Edge Deep Learning Enabled Freezing of Gait Detection in Parkinson’s Patients

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Abstract—This paper presents the design of a wireless sensor network for detecting and alerting the freezing of gait (FoG) symptoms in patients with Parkinson’s disease. A novel button pin type sensor node design is developed for easy attachment. Three sensor nodes, each integrating a 3-axis accelerometer, can be placed on a patient at ankle, thigh, and truck. Each sensor node can independently detect FoG using an on-device deep learning (DL) model, featuring a squeeze and excitation convolutional neural network (CNN). The DL model outputs from the three sensor nodes are processed in a central node using a majority voting algorithm. In a validation using a public dataset, the prototype developed achieved a FoG detection sensitivity of 88.8% and an F1 score of 85.34%, using less than 20 k trainable parameters per sensor node. Once FoG is detected, an auditory signal will be generated to alert users, and the alarm signal will also be sent to mobile phones for further actions if needed. The sensor node can be easily recharged wirelessly by inductive coupling. The system is self-contained and processes all user data locally without streaming data to external devices or the cloud, thus eliminating the cybersecurity risks and power penalty associated with the wireless data transmission. The developed methodology can be used in a wide range of applications.

I. INTRODUCTION

Parkinson’s disease (PD) is a neurodegenerative disorder that affects more than 8.5 million people worldwide [1]. Patients with PD experience a multitude of movement disorders. A prevalent disorder in the late stages of PD is freezing of gait (FoG), which impedes a patient’s walking and turning, increasing instability and risk of falls and injuries [2]. Although there is no known cure for FoG, there are treatment methods, including pharmaceutical treatment and invasive or non-invasive stimulation [3]. Invasive approaches can achieve high clinical efficacy, but come with risks and adverse effects [4]. Auditory stimulation is a non-invasive approach that is safe to implement and has a high success rate for certain groups of patients [5]. However, this approach requires that patients with PD are assisted by clinicians.

Recently, machine learning methods, including deep learning (DL) models, have been developed to detect FoG automatically without involving human in the loop [3]. [6–8]. These methods potentially permit low-cost treatment at home or long-term operation using wearable devices. However, the DL models in existing work demand high computational power, and thus are not suitable for low-power devices. Although processing can be offloaded to the cloud [9], these approaches have major drawbacks in: (1) dependence on the Wi-Fi or cellular network, which prevents offline use, (2) continuous data transmission poses a power penalty, and (3) wireless data transmission poses cybersecurity concerns [10]. There is a compelling need for self-contained sensors that can detect FoG locally and generate alerts in real time [11].

In this work, we fill this important research gap by developing a wireless sensor system that can detect FoG with an edge DL model. The system consists of a central node and several sensor nodes. Each sensor node integrates a low-power microcontroller (MCU) with a wireless module that supports Bluetooth and a 3-axis accelerometer [12]. A lightweight DL model with less than 20 k trainable parameters was integrated in the MCU to detect FoG. The sensor node will notify the central node when FoG is detected; the central node will process inputs from all sensor nodes and generate an auditory stimulus via an integrated speaker once pre-defined conditions are met. All nodes are battery powered and can be easily recharged wirelessly by inductive coupling.

The rest of the paper is organized as follows. Section II first introduces the FoG detection algorithm, presents the wireless sensor hardware design, and discusses the deployment of the algorithm into the hardware. The experimental results are given in Section III and compared with the state-of-the-art work. Section IV concludes the paper.

II. METHODS

A. Development of the Deep Learning Model

The DL model was trained and validated using a public dataset reported by M. Bachlin and colleague [8], referred to as the Daphnet dataset in this article. The Daphnet dataset consists of acceleration measurements taken from 10 patients with PD tracked in a controlled environment performing three types of tasks: straight walking, walking with numerous turns, and simulated activity of daily living (ADL) such as fetching coffee and opening doors. Measurements were taken from the ankle, thigh, and truck of patients and sampled at 64 Hz. The measurements were labeled by experts with the FoG status: label 2 is set for freezing, label 1 is for non-freezing, and label 0 is for experiment-irrelevant activities, such as debriefing. Data from the 5th and the 10th patients were omitted from the experiments because they did not experience freezing during the experiments.

We adopted a k-fold cross-validation strategy for training the model, with 20% of the data retained for testing. A hard
Fig. 1. The DL model architecture and the three-sensor majority voting mechanism. Each of the 3 sensor nodes process an 128 x 3 input tensor through a CNN with identical architecture but different weights, and produce an output ranging in [0,1]. FoG alert simulations are only activated when at least 2 sensor output are greater than 0.4, a low-pass filter that yield the largest area under ROC curve saturation limit of 5 g was applied to all data, eliminating outliers that could alter the data scaling. The data was filtered through a low-pass filter with a 20 Hz cutoff frequency to reduce noise. This cutoff was chosen because FOG events are best predicted by signals originating from the 0-3 Hz "locomotor" band and the 3-8 Hz "freeze" band [13]. Then, the filtered data was normalized to facilitate model training. Finally, the data was segmented into windows of 128 samples with 64 overlap samples between windows, translating to 2-sec windows with a 1-sec overlap. If a window contained one or more irrelevant data points (labeled 0), the window was discarded. Then, windows consisting of more than 40% freezing points were labeled as freezing, and the remaining windows were labeled as non-freezing. The 40% threshold was tuned as a hyper-parameter. The labeled windows were then shuffled and used in the training and validating of the model.

We developed a squeeze and excitation CNN model, as shown in Fig. 1. A three-layer CNN, with 1-D max pooling between convolutional layers, was used to learn feature data from the dataset while reducing the required number of training parameters. The model was simplified using only native Keras layers to facilitate better translation to a Tensorflow Lite compatible model for implementation on the embedded hardware. This CNN was built and trained using the Tensorflow Keras 2.10.0 library. The output of the convolutional layers was fed into a pair of dense layers separated by a dropout layer and then a final output layer using sigmoid activation for binary classification. Dropout was implemented to increase the stochasticity of training and combat overfitting due to the limited data provided. It was noted that the number of freezing and non-freezing frames in the dataset were not equal. This was expected as the majority of subject time was spent in a non-freezing state. Thus, class weighting was implemented as suggested in the Keras training documentation [14]. Additionally, a bias was initialized on the prediction layer to further account for this data imbalance and reduce the required number of training epochs to minimize loss.

B. Wireless Sensor Hardware Design

All nodes use a 32-bit MCU (nRF52840, Nordic Semiconductor) featuring an ARM Cortex M4 CPU with floating point unit (FPU) running at 64 MHz [15], [16]. The MCU also integrates a wireless module that supports Bluetooth 5.3 multiprotocol radio, including mesh networking [17]. The MCU integrates 1 MB Flash memory and 256 kB SRAM. The sensor node integrates a 3-axis accelerometer (LSM9DS1, STMicroelectronics), which has a programmable full-scale acceleration from ±2 g to ±16 g. A speaker is integrated into the central node, which can produce a programmable auditory stimulus of up to 80 dB. Wireless inductive power transfer is used to charge the battery. A carrier frequency of 250 Hz is used. The coil has an inductance of 60 μH. A power management module regulates the charging current. An on-device low-drop-out regulator (LDO) is used to power the MCU and the sensors. The debugging and programming interface (DPI) allows us to update the program and DL model.

C. Deployment of the DL Model on the Hardware

The selected 32-bit MCU nRF52840 is suitable for the computational demand of this work. Tensorflow Lite was used to convert the DL model developed in Python to a C++ model that can be executed on the MCU. The converted model occupied 478 kB of memory, which was less than the Flash memory integrated in the MCU. To validate hardware deployment and test the performance of the DL model, testing data from the Daphnet dataset was sent to the MCU from a computer host (rather than directly from the accelerometers). A full buffer of 128 values was sent before each prediction was made. This allowed results to be directly compared with model performance with its non-quantized counterpart. A median filter and a first-order discrete low-pass filter with a 20 Hz cutoff frequency were implemented in the MCU to mirror the preprocessing performed during model training and validation. The data was also min-max normalized. On the MCU, the filtered data was stored in a rolling buffer of 128 data points, which was treated as an input window on which the model would make predictions. Due to the simplicity and compressed size of the CNN model developed, minimal changes were required to implement it on the embedded hardware.

III. RESULTS

We used accuracy, sensitivity, specificity, and F1 score as metrics for testing the performance of the developed DL
TABLE I
MODEL PERFORMANCE COMPARISON WITH THE STATE-OF-THE-ARTS.

| Reference          | Year | Model Architecture        | Accuracy | Sensitivity | Specificity | F1 score | # Trainable Parameters |
|--------------------|------|----------------------------|----------|-------------|------------|----------|------------------------|
| Rodriguez-Martín   | 2017 | SVM with Wrist Sensor      | 83.66%   | 88.09%      | 80.09%     | –%       | –                      |
| San-Segundo        | 2019 | CNN+MLP                    | –%       | 92.3%       | 92.8%      | 94.8%    | 5,001,273              |
| Tautan             | 2020 | 1D CNN                     | –%       | 83.77%      | 81.78%     | –%       | –                      |
| Sigcha             | 2020 | Random Forest              | –%       | 87.8%       | 87.6%      | –%       | 298,500                |
| Mekruksavanich     | 2021 | Squeeze and Excite CNN     | 95.66%   | 95.66%      | –%         | 95.56%   | 32,450                 |
| Mesin              | 2022 | SVM                        | 88%      | 85.14%      | 88.38%     | 86.73%   | NA                     |
| This work (Python) | 2022 | CNN+Majority Voting        | 83.00%   | 85.40%      | 82.70%     | 85.50%   | 19,995 each node       |
| This work (Embedded)| 2022| CNN+Majority Voting        | 81.48%   | 88.80%      | 80.71%     | 85.34%   | 19,995 each node       |

model. These metrics are defined as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$  \hspace{1cm} (1)

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$  \hspace{1cm} (2)

$$\text{Specificity} = \frac{TN}{TN + FP}$$  \hspace{1cm} (3)

$$F1 = \frac{2TP}{2TP + FN + FP}$$  \hspace{1cm} (4)

where $TP$ is the true positive assessment, $TN$ is the true negative assessment, $FP$ is the false negative assessment and $FN$ is the false positive assessment. Sensitivity and specificity give a sense of the propensity of the model for the prediction of $TP$ and $TN$, respectively. F1 score is measure of a test’s accuracy and is preferable when the dataset has imbalanced class distribution, such as in our case.

These metrics were obtained with a four-fold cross-validation on an aggregated set of patient data from the Daphnet dataset. Table I shows the metrics of the developed model, before and after the quantization and hardware deployment. Fig. 2 shows the receiver operating characteristic (ROC) curves of the model before and after hardware implementation. Performance metrics after hardware deployment are comparable to the Python implementation, indicating that the model translated successfully into the MCU. The development of the DL model in this work was limited by the hardware resources available in the MCU. As a result, we exclusively used native Keras layers. However, even with hardware constraints, our model was able to achieve a performance that is comparable to the state-of-the-art works. If resources permit, long short-term memory (LSTM) models could also be effective, as they take advantage of the time-series nature of the data [21]. In addition, we could use data augmentation techniques to further improve model performance as well as generalizability.

The nRF52840 MCU operates with a constant 3.3 V power supply. The measured current consumption during the inference of the DL model was 21 mA and the inference time was 0.21 s. Since the inference frequency of the model is 1 Hz, the active time of the DL engine is 21 %, resulting in a average current of 4.4 mA. The current consumption of the accelerometer is less than 0.1 mA. The total sensor node device consumes less than 5 mA current, including BLE wireless communication. The wireless charging function of the device has also been fully validated on the bench. The integrated coil can provide a charging current of up to 150 mA with a coupling distance of 1 to 3 cm.

IV. CONCLUSION

This paper presents the design of a wireless sensor network for detecting and alerting FoG using edge DL. A novel button pin type wireless sensor node is developed. A light weighted DL model was developed and deployed in distributed sensor nodes. The model was validated using a public dataset and achieved a performance comparable to that of state-of-the-art work without hardware implementation.

In future work, we plan to use the developed wireless sensor nodes to collect data from healthy subjects and patients with PD, and further optimize the DL model based on the data we collected. In addition, the developed wireless sensors with edge DL can be used in other pre-clinical and clinical experiments, and hold promise in improving the quality of life.
of a large patient populations with a variety of neurological disorders.

REFERENCES

[1] W. H. Organization, “Launch of who’s parkinson disease technical brief,” 2019.
[2] T. Bikias, D. Iakovakis, S. Hadjidimitriou, V. Charisis, and L. J. Hadjileontiadis, “Deepfog: an imu-based detection of freezing of gait episodes in parkinson’s disease patients via deep learning,” Frontiers in Robotics and AI, p. 117, 2021.
[3] M. J. Armstrong and M. S. Okun, “Diagnosis and treatment of parkinson disease: a review,” Jama, vol. 323, no. 6, pp. 548–560, 2020.
[4] S. Bratsos, D. Karponis, and S. N. Saleh, “Efficacy and safety of deep brain stimulation in the treatment of parkinson’s disease: a systematic review and meta-analysis of randomized controlled trials,” Cureus, vol. 10, no. 10, 2018.
[5] A. P. S. Pereira, V. Marinho, D. Gupta, F. Magalhães, C. Ayres, and S. Teixeira, “Music therapy and dance as gait rehabilitation in patients with parkinson disease: a review of evidence,” Journal of geriatric psychiatry and neurology, vol. 32, no. 1, pp. 49–56, 2019.
[6] A. Tăuţan, A. Andrei, and B. Ionescu, “Freezing of gait detection for parkinson’s disease patients using accelerometer data: Case study.” International Conference on e-Health and Bioengineering (EHB) year =2020.
[7] R. San-Segundo, H. Navarro-Hellín, R. Torres-Sánchez, J. Hodgins, and F. De la Torre, “Increasing robustness in the detection of freezing of gait in parkinson’s disease,” Electronics, vol. 8, no. 2, p. 119, 2019.
[8] S. Mekruksavanich and A. Jitpattanakul, “Detection of freezing of gait in parkinson’s disease by squeeze-and-excitation convolutional neural network with wearable sensors.” 2021.
[9] X. Liu and A. G. Richardson, “Edge deep learning for neural implants: a case study of seizure detection and prediction,” Journal of Neural Engineering, vol. 18, no. 4, p. 046034, 2021.
[10] X. Liu, A. G. Richardson, and J. Van der Spiegel, “An energy-efficient compressed sensing-based encryption scheme for wireless neural recording,” IEEE Journal on Emerging and Selected Topics in Circuits and Systems, vol. 11, no. 2, pp. 405–414, 2021.
[11] X. Liu, M. Zhang, A. G. Richardson, T. H. Lucas, and J. Van der Spiegel, “A 12-channel bidirectional neural interface chip with integrated channel-level feature extraction and pid controller for closed-loop operation,” in 2015 IEEE Biomedical Circuits and Systems Conference (BioCAS). IEEE, 2015, pp. 1–4.
[12] X. Liu, H. Zhu, T. Qiu, S. Y. Sritharan, D. Ge, S. Yang, M. Zhang, A. G. Richardson, T. H. Lucas, N. Engheta et al., “A fully integrated sensor-brain-machine interface system for restoring somatosensation,” IEEE Sensors Journal, vol. 21, no. 4, pp. 4764–4775, 2020.
[13] S. T. Moore et al., “Autonomous identification of freezing of gait in parkinson’s disease from lower-body segmental accelerometry,” Journal of NeuroEngineering and Rehabilitation, vol. 10, p. 19, 2013.
[14] “Classification on imbalanced data.” Tensorflow, 2022.
[15] X. Liu, H. Zhu, M. Zhang, X. Wu, A. G. Richardson, S. Y. Sritharan, D. Ge, Y. Shu, T. H. Lucas, and J. Van der Spiegel, “A fully integrated wireless sensor-brain interface system to restore finger sensation,” in 2017 IEEE International Symposium on Circuits and Systems (ISCAS). IEEE, 2017, pp. 1–4.
[16] X. Liu, M. Zhang, X. Wu, A. G. Richardson, S. T. Maldonado, S. DeLuccia, Y. Ghendt, T. H. Lucas, and J. Van der Spiegel, “A wireless Neuroposthetic for augmenting perception through modulated electrical stimulation of somatosensory cortex,” in 2017 IEEE International Symposium on Circuits and Systems (ISCAS). IEEE, 2017, pp. 1–4.
[17] L. Mesin et al., “A multi-modal analysis of the freezing of gait phenomenon in parkinson’s disease,” Sensors, vol. 22(7), p. 2613, 2022.
[18] L. Sigcha, N. Costa, I. Pavón, S. Costa, P. Arezes, J. M. López, and G. De Arcas, “Deep learning approaches for detecting freezing of gait in parkinson’s disease patients through on-body acceleration sensors,” Sensors, vol. 20, no. 7, p. 1895, 2020.