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Classification of the Gait Pattern in Polymyalgia Rheumatica Patients Using Recurrent Neural Networks

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***Abstract*—The early detection of movement disorders is essential for clinicians in many diseases, and it forms an integral part of effective treatment planning for patients. Polymyalgia rheumatica (PMR) is an autoimmune musculoskeletal disease that affects muscles around the pelvic girdle and shoulder blade. It is currently unknown how the strained hip muscles around the pelvic girdle create mobility limitations in patients. This study presents an algorithm for the classification of the hip muscle activation pattern in clinical gait analysis using recurrent neural networks (RNNs). RNNs was chosen because of its ability to capture temporal dependencies and process sequential electromyography (EMG) data in gait classification. A clinical gait assessment was conducted at KATH hospital which collected 250 gait segments from 18 PMR patients and 7 healthy control subjects. EMG signals were recorded from the vastus lateralis (VL), rectus femoris (RF), biceps femoris (BF), and semitendinosus (SE). Different optimizers were used in the RNN model to classify the hip muscle activation of the two groups to discriminate the gait pattern. Four optimizers (Adamax, Adagrad, SGD, and RMSprop) were used to evaluate the best optimizer for the RNN model. The accuracy results recorded from a cross-validation were, Adamax = 89%, Adagrad = 83%, SGD = 85%, and RMSprop = 78%. Adamax was the best performing optimizer while RMSprop was the least performing in the gait classification. An average accuracy of 84% from the four optimizers was sufficient to distinguish the gait pattern of the two groups. The findings of this study are useful in discriminating gait patterns based on hip muscle activation. This will provide essential information for the early detection of gait impairments by clinicians to make more informed and timely decisions.**

Keywords*— *Gait, classification, pattern, optimizer, muscle.

I. INTRODUCTION

Movement disorders often occur in the elderly, people with physical injuries, and with musculoskeletal diseases. Human movement is largely controlled by the musculoskeletal and nervous systems. Muscular disorders may limit mobility in the lower extremity joints of the hips, knees, and ankles. Polymyalgia rheumatica (PMR) is a common autoimmune muscular disease, which is prevalent in older people, usually over the age of 50 years. [1] This disorder is usually characterized by muscle stiffness around the shoulder blade and pelvic girdle. Furthermore, the disease is associated with muscle pain and weakness that may impair the functioning of muscles. Electromyography (EMG) sensors have been introduced to extract muscle activation information for diagnostic purposes. EMG sensors measure muscle electrical activation because of biological processes during muscle contraction [2]. EMG sensors can be invasive or non-invasive used in recording the muscle activities of the motor unit and provide information about the muscle. The signals captured from these sensors are used for motion detection. The recognition of human motion based on EMG signals has widely been accepted by researchers as a promising technique for rehabilitation monitoring and prosthetic systems. [3] [4] EMG pattern recognition can be examined in online or offline mode where offline mode aims to achieve high accuracy. [5] There has been a surge in gait analysis with EMG data that has proven to be useful for clinicians. Machine learning models have been used in the past for gait analysis with EMG data to determine gait abnormality. [6] [7] These studies have reported the use of traditional machine learning models such as support vector machine (SVM), k-nearest neighbors (KNN), decision tree (DT), and random forest (RF). However, traditional machine learning models had some limitations in their performance for different classification problems. Deep learning (DL) models have been employed in recent times which show great potential in analyzing EMG data [8] and they address some challenges that exist with traditional machine learning models. Deep neural networks (DNNs) were also developed based on artificial neural networks (ANNs) which are mostly used as classifiers after manual feature extraction. [9] Due to the availability of large datasets, deep learning has proven to be even more effective because it extracts high-level features and potentially learns hierarchical representations from low-level input samples. [10] Although surface electromyography (sEMG) signals are time-series and thus exhibit time dependence, deep learning techniques have proven to be a powerful tool for analyzing this type of data. Furthermore, deep learning provides the advantage of stability and reduces ambient noise-related errors, especially for EMG classification in real-time applications. [11] The processing of surface EMG signals with deep neural network (DNN) architecture has led to significant improvements in classification problems. DNN architecture has been used previously for the recognition of upper extremity gestures by converting sEMG signals into images. [12] [13] One of the most used deep learning models is the convolutional neural network (CNN). However, with CNN the target learning features are not effective in representing temporal properties of surface EMG data. Therefore, recurrent neural networks (RNNs) based on Long Short-Term Memory (LSTM) have been proposed in recent works for sEMG classification. [14][15] RNNs use their memory to process sequences of variable length making it a beneficial competitor to NN and CNN.

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Nasri et al [16] presented the classification of EMG data for six hand gestures with recurrent neural networks. An accuracy of 77.85% was achieved in this study. To improve the accuracy of this classification, Koch et al [17] introduced a new loss function for the output of the RNN model where the prediction had more weight with a 10% improvement in true prediction accuracy. Reza et al [18] presented a real-time EMG classification via recurrent neural networks. EMG signals were extracted from hybrid time-frequency domain in a discrete wavelet transform. The authors introduced two sets of neural network-based architectures to minimize the prediction delay time and improve the classification accuracy. The results obtained from the proposal architectures outperformed other methods with a classification accuracy of 96% in 600 msec. Marco et al [19] presented a powerful approach for the detection of the muscle activation patterns of surface EMG signals in a gait analysis based on LSTM-RNNs. Results show that LSTM-MAD outperforms other approaches used with higher value of F1-score > 0.91 and Jaccard > 0.85 in the study. The proposed model was suitable for the discrimination of muscle activity for the gait analysis, rehabilitation, and prosthetic purposes. In [20] an LSTM model was used for the classification of the pathological and healthy gait patterns based on the sensory and goniometer dataset. The authors applied two different training optimizers which were adaptive moment estimation (ADAM) and Stochastic Gradient Descent (SGD) to train the LSTM model. The results from the two optimizers were compared for their performance. The ADAM optimizer achieved an overall accuracy of 91.72% which surpassed the 79.18% achieved with the SGD optimizer.

Inspired by previous work using RNNs, this paper adopts a similar approach with different optimizers for clinical gait classification. The main research question is to find the best optimizer that uses RNNs to identify gait patterns. Currently, it is not known if the strained hip muscles around the pelvic girdle affect the movement pattern of PMR patients. The motivation for this study is to use clinically available EMG data to determine recurrent neural network-induced gait disturbances, which are of great importance to clinicians. RNNs was chosen because of its ability to capture temporal dependencies and process EMG data for gait classification. RNNs are well suited for EMG classification because they can successively model the time dependence of EMG signals. Furthermore, RNNs can process variable-length input sequences and produce variable-length output sequences, therefore making it more suitable for EMG classification problems, where the length of the input signal may vary with the duration of muscle activity. In this paper, we presented a clinical gait classification of PMR patients versus healthy control subjects using RNNs with different optimizers. The main contributions of this paper are,

- Classification of strained hip muscles activation of PMR patients using RNNs with different optimizers and concluding on the best optimizer.
- Performance assessment in discriminating the gait pattern between PMR patients and healthy control subjects based on the RNNs model.

II. MATERIALS AND METHODS

A. *Datasets Collections*

The dataset used in this study was obtained from Komfo Anokye Teaching Hospital (KATH), where a clinical gait assessment was conducted from August to September 2022. The dataset included EMG data obtained from 18 patients with Polymyalgia rheumatica and 7 healthy control subjects. The patients were made up of 12 females and 6 males while the healthy control subjects were 5 females and 2 males. The age range for the participants was between 54 to 63 years. Ethical approval for the study was given by Brunel University which complies with the Helsinki declaration. Trigno Avanti from Delsys, a non-invasive sensor was used, to record the muscle signals. The muscles recorded were, vastus lateralis (VL), rectus femoris (RF), biceps femoris (BF), and semitendinosus (SE). Figure 1 shows the hip muscles recorded for the classification. These were the strained hip muscles around the pelvic girdle area which are mostly affected by the disease. The hair on the skin of participants was shaved and cleaned to give the Trigno Avanti sensor good conductive and accurate readings. The participants were asked to conduct 10 separate gait activity at their normal speed in a straight pathway. In total 250 gait segments were recorded where each participant conducted 10 gait trials. The EMG signals from patients were indexed as 1 while control subjects were indexed as 0 for the classification.

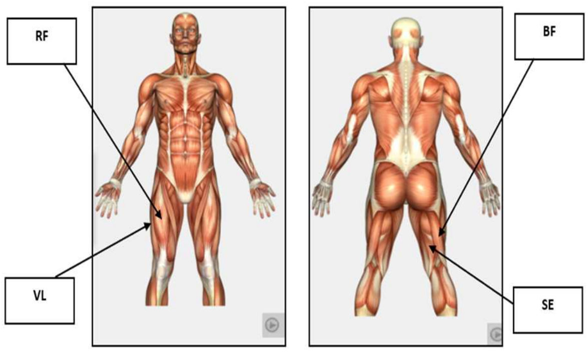

Fig. 1. Hip Muscles recorded.

B. *EMG Processing*

The raw EMG signals recorded from the participants were pre-processed for the classification. The signals were processed by using a high pass FIR filter with a linear phase and a cut of frequency between 20 Hz to 450 Hz. This frequency range gives the most effective function of muscle activities. [21] Figures 2 and 3 show the raw EMG and the enveloped signal respectively used for the analysis.

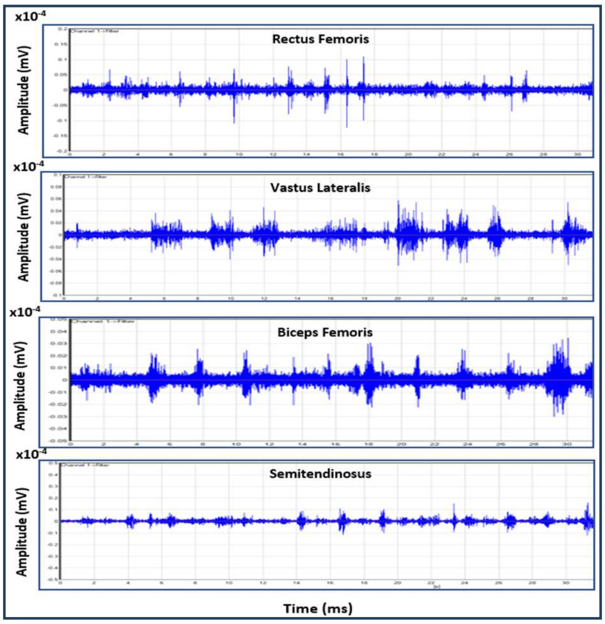

Fig. 2. The raw EMG signals recorded from the hip muscles of participants in the gait cycle.

C. EMG Features Extraction

In the time and frequency domain, extraction functions were applied directly in the window of the raw EMG signals recorded from the muscles. The are many features extracted from EMG data that were used in previous literature. In this study, we used 10 statistical extraction features in the time and frequency domain. The features extracted were, Root Mean Square (RMS), Mean Absolute Value (MAV), Integrated EMG (IEMG), Simple Square Integral (SSI), Variance of EMG (VAR), Modified Mean Absolute Value (MMAV), Mean Frequency (MNF), Median Frequency (MDF), Mean Power (MNP) and Total Power (TP) which are similar features used by Sikidar et al [22].

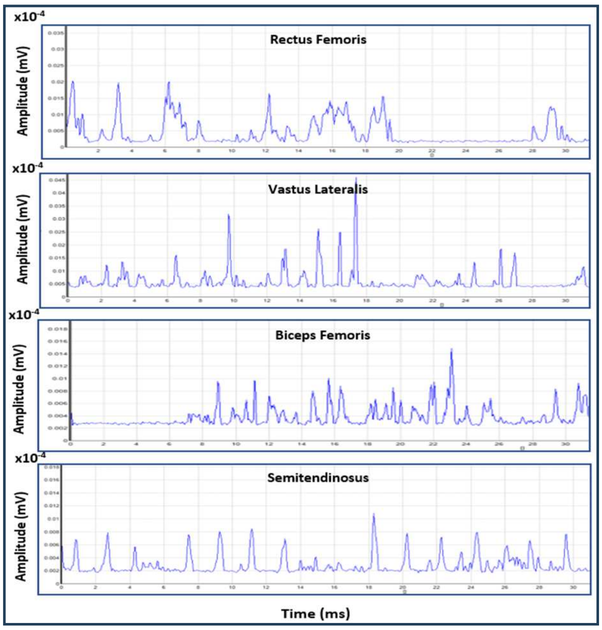

Fig. 3. The enveloped EMG signals in the gait cycle.

A sliding windowing technique was used to process and analyse the EMG signals. Sliding windowing divides the continuous signal into windows of fixed lengths, with some overlap between successive windows. This approach allows for both short-term and long-term muscle activity to be captured, providing a more comprehensive representation of signals.[23] Additionally, this approach enables the acquisition of temporal information and dependencies of the EMG signals recorded. To obtain successive subsets of the EMG data we combined the window length ranges between 10ms ~150ms.

III. PROPOSED MODEL

The proposed model workflow in Figure 4 shows the classification in various phases. These phases were signal processing, feature extraction, and deep learning training of the RNNs model with different optimizers. The RNNs model was then evaluated for classification accuracy.

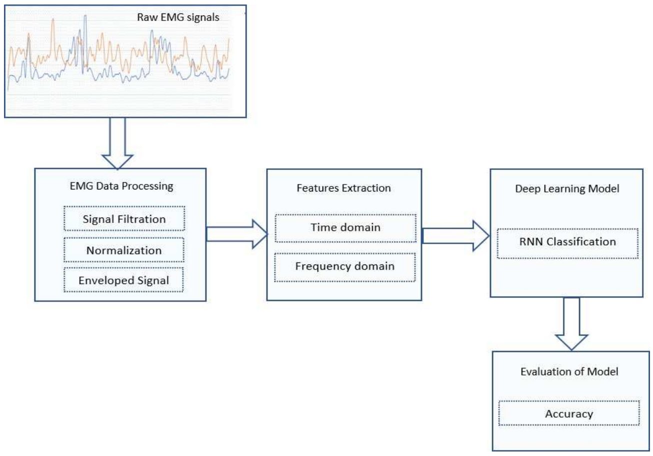

Fig. 4. Proposed model workflow.

A. RNN Architecture

The RNN architecture consists of three layers which are the input, hidden, and output layers [24]. The input layer takes the processed EMG signal as a feature vector and then returns an output. The feature vector represents a set of numerical features extracted from the EMG signal and used as input to the RNN model for classification. To classify these EMG signals using an RNN model, it is important to transform the EMG data into a format that the model can understand and learn. This transformation extracts meaningful features from the EMG signal to represent the underlying patterns. In a case where the neural network is deep, there are multiple hidden layers. From Figure 5, it is observed that the RNN architecture use a periodic hidden state. In this way, data can be passed on from one timestep to another, where each of these steps depends on the previous one. The RNN architecture description,

- The input layer at time t-1 is plugged into RNN hidden layer. The RNN cell then produces an output Y'_{t-1} from a memory state input h_{t-1}. The memory state is a result of input X_{t-1} and a previous value of the memory state h_{t-2} in the RNN cell. In the initial timestep, it assumed that h_0 is a zero vector.

- The resultant input X_{t-1} produces an output Y'_{t-1} the RNN architecture moves several time steps forward until a final step is reached for prediction.

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- In the hidden layer the data is passed from one timestep which is a memory h_{t-1} to the next memory h_t thus the next memory depends on the previous memory value. For a given matrix **U** connects the input layer to the hidden layer while **V** which connects the hidden layer to the output layer. **W** connects the memory layers together. In the process of computing the variables is given by equation (1).

$$h_t = tanh(UX_t + Wh_{t-1}) \qquad (1)$$

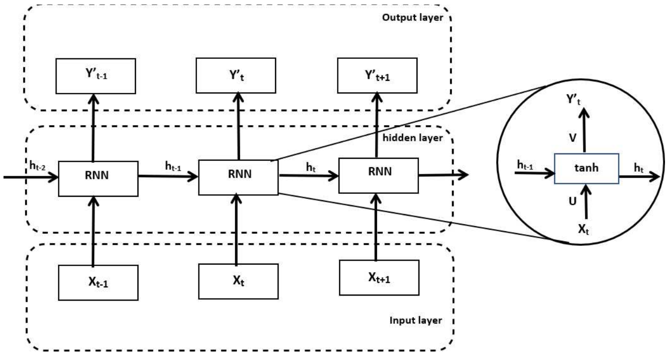

Fig. 5. RNN Architecture [24]

B. RNN Training

In training the RNN model, we used 80% of the dataset for training and 20% for testing. A cross-validation was used in evaluating the performance of each optimizer in the classification. In the training, patients were indexed as 1 while healthy control subjects were indexed as 0 for the two classes. To test the effectiveness of the RNN model for gait classification, we used four different optimizers namely Stochastic gradient descent (SDG), Adaptive moment estimation Max (Adamax), Adagrad, and RMSprop.

- Stochastic Gradient Descent (SGD): It is one of the simplest and most widely used optimization algorithms. SGD updates the model parameters at each training iteration by computing the gradient of the loss function with respect to the parameters. It performs parameter updates based on a small set of randomly selected training samples to increase computational efficiency.
- AdaGrad: This optimization algorithm adjusts the learning rate of each parameter based on the past gradient sum of squares. Rare features get major updates and common features get minor updates. AdaGrad is well suited for processing sparse data and is commonly used in natural language processing.
- RMSprop: It is an optimization algorithm that adjusts the learning rate of each parameter based on the average of the last quadratic gradients. This reduces learning rate variabilities or fluctuations and allows rapid convergence, especially in low-gradient scenarios.
- Adamax: It is a variant of Adam that replaces the second moment of the gradient with the infinity norm. It is more robust for heavy gradients and is suitable for models with sparse gradients.

These optimizers were evaluated for their performance in the classification problem. The metrics used for the performance evaluation were accuracy, precision, recall, and F1-score.

Accuracy: It is one of the simplest ways of evaluating a classifier performance. It describes the ratio of the number of correct predictions over the total data instances in the class.

$$\textbf{Accuracy} = \frac{T_p+T_n}{T_p+T_n+F_p+F_n} \qquad (2)$$

Precision: It defines the ratio of the true positive outcomes divided by the total prediction of true positives and false positives in a specific class.

$$\textbf{Precision} = \frac{T_p}{T_p+F_p} \qquad (3)$$

Recall: It is defined as the ratio of accurately positive class observation that is identified in a model.

$$\textbf{Recall} = \frac{T_p}{T_p+F_n} \qquad (4)$$

F1-score: It is defined as the overall measure of the precision and recall. It is the weighted harmonic average of accuracy and sensitivity.

$$\textbf{F1-score} = \mathbf{2} \times \frac{\textbf{Precision}*\textbf{Recall}}{\textbf{Precision}+\textbf{Recall}} \qquad (5)$$

where T_P = True Positive, F_P = False Positive, T_N = True Negative and F_N = False Negative.

TABLE I
OPTIMIZERS PERFORMANCE REPORT

Optimizer	**Adamax**			**Adagrad**			**SGD**			**RSMprop**		
Metrics	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
0	1.00	0.85	0.92	0.86	0.92	0.89	1.00	0.67	0.80	0.91	0.77	0.83
1	0.71	1.00	0.83	0.75	0.60	0.67	0.78	1.00	0.88	0.57	0.80	0.67
accuracy	—	—	0.89	—	—	0.83	—	—	0.85	—	—	0.78
macro avg.	0.86	0.92		0.80	0.76		0.89	0.83		0.74	0.78	
			0.88			0.78			0.84			0.75
weighted avg.	0.92	0.89	0.89	0.83	0.83	0.83	0.88	0.85	0.84	0.82	0.78	0.79

IV. Results and Discussion

In this section, the classification results of RNN model with different optimizers used for our EMG data are presented. Table I shows the classification performance for accuracy, precision, recall and F1-score. From the classification report shown in Table I, we recorded the performance of each optimizer in classifying the hip muscle activation pattern in a clinical gait assessment. The F1-score for the model used was processed based on the test data to take care of the imbalance class. The imbalance occurred because 180 gait segments were collected from patients and 70 gait segments from healthy controls. To test the prediction for the healthy and impaired gait patterns the optimization algorithms were compared. From Table I, Adamax had an accuracy of 0.89, Adagrad was 0.83, SDG was 0.85 and RSMprop was 0.78 for the

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classification. An average accuracy of 0.84 from the four optimizers was sufficient to distinguish the gait pattern of the two groups. Precision is important in deep learning classification as it focuses on the accuracy of positive predictions, especially in scenarios involving high costs associated with class imbalances. This was required to make informed decisions and accurately assess the performance of the optimizers in the RNN model. The macro average value in the classification report was used to determine the performance metrics across two classes. The macro average precision values recorded for the optimizers were,

- Adamax: The macro average value for precision recorded was 0.86 in the gait classification.
- Adagrad: For this optimizer, the precision macro average value was 0.80 for the classification.
- SGD: For this optimizer the macro average value recorded for precision was 0.89 in the classification.
- RMSprop: The macro average precision value recorded was 0.74 for this optimizer.

The graphs for the performance of the optimizers in the RNN model are shown in Figure 6. The optimizers were evaluated in discriminating the gait patterns between the two groups. From Figure 6, we observed that Adamax was the best optimizer with 0.89 accuracy while the accuracy of RSMprop was 0.78 which was the least performing. SGD and Adagrad were good with classification accuracies of 0.85 and 0.83 respectively. Adamax recorded the highest accuracy in discriminating between healthy and impaired gait patterns. In terms of sensitivity Adamax and SDG performed better in correctly predicting impaired gait patterns compared to Adagrad and RMSprop. It was noted that Adagrad was the least sensitive optimizer in identifying impaired gait patterns. For the F1-score, the SGD optimizer outperformed Adamax with 0.88 while Adamax recorded 0.83 in identifying impaired gait. Adagrad and RSMprop performed poorly for F1-score in identifying impaired gait patterns. Figure 7 shows the ROC curve for each of the optimizers used in the classification. ROC curves are essential tools in deep learning classification for evaluating performance, comparing models, and handling imbalanced datasets. From Figure 7, it is observed that adamax was the best while RMSprop was the least performing.

In [20] the authors focused on using sensory signals to clinically assess human gait and diagnose neurological disease. They used a deep learning approach, specifically LSTM-RNN to classify healthy and unhealthy gait patterns using a sensory dataset. The performance of two optimization algorithms, Stochastic Gradient Descent (SGD) and ADAM, were compared in the classification process. The results indicated that the test classification accuracies of SGD and ADAM were 79.18% and 91.72%, respectively.

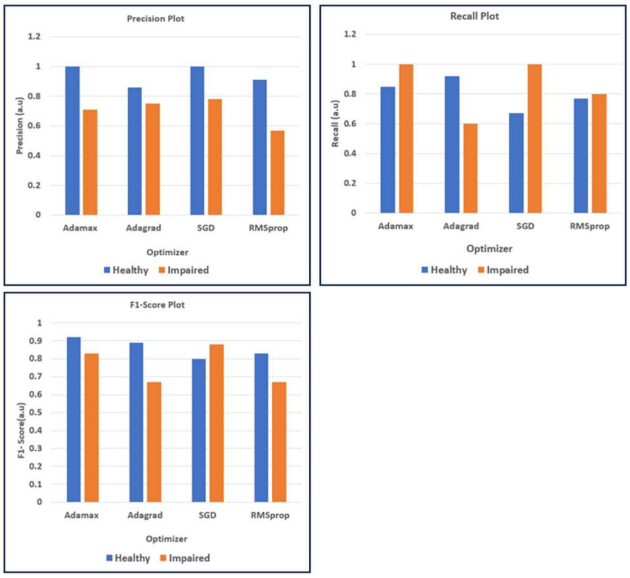

Fig. 6. Graphs of the optimizers performance

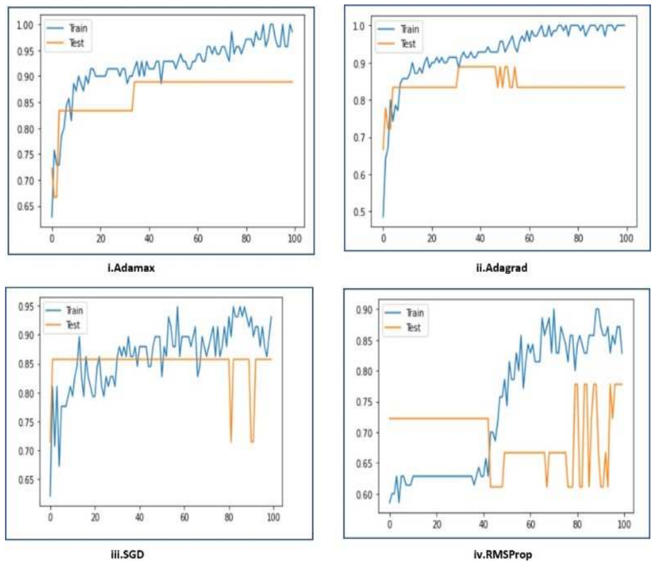

Fig. 7. Accuracy plot for the optimizers

Comparing the previous study conducted by Narayan [20] to our study, we used RNNs with four different optimizers to determine the best algorithm for classifying the gait patterns between PMR patients and healthy controls. Our results showed that Adamax had the highest accuracy at 89%, and SGD at 85%. The results showed that the Adamax optimizer outperformed the SGD in classifying healthy and unhealthy walking patterns when applying RNNs**.** The performance of the SGD optimizer in the RNNs was better compared to the LSTM-model in previous work. In addition, we used four optimizers to evaluate the performance of the RNNs which address one shortcoming of Narayan's work [20] that used only two optimization algorithms. Furthermore, a comparison of this study with a recent work by Kumar et al [25] on gait disturbance based on EMG data. We used RNNs with different optimizers, but in previous work, the author investigated machine and deep learning techniques for classifying gait patterns. Whereas in the previous study, RNNs achieved an accuracy of 91.3%, our results indicated that the best optimizer recorded 89% in identifying gait patterns between patients and controls. The accuracy achieved in this work is significant compared to the marginal difference in other previous works. The limitation of this work involves the imbalance of data between patients and healthy controls. Even though the dataset was imbalanced, we used appropriate metrics which considered both classes in terms of precision, recall, F1-score, and ROC curve. Another measure we used to mitigate this limitation was to increase the sample of the minority class (control subjects) by using the synthetic minority oversampling technique (SMOTE). With this technique, we increased the sample size of control subjects and reduced the sample size of patients by randomly removing instances in training with the RNNs model. The results obtained from this analysis are promising and would be essential in the detection of gait disorders. This will provide useful information for designing rehabilitation protocols.

V. Conclusions & Further Work

The early detection of gait impairments plays an integral role in designing appropriate treatment plans for patients with musculoskeletal disease. In this study, we presented the RNNs model using different optimizers to discriminate the gait pattern of polymyalgia rheumatica patients and healthy control subjects. The results indicated that Adamax was the best-performing optimizer with an accuracy of 89% while the least-performing was RMSprop at 78%. Adagrad and SGD performed fairly well with an accuracy of 83% and 85% respectively. Overall, the performance of the optimizers was significant to distinguish the gait pattern of the two groups. This information would be useful to clinicians to assist in the early detection of gait disorders and adopt corrective measures. In the future, this model may be extended for the classification of muscles of the lower extremities for other musculoskeletal diseases. We would also investigate the possibility of using Transformers for EMG classification with a balanced large dataset.

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References

[1] U. P. Manouchehr Saljoughian, "Polymyalgia rheumatica: A severe, self- limiting disease." Department of Pharmacy, June 2012.

[2] J. He, D. Zhang, N. Jiang, X. Sheng, D. Farina, and X. Zhu, "User adaptation in long-term, open-loop myoelectric training: implications for emg pattern recognition in prosthesis control," Journal of neural engineering, vol. 12, no. 4, p. 046005, 2015.

[3] R. C. de Freitas, G. R. Naik, M. J. S. Valenca, B. L. D. Bezerra, R. E. de Souza, and W. P. dos Santos, "Surface electromyography classification using extreme learning machines and echo state networks," Research on Biomedical Engineering, vol. 38, no. 2, pp. 477–498, 2022.

[4] J. O. Pinzon-Arenas, R. Jime´nez-Moreno, and A. Rubiano, "Percentage estimation of muscular activity of the forearm by means of emg signals based on the gesture recognized using cnn," Sensing and Bio-Sensing Research, vol. 29, p. 100353, 2020.

[5] S. Rouhani, T. Rahman, and V. Gogate, "Algorithms for the nearest assignment problem.," in IJCAI, pp. 5096–5102, 2018.

[6] C. Morbidoni, A. Cucchiarelli, V. Agostini, M. Knaflitz, S. Fioretti, and F. Di Nardo, "Machine-learning-based prediction of gait events from emg in cerebral palsy children," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 29, pp. 819–830, 2021.

[7] Y. Guo, R. Gravina, X. Gu, G. Fortino, and G.-Z. Yang, "Emg-based abnormal gait detection and recognition," in 2020 IEEE International Conference on Human-Machine Systems (ICHMS), pp. 1–6, IEEE, 2020.

[8] M. Atzori, M. Cognolato, and H. Muller, "Deep learning with convolutional neural networks applied to electromyography data: A resource for the classification of movements for prosthetic hands," Frontiers in neurorobotics, vol. 10, p. 9, 2016.

[9] K. H. Walse, R. V. Dharaskar, and V. M. Thakare, "Pca based optimal ANN classifiers for human activity recognition using mobile sensors data," in Proceedings of First International Conference on Information and Communication Technology for Intelligent Systems: Volume 1, pp. 429– 436, Springer, 2016.

[10] Q. Zhang, L. T. Yang, Z. Chen, and P. Li, "A survey on deep learning for big data," Information Fusion, vol. 42, pp. 146–157, 2018.

[11] D. Xiong, D. Zhang, X. Zhao, and Y. Zhao, "Deep learning for emg-based human-machine interaction: A review," IEEE/CAA Journal of Automatica Sinica, vol. 8, no. 3, pp. 512–533, 2021.

[12] W. Geng, Y. Du, W. Jin, W. Wei, Y. Hu, and J. Li, "Gesture recognition by instantaneous surface emg images," Scientific reports, vol. 6, no. 1, p. 36571, 2016.

[13] W. Wei, Y. Wong, Y. Du, Y. Hu, M. Kankanhalli, and W. Geng, "A multi- stream convolutional neural network for semg-based gesture recognition in muscle-computer interface," Pattern Recognition Letters, vol. 119, pp. 131–138, 2019.

[14] F. Quivira, T. Koike-Akino, Y. Wang, and D. Erdogmus, "Translating semg signals to continuous hand poses using recurrent neural networks," in 2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI), pp. 166–169, IEEE, 2018.

[15] T. Sun, Q. Hu, P. Gulati, and S. F. Atashzar, "Temporal dilation of deep lstm for agile decoding of semg: Application in prediction of upper- limb motor intention in neurorobotics," IEEE Robotics and Automation Letters, vol. 6, no. 4, pp. 6212–6219, 2021.

[16] N. Nasri, S. Orts-Escolano, F. Gomez-Donoso, and M. Cazorla, "Inferring static hand poses from a low-cost non-intrusive semg sensor," Sensors, vol. 19, no. 2, p. 371, 2019.

[17] P. Koch, H. Phan, M. Maass, F. Katzberg, R. Mazur, and A. Mertins, "Recurrent neural networks with weighting loss for early prediction of hand movements," in 2018 26th European Signal Processing Conference (EUSIPCO), pp. 1152–1156, IEEE, 2018.

[18] R. B. Azhiri, M. Esmaeili, and M. Nourani, "Real-time emg signal classification via recurrent neural networks," in 2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), pp. 2628–2635, IEEE, 2021.

[19] M. Ghislieri, G. L. Cerone, M. Knaflitz, and V. Agostini, "Long short-term memory (lstm) recurrent neural network for muscle activity detection," Journal of Neuro Engineering and Rehabilitation, vol. 18, pp. 1–15, 2021.

[20] J. Narayan, S. Johri, and S. K. Dwivedy, "LSTM neural network-based classification of sensory signals for healthy and unhealthy gait assessment," in Predictive Modeling in Biomedical Data Mining and Analysis, pp. 207–223, Elsevier, 2022.

[21] S. Heywood, Y. H. Pua, J. McClelland, P. Geigle, A. Rahmann, K. Bower, and R. Clark, "Low-cost electromyography–validation against a commercial system using both manual and automated activation timing thresholds," Journal of Electromyography and Kinesiology, vol. 42, pp. 74–80, 2018.

[22] Sikidar, Arnab, et al. "Classification of mild and severe adolescent idiopathic scoliosis (AIS) from healthy subjects via a supervised learning model based on electromyogram and ground reaction force data during gait." *Biocybernetics and Biomedical Engineering* 42.3 (2022): 870-887.

[23] Tanaka, Taichi, et al. "Sliding-Window Normalization to Improve the Performance of Machine-Learning for Real-Time Motion Prediction using Electromyography" Sensors 22. 13(2022): 5005

[24] S. Kostadinov, Recurrent Neural Networks with Python Quick Start Guide: Sequential learning and language modeling with TensorFlow. Packt Publishing Ltd, 2018.

[25] Kumar, Manoj, Dr Pratiksha Gautam, and Dr Vijay Bhaskar. "Effect of Machine Learning Techniques for Efficient Classification of EMG Patterns in Gait Disorders." *IJEER* 10.2 (2022): 117-121.