International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Machine Learning-Based Gait Analysis for Distinguishing Older and Younger Walking Patterns in Neurodegenerative Diseases

T.H. Lee[1], E.F. Shair*[2], A.R. Abdullah[3], K.A. Rahman[4], N. Nazmi[5]

Submitted:13/03/2024 **Revised**: 28/04/2024 **Accepted**: 05/05/2024

Abstract: Neurodegenerative diseases like Parkinson's Diseases, Alzheimer's Diseases, Multiple sclerosis and Huntington's disease can severe a person's walking style due to their impact on the brain and the nervous system. Gait analysis, which involves the study of a person's walking pattern and movement, plays a crucial role in the diagnosis and monitoring of these diseases. By examining changes in gait parameters such as stride length, walking speed, and balance, healthcare professionals can gather important information about the underlying neurological impairments and track disease progression. Gait analysis involves the measurement of various parameters, including the stride interval. Changes in the stride interval can indicate alterations in motor control and gait stability, allowing healthcare professionals to assess the severity of neurodegenerative diseases and monitor the effectiveness of treatment interventions. There is lack of research in studying the effect of Continuous Wavelet Transform (CWT) in stride intervals of the young people and old people. It is not clear whether the CWT is a feasible feature extraction method to classify the stride interval of old people and young people. The objective of this paper is to apply Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Random Forest algorithms to the maximum Root Mean Square (RMS) value of CWT to determine the most effective machine learning techniques for distinguishing between older and younger walking patterns. KNN stands out the best in performance by scoring 93% for all weighted average (precision), weighted average (recall) and weighted average (f1-score). SVM comes out second in performance by scoring 86% for weighted average (precision), 83% for weighted average (recall) and 84% for weighted average (f1-score) with the shortest processing time, 3.2302s. From the boxplot of the Maximum CWT RMS of the young and the old people, it can be seen that the stride interval of the young people is higher and more diverse than the old people.

Keywords: *Gait analysis, neurodegenerative diseases, continuous wavelet transform, machine learning, walking patterns*

1. Introduction

Stride intervals, integral to understanding human locomotion, describe the temporal aspect between two successive footfalls of the same foot, essentially marking the cycle from one step to the next [1], [2]. Within the realm of sports science and rehabilitation, monitoring and analyzing stride intervals can reveal patterns or deviations that may indicate fatigue, asymmetry, or potential for injury [3], [4]. Furthermore, the concept extends beyond athletic performance, offering researchers a window into the neuromuscular health of individuals, as changes in stride intervals can sometimes be early indicators of conditions affecting motor control, such as Parkinson's disease [5]–[8]. Machine learning is a rapidly growing field that involves the development of algorithms and models that can learn and make predictions from data without being explicitly programmed [9]. Traditionally, stride interval analysis was carried out by human experts, which was time-consuming and prone to human error. However, with the advent of machine learning, this process has been greatly streamlined and improved [10], [11]. One of the machine learning techniques used in analyzing stride intervals is the Support Vector Machine (SVM). SVM is a supervised learning algorithm that is commonly used for classification and regression tasks [12], [13]. SVM works by finding the optimal hyperplane that can separate data points of different classes in a high-dimensional space [14], [15]. Other than SVM, other machine learning techniques such as decision trees, random forests, and k-nearest neighbors have also been applied to the analysis of stride interval [16]. These methods work by identifying patterns and relationships in the data and using them to make predictions about new data points [17]. Current research does not clearly show the difference between young gait and old gait in terms of characteristic of the continuous wavelet transform on the stride interval. It is widely believed that the long – range correlations in old gait are reduced while the is higher stability in the young gait.

[1] Rehabilitation and Assistive Technology Research Group, Faculty of Electrical Technology and Engineering, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia
ORCID ID : 0009-0002-4212-5955
[2] Rehabilitation and Assistive Technology Research Group, Faculty of Electrical Technology and Engineering, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia
ORCID ID : 0000-0002-0360-063X
[3] Rehabilitation and Assistive Technology Research Group, Faculty of Electrical Technology and Engineering, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia
ORCID ID : 0000-0002-8381-8662
[4] Rehabilitation and Assistive Technology Research Group, Faculty of Electrical Technology and Engineering, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia
ORCID ID : 0009-0006-8285-8829
[5] Malaysia-Japan International Institute of Technology, Universiti Teknologi Malaysia, Jalan Sultan Yahya Petra, 54100 Kuala Lumpur, Malaysia
ORCID ID : 0000-0002-4757-9596
** Corresponding Author Email: ezreen@utem.edu.my*

1.1. Past Research

Gait of the old people and young people are becoming a research of great interest to many researchers. It was reported that the spatial parameters of the gait analysis of turning with amplitudes of 90°, 180° and 360° were higher for elderly because more time and steps are required to turn. It was suggested that turning can enhance the sensitivity to detect the biomechanical differences between young and old people [18]. The walking speed, stride length, step width and stride time were becoming the key parameters to analyze the performance of age simulation suit to simulate the aging process to be experimented in young adults [19]. The computation of DFA showed that stride interval was more random in elders and subjects with Parkinson's disease [20]. CWT could be used on the time spectrum to analyze the gait pattern coupled with the use of Kalman filter [21]. Another research proposed the feeding of optimum statistical and entropy features that were extracted from the decomposed wavelet coefficients of the time series data [22]. CWT could be used on the analysis of the surface – electromyography (sEMG) signal to study the muscle activity of Parkinson's subjects [23]. The accuracy of 96.75% was achieved in the classification of 3 different neurodegenerative diseases by combining a novel neural network architecture and CWT [24]. One research utilised CWT to extract the main curve points of the ankle joints like peaks and valleys to analyze the performance of karate skills [25]. The classification of human activity could achieve accuracy of 97.48% and F1 score of 97.52% by performing Convoluted Neural Network (CNN) on the scalogram derived from CWT [26]. According to one research, CWT could be used on the acceleration and angular velocity of medial – lateral (ML), vertical (VT) and anteriorposterior (AP) which were collected from inertial measurement unit (IMU) sensors on the six lower limb locations to calculate the power spectral density. The result showed there were significant differences of the signals from male and female [27]. CWT was very useful in transforming the signal into time – frequency features which could then be extracted by CNN which helped to achieve the accuracy of 99.26% for human activity recognition [28]. Besides, 1D – CNN model could be trained on the signals that were decomposed by CWT for gait abnormality detection [29].

2. Materials and Methods

Fig. 1 shows the overall flow chart of the experiment. The research starts with data collection from Physionet. The CWT instantaneous RMS of the data is collected, and the maximum values are derived. Then, the maximum values are then fed to the one-dimensional SVM, one-dimensional KNN and one-dimensional random forest. The accuracy, precision and F1 – score of the machine learning techniques are then computed to identify the best machine learning technique to be used in this research,

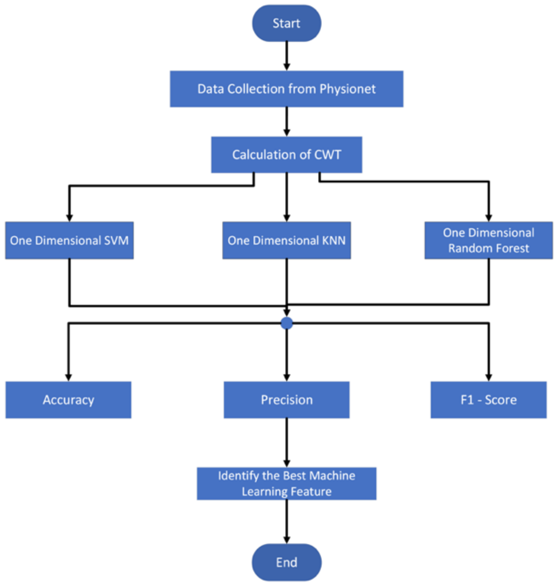

Fig. 1. The Overall Flow Chart of the Experiment

2.1. Data Acquisition and Feature Derivation

Data from the Gait in Aging and Disease Database on Physionet was used to gather stride interval information from five elderly individuals (average age of 74.6) and five young individuals (average age of 24.4) [30]. Both groups were directed to walk in a circular path for approximately 15 minutes. Feature extraction was conducted using CWT methods.

The CWT is a powerful tool for analyzing signals by decomposing them into a set of wavelets, which are localized in both time and frequency domains. The formula for the CWT of a signal f(t) with respect to a mother wavelet, ψ(t) is represented in Eq.(1) [31],[32].

$$fW(a,b) = \int f(t) \frac{1}{\sqrt{a}} \psi^* \left(\frac{t-b}{a}\right) dt \tag{1}$$

W(a,b) is the wavelet transform of the function f(t). ψ^* (t) is the complex conjugate of the wavelet function, ψ(t). a and b are the scale and translation parameters, respectively.

The choice of the mother wavelet is crucial, as it determines the time-frequency resolution and the ability to capture specific features of the signal. One commonly used mother wavelet is the Morlet wavelet, defined by its Fourier Transform as in Eq.(2) [33].

$$\hat{\psi}(\omega) = \pi^{-\frac{1}{4}} e^{-\frac{\omega}{2}} e^{i\omega_0 \omega} \tag{2}$$

$\hat{\psi}(\omega)$ is the Fourier Transform of the wavelet function, $\psi(t)$. ω is the frequency variable. ω_0 is a constant frequency offset. The $e^{-\frac{\omega}{2}}$ term is a Gaussian Function, which gives the wavelet its shape in the frequency domain. The $e^{i\omega_0\omega}$ term is a complex exponential that shifts the wavelet in the frequency domain. The mother wavelet used in this project is the Morlet wavelet.

2.2. Machine Learning

The classification of old and young gaits, using a mix of synthetic and original data in this paper, employs three different machine learning techniques, which are SVM, KNN and Random Forest.

The key idea behind SVMs is to find the optimal hyperplane that separates different classes of data points with the maximum margin [34]. One of the key advantages of SVMs is their ability to handle non-linear decision boundaries by using kernel functions [35]. Kernel functions map the input data into a higher-dimensional feature space, where a linear hyperplane can separate the classes effectively. The different types of kernel functions include polynomial kernel, Radial Basis Function (RBF) kernel, linear kernel and sigmoid kernel [36].

The formulation of the hyperplane of SVM can be expressed in Eq.(3), subject to constraints, $y_i = (w^T x_i + b) \geq 1 - \xi_i, \xi_i \geq 0$.

$$W\min \left(\frac{1}{2}||w||^2\right) + C\sum \xi_i \tag{3}$$

K-Nearest Neighbors (KNN) is a non-parametric, supervised machine learning algorithm used for classification and regression tasks. It is a simple yet powerful algorithm that classifies new data points based on their similarity to the existing data points in the training set [37]. The core idea behind KNN is to find the k nearest neighbors of a new data point and assign it the class label that is most common among those k neighbors. One of the key advantages of KNN is its simplicity and ease of implementation. It does not require any prior knowledge about the data distribution, and it can handle multi-class classification problems naturally.

The mathematical formulation of KNN involves calculating the distance between the new data point and all the training data points, and then selecting the k nearest neighbors based on the smallest distances [38]. The most commonly used distance metric is the Euclidean distance, but other metrics like Manhattan distance or Minkowski distance can also be used. The classification decision is made by taking a majority vote among the k nearest neighbors, where the new data point is assigned the class label that is most frequent among its k nearest neighbors.

Random forest is a powerful ensemble learning algorithm that combines multiple decision trees to improve predictive performance and robustness. The mathematical formulation of the random forest involves the following steps [39]:

1) A bootstrap sample of size N is drawn from the original data, where N is the size of the training data.
2) An unpruned decision tree is grown on the bootstrap sample, with the following randomization.
    a) At each node, m features are randomly selected from the total M features, where $m \ll M$.
    b) The best split among the m features is chosen.
3) Steps 1 and 2 are repeated to grow a forest of trees equivalent to n_estimators.
4) The prediction for a new instance is made by aggregating the predictions of all the individual trees in the forest. For classification tasks, the majority vote of the trees is taken.

The SVM algorithm employs a random search approach to discover the optimal combination of parameter values, aiming to achieve the most favorable outcome. Table 1 displays the parameters included in the random search algorithm. The random search involves randomly sampling candidate solutions from the search space and evaluating their fitness or objective function value. Random search space consists of four key steps which are listed below [40],[41]:

1) The search space is defined. The range or domain of the variables or parameters to be optimized is specified.

2) General candidate solutions within the defined search space are randomly generated.

3) For each randomly generated candidate solution, its fitness or objective value function is evaluated.

4) Steps 2 and 3 are repeated for a specified number of iterations.

Table 1. The Range of Variables in SVM's Random Search Method

Parameters	Values
C	Between 0 and 1000
γ	Between 0 to 1
Kernel	Linear, Polynomial, RBF, Sigmoid
Random state	None, 42

Based on Table 1, the $'C'$ parameter controls the regularization strength in the SVM model. The $'\gamma'$ parameter defines how much influence a single training example has. A small $'\gamma'$ value means the kernel considers a wider area around each training instance, effectively using a larger radius of influence. A large $'\gamma'$ value means the kernel only considers very close training instances, using a smaller area of influence. In a random state, 'None' means that the random state is not fixed and will be different each time and '42' means that the same random initialization will be produced every time.

The grid search cross-validation technique is used in KNN to determine optimal parameter values that yield the best results. Table 2 displays the parameters included in the grid search cross-validation process. Grid search cross-validation is a technique used in machine learning to tune the hyperparameters of a model by systematically evaluating its performance across a grid of hyperparameter values. Grid search cross-validation consists of the following steps [42]:

1) The hyperparameter search space is defined by specifying the range or set of values for each parameter to be tuned.
2) A grid is created by considering all possible combinations of the hyperparameter values.
3) For each combination in the grid:
    a) The model is trained using that set of hyperparameters.
    b) The model's performance is evaluated using cross-validation on a held-out validation set.
4) The hyperparameter combination that yields the best performance metric on the validation set is selected.

Table 2. The Range of Variables in KNN's Grid Search Cross – Validation Technique

Parameters	Values
k_range	Between 1 and 31
weight_options	uniform, distance
algorithm_options	auto, ball_tree, kd_tree, brute
p_values	1,2

Based on Table 2, 'k_range' represents the values for the 'n_neighbors' parameter in the KNN algorithm, which determines the number of nearest neighbors to consider when making predictions. The 'weight_options' determines how the contributions of the neighbors are weighted when making predictions. The 'uniform' assigns equal weights to all neighbors, while 'distance' assigns weights inversely proportional to their distances from the target point. The 'algorithm_options' determines the algorithm used to compute the nearest neighbors. The 'auto' allows the algorithm to decide the most appropriate strategy based on the input data, while the other options specify the specific algorithm to use. The 'p_values' represents the possible values for the p parameter in the Minkowski distance metric used by the KNN algorithm. When 'p_values'=1, it corresponds to the Manhattan distance, and when 'p_values'=2, it corresponds to the Euclidean distance.

Similar to SVM, Random Forest utilizes a random search approach to identify the most effective parameter values that lead to optimal results. Table 3 displays the parameters included in the random search algorithm for Random Forest.

Table 3. The Range of Variables in Random Forest's Random Search Method

Parameters	Values
n_estimators	Between 200 and 2000
max_depth	Between 10 and 110
min_samples_split	2,5,10
min_samples_leaf	1,2,4

Based on Table 3, 'n_estimators' represents the number of decision trees to be used in the Random Forest algorithm. The 'max_depth' represents the maximum depth of the trees in the Random Forest. A larger value of 'max_depth' allows the trees to grow deeper, potentially capturing more complex patterns in the data. The 'min_samples_split' represents the minimum number of samples required to split an internal node in the decision trees. A higher value for 'min_samples_split' can help prevent overfitting on noisy or insignificant data. The 'min_samples_leaf' represents the minimum number of samples required to be at a leaf node.

The machine learning's performance for SVM, KNN and Random Forest are evaluated using metrics such as precision, recall, and the F1 score which are represented in Eq. (4), (5) and (6) respectively.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (4)$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (5)$$

$$PF1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (6)$$

3. Results and Discussions

Fig. 2 shows the boxplot of the maximum CWT RMS for old and young gait. Fig. 2 shows that the maximum CWT RMS of the stride interval of the young people is higher than that of old people which indicates that the stride interval of the young people is higher. The range of the maximum CWT RMS of the young people which can be seen from the length of the boxplot is higher than that of the old people which indicates that the stride interval of the young people is more diverse.

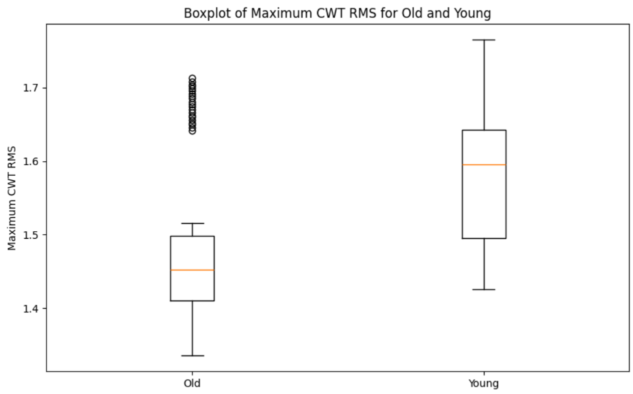

Fig. 2. The Boxplot of Maximum CWT RMS for Stride Interval of Old and Young Gait

Tables 4, 5, and 6 display the optimal parameters for Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forest models, respectively.

Table 4. SVM's Variables Derived by Random Search Method

Parameters	Values
C	255.14251480865047
γ	0.43036282552725214
Kernel	RBF
Random state	42

Table 5. KNN's Variables Derived by Grid Search Cross-Validation Method

Parameters	Values
k_range	16
weight_options	uniform
algorithm_options	auto
p_values	1

Table 6. Random Forest's Variables Derived by Random Search Method

Parameters	Values
n_estimators	1200
max_depth	50
min_samples_split	10
min_samples_leaf	4

The classification reports, which are based on a single input of Maximum CWT RMS, are displayed in Fig. 3, Fig. 4 and Fig. 5. These reports are generated using SVM, KNN, and Random Forest algorithms respectively.

```
              precision    recall  f1-score   support

           0       0.71      0.94      0.81        16
           1       0.95      0.77      0.85        26

    accuracy                           0.83        42
   macro avg       0.83      0.85      0.83        42
weighted avg       0.86      0.83      0.84        42
```

Fig. 3. The SVM's Classification Report with a Singular Input, Maximum CWT RMS

```
              precision    recall  f1-score   support

           0       0.88      0.94      0.91        16
           1       0.96      0.92      0.94        26

    accuracy                           0.93        42
   macro avg       0.92      0.93      0.93        42
weighted avg       0.93      0.93      0.93        42
```

Fig. 4. The KNN's Classification Report with a Singular Input, Maximum CWT RMS

```
              precision    recall  f1-score   support

           0       0.76      0.81      0.79        16
           1       0.88      0.85      0.86        26

    accuracy                           0.83        42
   macro avg       0.82      0.83      0.83        42
weighted avg       0.84      0.83      0.83        42
```

Fig. 5. The Random Forest's Classification Report with a Singular Input, Maximum CWT RMS

The machine learning outcomes of the SVM and KNN, each with a single input of Maximum CWT RMS, are depicted in the visual graphs presented in Fig. 6 and Fig. 7.

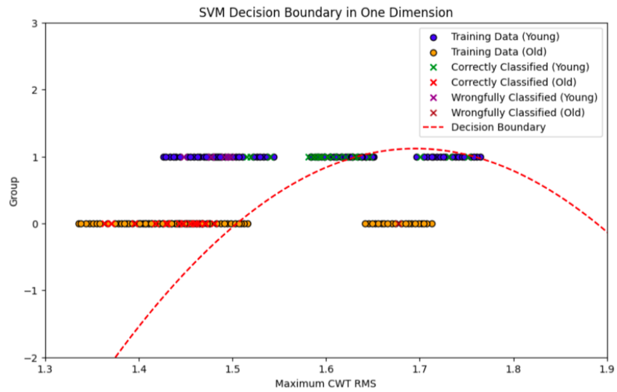

Fig. 6. The Graphical Representation of SVM with a Singular Input, Maximum CWT RMS

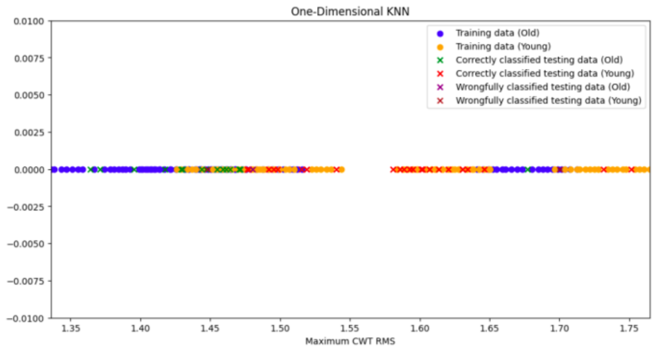

Fig. 7. The Graphical Representation of KNN with a Singular Input, Maximum CWT RMS

Fig. 8 illustrates a decision tree derived from a random forest model with only one input, which is the Maximum CWT RMS.

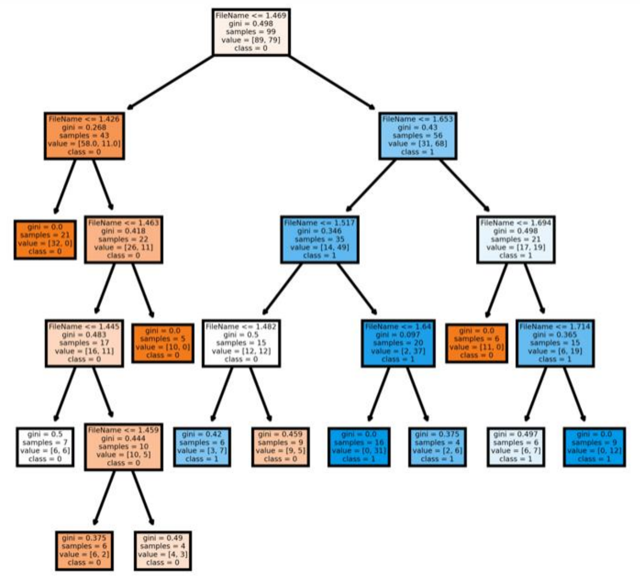

Fig. 8. A Single Decision Tree from the Collection of 1200 Decision Trees with Single Input, Maximum CWT RMS

Fig. 9 displays the outcomes of SVM, including 15 instances of true negatives, 1 false positive, 6 false negatives, and 20 true positives. Fig. 10 depicts the results of KNN, comprising 15 true negatives, 1 false positive, 2 false negatives, and 24 true positives. Fig. 11 showcases the results of the random forest, with 13 true negatives, 3 false positives, 4 false negatives, and 22 true positives.

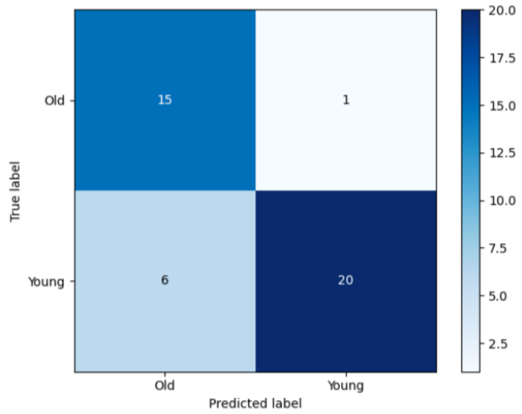

Fig. 9. The Confusion Matrix for SVM that Uses Single Input, Maximum CWT RMS

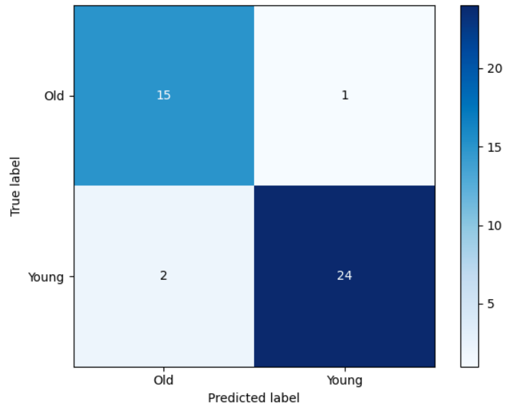

Fig. 10. The Confusion Matrix for KNN that Uses Single Input, Maximum CWT RMS

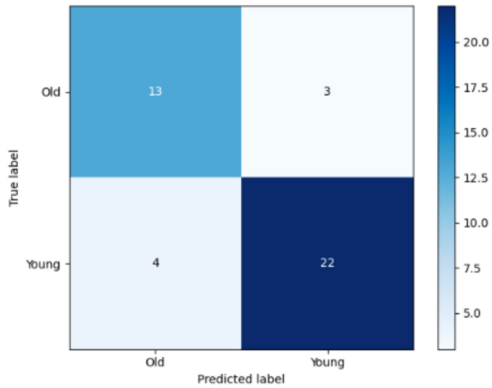

Fig. 11. The Confusion Matrix for the Random Forest that Uses a Single Input, Maximum CWT RMS

Table 7 presents the computation durations for SVM, KNN, and Random Forest when applied to the maximum CWT RMS. A glance at Table 7 reveals that SVM has the quickest processing time of 3.2302 seconds, while Random Forest takes the longest time, clocking in at 280.9027 seconds.

Table 7. The Duration Required for SVM, KNN, and Random Forest to Process the Maximum CWT RMS

Algorithm	Processing Time (sec)
SVM	3.2302
KNN	17.3960

Random Forest	280.9027

Table 8 presents a summary of the weighted averages for precision, recall, and the f1-score, as per the classification report for various algorithm implementations, including SVM, KNN, and Random Forest. An examination of Table 8 reveals that, in terms of the weighted averages of precision, recall, and the f1-score, KNN outperforms both SVM and Random Forest.

Table 8. A Synopsis of the Weighted Mean Derived from the Classification Report of SVM, KNN, and Random Forest, using a Single Input, the Maximum CWT RMS

Algorithm	Weighted Average (Precision)	Weighted Average (recall)	Weighted Average(f1-score)
SVM	0.86	0.83	0.84
KNN	0.93	0.93	0.93
Random Forest	0.84	0.83	0.83

4. Conclusions

The result of the random search method for SVM shows that the value of $'\boldsymbol{C}'$ of 255.143, and the value of $'\boldsymbol{\gamma}'$ of 0.430 with the use of RBF kernel and random state of 42 offers the best performance of SVM. The result of the grid search cross-validation technique for KNN shows that the uniform vote of the nearest 16 neighbors with the use of the 'auto' algorithm and calculation of distance using Manhattan distance offers the best performance. The testing of the machine learning system in classifying the old gait and young gait shows the following result. The result of the random search method for random forest shows that the number of decision trees of 1200, the maximum depth of trees of 50, the minimum number of samples required to split an internal node in the decision tree is 10 and the minimum samples of leaf required to be at a leaf node to be 4. KNN stands out the best in performance by scoring 93% for weighted average (precision), weighted average (recall) and weighted average (f1 – score). SVM comes out second in performance by scoring 86% for weighted average (precision), 83% for weighted average (recall) and 84% for weighted average (f1-score) with the shortest processing time, 3.2302s. From the boxplot of the Maximum CWT RMS of the young and the old people, it can be seen that the stride interval of the young people is higher and more diverse than the old people.

Acknowledgement

The authors acknowledge the support and funding provided by the Ministry of Higher Education (MOHE) of Malaysia and Universiti Teknikal Malaysia Melaka (UTeM) through the Fundamental Research Grant Scheme (FRGS), No: FRGS/1/2023/SKK06/UTEM/02/1. The authors are also thankful for the Kesidang Scholarship bestowed by the UTeM.

References

[1] Jillian A. Fairley, Ervin Sejdić, and Tom Chau, 'The Effect of Treadmill Walking on the Stride Interval Dynamics of Children', Human Movement Science 29, no. 6 (1 December 2010): 987–98, https://doi.org/10.1016/j.humov.2010.07.015

[2] Philippe Terrier, 'Complexity of Human Walking: The Attractor Complexity Index Is Sensitive to Gait Synchronization with Visual and Auditory Cues', *PeerJ* 7 (1 August 2019): e7417, https://doi.org/10.7717/peerj.7417

[3] Hesham Sayed Ahmed, 'Analysis of Gait Efficiency and Foot Placement for Egyptian Race Walker', *International Journal of Sports Science and Arts* 008, no. 008 (1 October 2018): 20–32, https://doi.org/10.21608/eijssa.2018.72888

[4] Klaus Mattes et al., 'A Longitudinal Study of Kinematic Stride Characteristics in Maximal Sprint Running', *Journal of Human Sport and Exercise* 9, no. 3 (2014): 686–99, https://doi.org/10.14198/jhse.2014.93.02

[5] Jintae Han et al., 'Effect of Muscle Vibration on Spatiotemporal Gait Parameters in Patients with Parkinson's Disease', *Journal of Physical Therapy Science* 26, no. 5 (2014): 671–73, https://doi.org/10.1589/jpts.26.671

[6] Sana M. Keloth, Sridhar P. Arjunan, and Dinesh K. Kumar, 'Variance of the Gait Parameters and Fraction of Double-Support Interval for Determining the Severity of Parkinson's Disease', *Applied Sciences* 10, no. 2 (January 2020): 577, https://doi.org/10.3390/app10020577

[7] M. Encarna Micó-Amigo et al., 'Potential Markers of Progression in Idiopathic Parkinson's Disease Derived From Assessment of Circular Gait With a Single Body-Fixed-Sensor: A 5 Year Longitudinal Study', *Frontiers in Human Neuroscience* 13 (19 February 2019), https://doi.org/10.3389/fnhum.2019.00059

[8] Chris J. Hass et al., 'Quantitative Normative Gait Data in a Large Cohort of Ambulatory Persons with Parkinson's Disease', ed. Wing-ho Yung, *PLoS ONE* 7, no. 8 (3 August 2012): e42337, https://doi.org/10.1371/journal.pone.0042337

[9] William W. Hsieh, 'Evolution of Machine Learning in Environmental Science—A Perspective', *Environmental Data Science* 1 (January 2022): e3, https://doi.org/10.1017/eds.2022.2

[10] Chun Kwang Tan et al., 'Differences in Muscle Synergy Symmetry Between Subacute Post-Stroke

Patients With Bioelectrically-Controlled Exoskeleton Gait Training and Conventional Gait Training', *Frontiers in Bioengineering and Biotechnology* 8 (29 July 2020), https://doi.org/10.3389/fbioe.2020.00770

[11] Edward Zhu1 et al., 'A Pose-Based Walking/Running Coach System for Cerebral Palsy Patients Using Artificial Intelligence and Computer Vision', *Computer Science& Information Technology (CS&IT)* 13, no. 13 (29 July 2023): 79, https://doi.org/10.5121/csit.2023.131307

[12] Jasmin Praful Bharadiya, 'Introduction of the Popular Machine Learning Algorithm', *International Journal of Innovative Science and Research Technology* 8, no. 5 (8 June 2023): 2504–8, https://doi.org/10.5281/zenodo.8020795

[13] Jackson Kamiri and Geoffrey Mariga, 'Research Methods in Machine Learning: A Content Analysis', *International Journal of Computer and Information Technology(2279-0764)* 10 (30 March 2021): 2279–0764, https://doi.org/10.24203/ijcit.v10i2.79

[14] Anil Kumar Mandle, 'Protein Structure Prediction Using Support Vector Machine', *International Journal on Soft Computing* 3, no. 1 (29 February 2012): 67–78, https://doi.org/10.5121/ijsc.2012.3106

[15] Cervantes et al., 'A Comprehensive Survey on Support Vector Machine Classification: Applications, Challenges and Trends', *Neurocomputing* 408 (30 September 2020): 189–215, https://doi.org/10.1016/j.neucom.2019.10.118

[16] Ezreen Farina Shair, Nur Jamaluddin, and Abdul Rahim Abdullah, 'Finger Movement Discrimination of EMG Signals Towards Improved Prosthetic Control Using TFD', *International Journal of Advanced Computer Science and Applications* 11 (1 October 2020): 244–51, https://doi.org/10.14569/IJACSA.2020.0110928

[17] Susmita Ray, 'A Quick Review of Machine Learning Algorithms', in *2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon)*, 2019, 35–39, https://doi.org/10.1109/COMITCon.2019.8862451

[18] Julian Madrid et al., 'Spatiotemporal Parameters during Turning Gait Maneuvers of Different Amplitudes in Young and Elderly Healthy Adults: A Descriptive and Comparative Study', Gait & Posture 99 (1 January 2023): 152–59, https://doi.org/10.1016/j.gaitpost.2022.11.010

[19] Thea Laurentius et al., 'Spatiotemporal Gait Parameters in Young Individuals Wearing an Age Simulation Suit Compared to Healthy Older Individuals', European Review of Aging and Physical Activity 19, no. 1 (18 November 2022): 29, https://doi.org/10.1186/s11556-022-00298-w

[20] Asma Channa, Najeeb ur Rehman Malik, and Nirvana Popescu, 'Association of Stride Rate Variability and Altered Fractal Dynamics with Ageing and Neurological Functioning', in 2021 23rd International Conference on Control Systems and Computer Science (CSCS), 2021, 509–14, https://doi.org/10.1109/CSCS52396.2021.00089

[21] XiangChen Wu et al., 'Step Detection in Complex Walking Environments Based on Continuous Wavelet Transform', Multimedia Tools and Applications 83, no. 12 (1 April 2024): 36603–27, https://doi.org/10.1007/s11042-023-15426-6

[22] J. Prasanna, S. Thomas George, and M. S. P. Subathra, 'Computer Aided Diagnosis of Neurodegenerative Diseases Using Discrete Wavelet Transform and Neural Network for Classification', in Computational Techniques in Neuroscience (CRC Press, 2023)

[23] Francesco Di Nardo et al., 'Simplified Muscle-Recruitment Strategy During Walking in Parkinson's Disease People: A Time-Frequency Analysis of EMG Signal', IRBM 44, no. 6 (1 December 2023): 100798, https://doi.org/10.1016/j.irbm.2023.100798

[24] Md. Ahasan Atick Faisal et al., 'NDDNet: A Deep Learning Model for Predicting Neurodegenerative Diseases from Gait Pattern', Applied Intelligence 53, no. 17 (1 September 2023): 20034–46, https://doi.org/10.1007/s10489-023-04557-w

[25] Ahmed Fathalla et al., 'Real-Time and Automatic System for Performance Evaluation of Karate Skills Using Motion Capture Sensors and Continuous Wavelet Transform', ed. Vittorio Memmolo, International Journal of Intelligent Systems 2023 (21 February 2023): 1–11, https://doi.org/10.1155/2023/1561942

[26] Olena Pavliuk, Myroslav Mishchuk, and Christine Strauss, 'Transfer Learning Approach for Human Activity Recognition Based on Continuous Wavelet Transform', Algorithms 16, no. 2 (n.d.): 77, https://doi.org/10.3390/a16020077

[27] Nizam U. Ahamed et al., 'Using Wavelet-Based Fractal Analysis of Inertial Measurement Unit Signals to Examine Gait Data from Men and Women during a Load Carriage Task', in 2020 IEEE 20th International Conference on Bioinformatics and Bioengineering (BIBE), 2020, 494–97, https://doi.org/10.1109/BIBE50027.2020.00085

[28] Anna Nedorubova, Alena Kadyrova, and Aleksey Khlyupin, 'Human Activity Recognition Using Continuous Wavelet Transform and Convolutional Neural Networks' (arXiv, 29 June 2021), https://doi.org/10.48550/arXiv.2106.12666

[29] Jayeeta Chakraborty and Anup Nandy, 'Discrete Wavelet Transform Based Data Representation in Deep Neural Network for Gait Abnormality Detection', Biomedical Signal Processing and Control 62 (1 September 2020): 102076, https://doi.org/10.1016/j.bspc.2020.102076

[30] Jeffrey M Hausdorff et al., ‘Gait in Aging and Disease Database’ ([object Object], 1999), https://doi.org/10.13026/C2C889

[31] Thomas A. Lubik, Christian Matthes, and Fabio Verona, ‘Assessing U.S. Aggregate Fluctuations Across Time and Frequencies’, SSRN Scholarly Paper (Rochester, NY, 20 February 2019), https://doi.org/10.2139/ssrn.3339121

[32] E. F. Shair et al., ‘EMG Processing Based Measures of Fatigue Assessment during Manual Lifting’, *BioMed Research International* 2017 (19 February 2017): e3937254, https://doi.org/10.1155/2017/3937254

[33] Vladimir Saveljev, ‘Wavelets and Continuous Wavelet Transform for Autostereoscopic Multiview Images’, *Applied Optics* 55, no. 23 (10 August 2016): 6275, https://doi.org/10.1364/AO.55.006275

[34] Henry Adams, Elin Farnell, and Brittany Story, ‘Support Vector Machines and Radon’s Theorem’ (arXiv, 16 September 2022), https://doi.org/10.48550/arXiv.2011.00617

[35] D. C. Diana et al., ‘Support Vector Based Classification for Adaptive Channel Equalization’, in *2023 Second International Conference on Electronics and Renewable Systems (ICEARS)*, 2023, 325–31, https://doi.org/10.1109/ICEARS56392.2023.10085218

[36] AAIN Eka Karyawati, Komang Dhiyo Yonatha Wijaya, and I. Wayan Supriana, ‘A COMPARISON OF DIFFERENT KERNEL FUNCTIONS OF SVM CLASSIFICATION METHOD FOR SPAM DETECTION’, *JITK (Jurnal Ilmu Pengetahuan Dan Teknologi Komputer)* 8, no. 2 (27 February 2023): 97–103, https://doi.org/10.33480/jitk.v8i2.2463

[37] Raja Sakti Arief Daulay, Syahril Efendi, and Suherman, ‘Review of Literature on Improving the KNN Algorithm’, *Transactions on Engineering and Computing Sciences* 11, no. 3 (3 June 2023): 63–72, https://doi.org/10.14738/tecs.113.14768

[38] Mizan Ali Khan and Abhishek Sharma, ‘Implementation of KNN Algorithm with BOA to Predict the Cancer with More Accurate Way’, in *2022 5th International Conference on Contemporary Computing and Informatics (IC3I)*, 2022, 509–14, https://doi.org/10.1109/IC3I56241.2022.10073060

[39] Gilles Louppe, ‘Understanding Random Forests: From Theory to Practice’ (arXiv, 3 June 2015), https://doi.org/10.48550/arXiv.1407.7502

[40] Marc Claesen and Bart De Moor, ‘Hyperparameter Search in Machine Learning’ (arXiv, 6 April 2015), https://doi.org/10.48550/arXiv.1502.02127

[41] Horia Mania, Aurelia Guy, and Benjamin Recht, ‘Simple Random Search Provides a Competitive Approach to Reinforcement Learning’ (arXiv, 19 March 2018), https://doi.org/10.48550/arXiv.1803.07055

[42] Tran Thanh Ngoc, Le Van Dai, and Dang Thi Phuc, ‘Grid Search of Multilayer Perceptron Based on the Walk-Forward Validation Methodology’, *International Journal of Electrical and Computer Engineering (IJECE)* 11, no. 2 (1 April 2021): 1742, https://doi.org/10.11591/ijece.v11i2.pp1742-1751