



Comparative Evaluation of Deep Neural Models for Parkinson's Disease Monitoring Using Multimodal Wearable Sensor Data

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Abstract

Parkinson's disease (PD) is a progressive neurological disorder for which continuous observation of motor and non-motor manifestations can support clinical assessment and long-term disease management. This study examines multimodal wearable sensor data and deep neural models for PD-related pattern analysis in a home-oriented monitoring setting. The framework integrates accelerometer, electromyography (EMG), gyroscope, and acoustic measurements with edge-level processing using a Raspberry Pi platform and wireless communication. Sensor observations collected during structured daily activities were used to compare convolutional, recurrent, and autoencoder-based deep-learning approaches reported in the source study. The primary experimental cohort reported in the methodology consisted of 50 participants, including 35 individuals with PD and 15 control participants. The source manuscript reports performance values between 97.8% and 99.8%; however, the final manuscript must explicitly define the metric and validation protocol supporting these values. The findings demonstrate the potential of multimodal sensing and deep learning for continuous PD monitoring while emphasizing that algorithmic outputs are decision-support signals rather than substitutes for clinical diagnosis.

Keywords

Parkinson's disease; wearable sensors; multimodal sensing; deep learning; EMG; accelerometer; recurrent neural networks; convolutional neural

networks; remote health monitoring

1. Introduction

Parkinson's disease is a chronic and progressive neurological condition characterized by motor and non-motor manifestations. Clinical assessment commonly considers tremor, bradykinesia, postural instability, and changes in speech or other physiological functions. Because symptom intensity may vary over time, periodic clinical observation may not capture all fluctuations experienced during daily life. This limitation has motivated research into sensor-assisted monitoring and computational methods for analysing longitudinal behavioural and physiological signals.

Wearable and connected sensing technologies provide a mechanism for collecting movement and biosignal data outside conventional clinical environments. Accelerometers and gyroscopes capture body motion, EMG sensors represent muscular activity, and acoustic sensors provide information related to voice variation. When these heterogeneous signals are combined, they create a multimodal representation that may contain complementary information about PD-related manifestations.



Deep neural networks are relevant because they can learn hierarchical representations from complex sensor data. Convolutional models can capture local patterns, recurrent architectures can model temporal dependencies, and autoencoder-based approaches can learn compact feature representations. However, high reported performance alone is insufficient to establish practical utility. Dataset quality, ground-truth definition, participant-level separation between training and testing data, and transparent reporting of evaluation metrics are essential.

The source study provides a real-time multimodal sensing framework combining inertial, muscular, and acoustic measurements with deep-learning analysis. This revised version reorganizes the work into a standard research structure, removes repeated descriptions, and explicitly identifies methodological details that require confirmation before submission.

The study aims to: (i) develop a multimodal wearable sensing framework for PD-related movement, muscular, and acoustic observations; (ii) compare deep neural approaches for analysing these observations; (iii) examine the feasibility of edge-enabled continuous monitoring; and (iv) identify the methodological conditions required for reproducible clinical decision-support research.

2. Literature Review

Machine-learning and deep-learning methods have increasingly been applied to neurological data, including movement signals, voice features, imaging data, and electrophysiological recordings [1], [2], [14], [19]. Deep learning has also been applied to high-dimensional healthcare data, where representation learning can reduce dependence on manually engineered features [11], [21]. For PD monitoring, wearable sensing is attractive because it supports repeated measurements during routine activities. Accelerometer and gyroscope signals describe kinematic characteristics, EMG captures muscular activity, and acoustic measurements provide complementary information concerning voice-related changes.

The practical challenges include sensor synchronization, signal quality, missing data, participant variability, and computational deployment. Existing work also demonstrates the importance of feature selection and validation strategy. Models trained on small cohorts may show optimistic results if observations from the same participant occur in both training and test partitions. Consequently, participant-level validation and clearly defined performance metrics are essential. The present study is positioned as a system-oriented comparison of deep-learning approaches using multimodal sensor observations for continuous monitoring rather than as a replacement for specialist diagnosis.

3. Methodology

3.1 System Architecture

The framework contains four layers: sensing, communication, edge processing, and remote monitoring. The sensing layer includes inertial and physiological devices that capture movement, muscular, and acoustic observations. Data are transferred through available communication channels to a processing platform. A Raspberry Pi 4 Model B is used as the edge-processing component in the reported implementation. Processed outputs can then be communicated to an authorized remote system for monitoring and alert generation.

3.2 Sensor Configuration

The reported setup combines a multimodal inertial measurement unit with accelerometer, EMG, and gyroscope capabilities; acoustic sensing through an Ultra-Thin PF sensor and HS-125 microphone; communication interfaces; and a Raspberry Pi processing unit. Accelerometer and gyroscope signals characterize movement and orientation, EMG captures muscular activity, and acoustic sensing observes voice-frequency variations.

Component	Reported configuration	Primary role
Multimodal wearable unit	MC-10 BioStamp / inertial multimodal unit	Movement, EMG and gyroscope observations
Acoustic sensing	Ultra-Thin PF and HS-125 microphone	Voice/acoustic variation
Communication	Bluetooth, GSM and relay interfaces	Transfer of sensor observations
Edge processor	Raspberry Pi 4 Model B	Execution of processing and model



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3.3 Participants and Data Collection

The methodology in the source manuscript reports a primary cohort of 50 participants: 35 participants identified as having PD and 15 control participants. Sensor observations were collected during structured activities including walking, drawing, drinking, standing and sitting, running, keyboard playing, and simple hand and leg exercises. These activities generated observations associated with functional, fine-motor, and gross-motor behaviour.

The source manuscript later states that measurements were obtained from 56 participants. This discrepancy must be reconciled using the original data records before submission. This revision therefore retains the 50-participant cohort as the primary experimental sample and does not present the 56-participant statement as a separate result.

3.4 Data Preparation and Model Evaluation

Multimodal sensor streams should be timestamped, synchronized, cleaned, normalized, and segmented into analysis windows. The source study compares convolutional neural network variants, recurrent neural network variants, and autoencoder-based models. For reproducibility, the final submission should specify the exact architecture of each model, including layers, activation functions, optimizer, learning rate, batch size, epochs, regularization, and modality-fusion strategy.

Participant-level separation should be used to avoid information leakage. Performance should be reported using accuracy, precision, recall, F1-score, specificity, and, where applicable, area under the ROC curve. If the reported 97.8%–99.8% values refer to accuracy rather than precision, the terminology should be corrected.

4. Results

The reported implementation connects multimodal sensing components to an edge-processing environment and transfers selected outputs to a remote monitoring system. Structured activities generated multi-axis accelerometer observations and movement features. EMG readings were used to examine variations in muscular activity, while acoustic measurements were included to observe voice-related frequency changes.

The source manuscript reports that the compared deep-learning techniques achieved performance values between 97.8% and 99.8%. Convolutional and recurrent approaches were described as producing closely comparable performance, while the recurrent model was considered suitable for dynamic temporal observations. These claims should be retained only after confirmation of the exact metric, dataset split, number of test instances, and validation procedure.

Because the source manuscript does not provide a complete numerical comparison for every model, this revision does not invent missing results. The final submission should include a model-comparison table containing accuracy, precision, recall, F1-score, specificity, and the validation protocol, together with confusion matrices or ROC curves when available.

5. Discussion

The principal contribution of the framework is the integration of heterogeneous sensor signals with deep-learning analysis in a continuous monitoring architecture. Combining movement, muscular, and acoustic information can provide a richer representation than relying on a single signal because PD manifestations are heterogeneous and may not be consistently reflected in one measurement channel.

Convolutional and recurrent approaches offer complementary advantages. Convolutional networks can extract local patterns from structured input windows, whereas recurrent architectures can model dependencies across successive observations. Autoencoder-based approaches can provide compact representations or support feature learning. Model selection should therefore consider predictive performance together with computational cost, robustness, interpretability, and feasibility for edge deployment.

Several limitations require explicit acknowledgement. The reported cohort is relatively small for a deep-learning study, participant-level validation is necessary, and the inconsistent participant counts must be resolved. The source text also does not fully document model hyperparameters or the exact data-partitioning procedure. The framework should therefore be treated as a monitoring and decision-support system rather than a clinically validated diagnostic



replacement. Future work should evaluate the approach on larger, independently collected cohorts and assess generalization across age groups, disease stages, devices, and real-world environments.

6. Conclusion

This study presents a multimodal wearable-sensing framework for analysing Parkinson's disease-related observations using deep neural models. The system integrates accelerometer, EMG, gyroscope, and acoustic measurements with edge-level processing and remote monitoring. The source experiment reports strong comparative performance for the evaluated models, with values between 97.8% and 99.8%, while recurrent and convolutional approaches were identified as suitable for dynamic sensor analysis.

The revised manuscript emphasizes that these findings must be supported by transparent documentation of the dataset, participant counts, ground-truth labels, metric definitions, and validation procedure. With these clarifications, the framework can provide a stronger basis for future research on continuous PD monitoring and multimodal AI-assisted healthcare systems. The system is intended to support observation and clinical decision-making; it is not a substitute for professional medical diagnosis.

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