further combination of both models did not significantly improve performance. Finally, discrimination of persons with PD from elderly people proved more difficult (0.93 accuracy) than discrimination from younger persons (0.83 accuracy).

Pau et al. [4] employed a single inertial sensor on the lower back to analyze the subjects' gait. Specifically, 449 elderly HCs were recruited and divided into three groups according to age. Acceleration signals were recorded while participants walked in a straight line. Spatial and temporal gait parameters and harmonic ratio were calculated. Finally, statistical analysis (i.e., two-way multivariate analysis of variance) was used to assess significant differences. Older subjects showed a reduction in gait speed, stride length, and cadence ($p < 0.001$), compared to younger participants. Furthermore, the harmonic ratio analysis revealed a general trend of linear decrease with age.

Pietrosanti et al. [5] used wearable inertial sensors to analyze the swinging movement of the forearms during walking. Fifty-eight PD patients and thirty-one age-matched HCs were enrolled and asked to wear sensors on each arm and upper back while performing a timed up-and-go test. The fast Fourier transform of the inertial data was generated and used to extract a series of harmonic features. The two-sample t-test was used to assess the differences between PD and HC subjects. In addition, Spearman's test was used to calculate the correlation between features and clinical scores. The results showed significant differences in arm swing characteristics between subjects with PD and HCs. Furthermore, the harmonic amplitude features correlated significantly with the clinical gait ($r = -0.64$), body bradykinesia ($r = -0.67$), and overall score ($r = -0.57$).

Casadei et al. [6] developed a systolic blood pressure monitoring system based on a wearable device. First, a public data set comprising photoplethysmographic (PPG) recordings of forty-seven subjects was used to train a DL algorithm. Subsequently, data from eight subjects were recorded using both a small wearable PPG sensor and a sphygmomanometer, which was used as a reference. The results showed that the performance of the system was up to standard, with an average absolute error of 3.85 mmHg.

Cesari et al. [7] investigated how wearable devices can be assembled and used to provide feedback to human subjects to improve gait and posture. This can be applied to the rehabilitation of motor disabilities of patients suffering from NDs. Twelve subjects were asked to perform certain postural and motor tasks on a proprioceptive board while being monitored via electromyographic sensors, a force platform, motion capture cameras, and wearable inertial sensors. From the pre-processed multimodal data, several time- and frequency-domain features were extracted and input to different ML models. Preliminary analysis showed that using the inertial sensor system in addition to the other data sources significantly improved performance. Furthermore, using only wearable motion sensors and an RF classifier, an F-score of 0.90 was obtained in the detection of the different phases of motor tasks.

Rana et al. [8] proposed a processing pipeline based on voice analysis for the computerized diagnosis of PD. The data set consisted of voice features extracted from twenty-three PD patients and eight HCs. The authors used different feature selection strategies and different ML classifiers. The proposed DL algorithm provided the best results, with an accuracy of 0.87.

Calvo-Ariza et al. [9] analyzed facial expressions (happiness, surprise, and anger) to discriminate between thirty-one PD patients and twenty-three HCs. The face was extracted from each video frame using a multi-task CNN cascade. Subsequently, two different feature sets, namely local binary patterns and histograms of oriented gradients, were extracted and given as input to a support vector machine for binary classification. The first feature set provided the best performance, achieving an accuracy of 0.80 for the happiness expression.

Sethuraman et al. [10] proposed a system for aiding the diagnosis of Alzheimer's disease (AD) from resting-state functional magnetic imaging (rs-fMRI). The data set comprised 152 patients, in which subjects with AD, mild cognitive impairment, and HCs were equally represented. The images were digitally processed and various frequency levels of the rs-fMRI time series were extracted. Finally, data transformation was applied to convert the time series into images to be input into the DL model. Two CNNs (AlexNet and Inception V2) were used for classification, which were then fine-tuned and optimized. The results showed excellent discrimination ability, with an accuracy of 0.97 and 0.83 in differentiating subjects with AD from HCs and subjects with MCI, respectively.

Besides the mere utilization of wearables for monitoring purposes, the integration of healthcare with the Internet of Things (IoT) presents numerous opportunities for patient monitoring. Nevertheless, a major challenge in the era of Healthcare 4.0 is identifying compromised and malicious nodes, which can threaten network security and user privacy. On such aim, Awan et al. [11] proposed a trust management approach for edge nodes based on ML to identify nodes with malicious behavior. The trust calculation was based on characteristics such as friendliness, trustworthiness, and cooperation. Data were preprocessed using feature selection and scaling and input into a naive Bayes classifier. The experiments were performed in different scenarios and attacks, varying the number of nodes in the network. The results showed that the proposed EdgeTrust system is able to recognize possible IoT attacks to maintain a robust environment. Furthermore, the low power consumption makes the system suitable for real-world scenarios.

3. Future Directions

In recent decades, the advancement of technologies and methodologies has facilitated scientific research in wearable sensors and data processing techniques for health monitoring, leading to a proliferation of wearable solutions for objective assessment, computer-aided diagnosis, and continuous monitoring of chronic disorders. However, challenges in the clinical validation of these solutions and patient compliance for long-term passive monitoring in daily life still persist. To address these challenges, the development of tiny sensors that can be attached to the body or smart textiles with embedded sensors has emerged as a promising solution. Additionally, while research on widely prevalent neurodegenerative disorders such as Parkinson's disease is extensive, there has been limited exploration of rare disorders such as ataxia, Huntington's disease, and progressive supranuclear palsy.

To develop effective, scalable, and clinically validated wearable sensor systems for human health monitoring, further research is necessary.

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References

1. Masi, G.; Amprimo, G.; Priano, L.; Ferraris, C. New Perspectives in Nonintrusive Sleep Monitoring for Neurodegenerative Diseases—A Narrative Review. *Electronics* **2023**, *12*, 1098. [CrossRef]
2. Sigcha, L.; Domínguez, B.; Borzì, L.; Costa, N.; Costa, S.; Arezes, P.; López, J.M.; De Arcas, G.; Pavón, I. Bradykinesia Detection in Parkinson's Disease Using Smartwatches' Inertial Sensors and Deep Learning Methods. *Electronics* **2022**, *11*, 3879. [CrossRef]
3. Carvajal-Castaño, H.A.; Pérez-Toro, P.A.; Orozco-Arroyave, J.R. Classification of Parkinson's Disease Patients—A Deep Learning Strategy. *Electronics* **2022**, *11*, 2684. [CrossRef]
4. Pau, M.; Bernardelli, G.; Leban, B.; Porta, M.; Putzu, V.; Viale, D.; Asoni, G.; Riccio, D.; Cerfoglio, S.; Galli, M.; et al. Age-Associated Changes on Gait Smoothness in the Third and the Fourth Age. *Electronics* **2023**, *12*, 637. [CrossRef]
5. Pietrosanti, L.; Calado, A.; Verrelli, C.M.; Pisani, A.; Suppa, A.; Fattapposta, F.; Zampogna, A.; Patera, M.; Rosati, V.; Giannini, F.; et al. Harmonic Distortion Aspects in Upper Limb Swings during Gait in Parkinson's Disease. *Electronics* **2023**, *12*, 625. [CrossRef]
6. Casadei, B.C.; Gumiero, A.; Tantillo, G.; Della Torre, L.; Olmo, G. Systolic Blood Pressure Estimation from PPG Signal Using ANN. *Electronics* **2022**, *11*, 2909. [CrossRef]
7. Cesari, P.; Cristani, M.; Demrozi, F.; Pascucci, F.; Picotti, P.M.; Pravadelli, G.; Tomazzoli, C.; Turetta, C.; Workneh, T.C.; Zenti, L. Towards Posture and Gait Evaluation through Wearable-Based Biofeedback Technologies. *Electronics* **2023**, *12*, 644. [CrossRef]
8. Rana, A.; Dumka, A.; Singh, R.; Rashid, M.; Ahmad, N.; Panda, M.K. An Efficient Machine Learning Approach for Diagnosing Parkinson's Disease by Utilizing Voice Features. *Electronics* **2022**, *11*, 3782. [CrossRef]
9. Calvo-Ariza, N.R.; Gómez-Gómez, L.F.; Orozco-Arroyave, J.R. Classical FE Analysis to Classify Parkinson's Disease Patients. *Electronics* **2022**, *11*, 3533. [CrossRef]
10. Sethuraman, S.K.; Malaiyappan, N.; Ramalingam, R.; Basheer, S.; Rashid, M.; Ahmad, N. Predicting Alzheimer's Disease Using Deep Neuro-Functional Networks with Resting-State fMRI. *Electronics* **2023**, *12*, 1031. [CrossRef]
11. Awan, K.A.; Ud Din, I.; Almogren, A.; Khattak, H.A.; Rodrigues, J.J. EdgeTrust: A Lightweight Data-Centric Trust Management Approach for IoT-Based Healthcare 4.0. *Electronics* **2023**, *12*, 140. [CrossRef]

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