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A Machine Learning Model for Predicting Critical Minimum Foot Clearance (MFC) Heights

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Abstract: Tripping is the largest cause of falls and low swing foot ground clearance during the mid-swing phase, particularly at the critical gait event known as Minimum Foot Clearance (MFC) is the major risk factor for tripping-related falls. Intervention strategies to increase MFC height can be effective if applied in real-time based on feed-forward prediction. The current study investigated the capability of machine learning models to classify the MFC into various categories using toe-off kinematics data. Specifically, three MFC sub-categories (less than 1.5cm, between 1.5-2.0cm and higher than 2.0cm) were predicted applying machine learning approaches. A total of 18,490 swing phase gait cycles' data were extracted from six healthy young adults, each walking for 5-minutes at a constant speed of 4km/h on a motorised treadmill. Both K-Nearest Neighbour (KNN) and Random-Forest were utilised for prediction based on the data from toe-off for five consecutive frames (0.025s duration). Foot kinematics data were obtained from inertial measurement unit attached to the mid-foot, recording tri-axial linear accelerations and angular velocities of the local coordinate. KNN and Random-Forest achieved 84% and 86% accuracy, respectively, in classifying MFC into the three sub-categories with run time of 0.39 seconds and 13.98 seconds respectively. The KNN-based model was found to be more effective if incorporated into an active exoskeleton as the intelligent system to control MFC based on the preceding gait event, toe-off due to its quicker computation time. The machine learning based prediction model shows promise for the prediction of critical MFC data indicating higher tripping risk.

Keywords: minimum foot clearance (MFC); tripping prevention; falls prevention; machine learning; gait prediction; gait biomechanics

1. Introduction

Falls are the critical issue among vulnerable populations including older adults, stroke survivors, Parkinson's patients and individuals with other neurological disorders [1-7]. For example, up to one in three older adults fall at least once a year while this figure is 40-58% for post-stroke individuals (within 1 year of their stroke) and 45-68% for people with Parkinsonism [8-14]. Due to slower reaction speeds and lower bone mineral density [15], these frail populations are prone to severe injuries that can lead to death or constant nursing care with large costs that can impact both individuals and national social security systems [15-17]. Falls prevention should be thus prioritised especially for vulnerable populations. Among various causes, tripping has been identified as the leading cause accounting for up to 53% of the entire falls incidences [18, 19].

Tripping can be defined as the unintentional swing foot's contact with the walking surface or an object on it with sufficient momentum that destabilises the walker [20]. During the swing phase of the gait cycle, the critical event in relation to tripping risk is minimum foot clearance (MFC), determined as the local minimum swing toe vertical displacement during the mid-swing phase [21-22]. Tripping at MFC has the high risk of forward balance loss and an associated fall because (i) low vertical clearance increases the likelihood of swing foot contact, (ii) swing foot travels at near-maximum speed generating the large impact in case of tripping at MFC and (iii) both feet stance does not provide the ideal supporting base against balance loss [22-25].

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Essentially, tripping prevention can be achieved if sufficient vertical displacement is provided at MFC [26]. There are various intervention techniques aiming to increase MFC height such as use of the special shoe-insole, biofeedback training and exercise intervention. The focus of our current research is to predict MFC heights in advance so that this can be incorporated into assistive devices (e.g. active exoskeletons) for actuation assistance when necessary [27-30]. For development of such technology, MFC height estimation should be based on wearable sensors such as inertial measurement units (IMUs) [31-37] and undertaken well in advance for the mechanical device to take action. Our previous work showed that MFC timing can be predicted from toe-off characteristics with a mean absolute error of 0.07 seconds [38].

In our current study, we have applied IMUs to record toe-off characteristics described by 3-axial accelerations and angular velocities. The objective is to find out whether kinematics data following toe-off could be utilised for the classification of MFC heights into categories (e.g., high, medium, low). Using the MFC characteristics in [21], the current study attempted to classify MFC into the following three sub-categories: (i) lower than normal (MFC < 1.5cm), (ii) safe range (1.5cm < MFC < 2cm), and (iii) well-above the safety requirement (MFC > 2cm)

2. Machine Learning Overview

Machine learning algorithms can extract and recognise features using mathematical relationships between different variables in the sample space [38]. Collection of mathematically related feature variables in a sample space forms the sample data for development of training and testing algorithms. Machine learning applications in gait and neurological studies, have created intrinsic understanding in previously under discovered areas, giving rise to wider applications involving neurological processes relating human gait from recognition of intention to physical locomotion [39-41]. In the current study, a supervised machine learning algorithm was used to make predictions on new unlabelled data points. K-Nearest Neighbour (KNN) uses distance measures to find K closest neighbours to a test dataset. Low MFC is associated with tripping falls [21]; therefore, our goal was to use machine learning algorithm to classify MFC heights into lower than normal, safe range and above safe range categories.

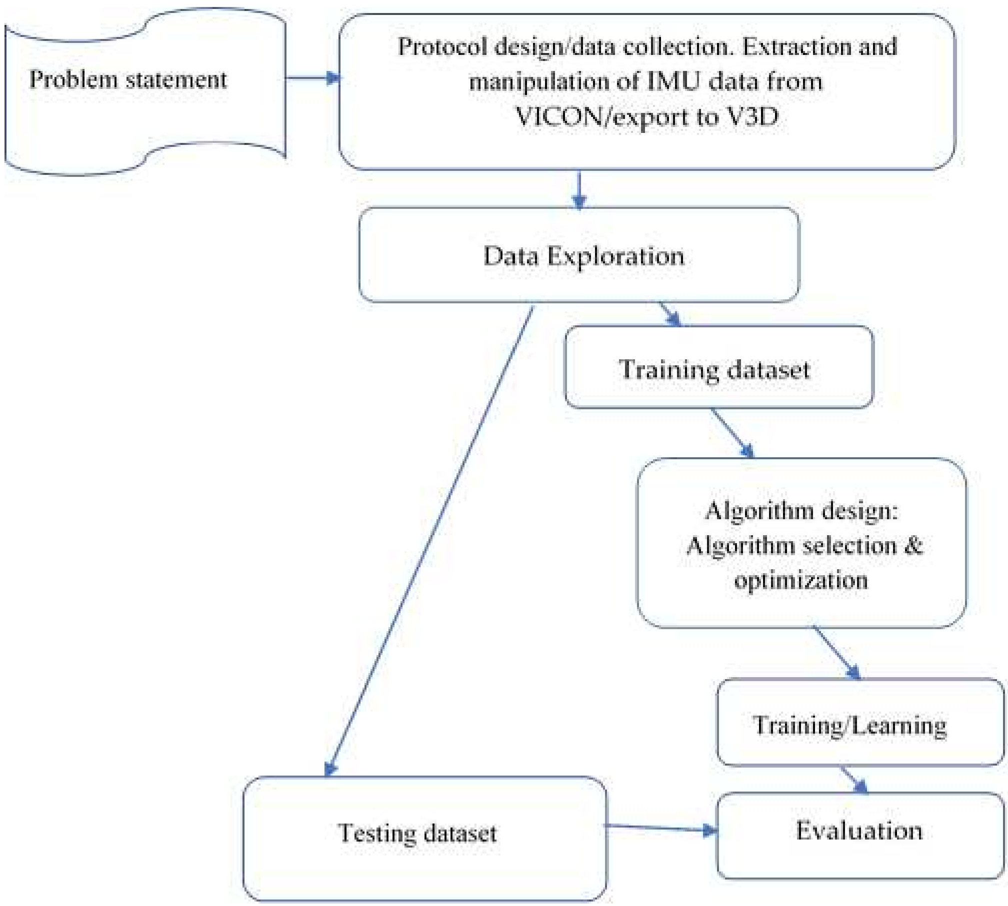

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Figure 2. Process diagram for the implementation of our ML algorithm, problem statement, algorithm development, training and performance evaluation.

3. Data Collection

3.1. Participants and Protocols

Six healthy young adults were recruited for the current research from the university volunteers. To be included in the study, participants were required to be healthy, capable of walking on the treadmill for 30 minutes without a break, free from injuries that affect their walking patterns and no previous history of injurious falls for at least for the past two years. The entire experimental protocol was explained by the researchers and informed consent form approved and mandated by Victoria University Research Ethics Committee was voluntarily signed by the participants prior to participation

Gait testing was conducted on the treadmill (AMTI) for 5 minutes at 4km/h, which was considered to be the reasonable preferred pace for healthy young individuals [41]. Vicon Bonita system (Nexus 2.12.1) with 10 cameras were utilised to track reflective markers at 200Hz, attached to the heel (the proximal end of the shoe) and the toe (the most anterior superior surface of the shoe). Low-pass Butterworth filter (6Hz) was applied to the obtained position data prior to analysis. Based on the kinematic conventions [42], toe-off and heel contact were first computed to define the swing phase. MFC was identified as the local minimum vertical displacement of the toe during the mid-swing phase from toe-off but when the clear local minimum was absent the alternative definition was applied utilising maximum horizontal velocity of swing toe [43].

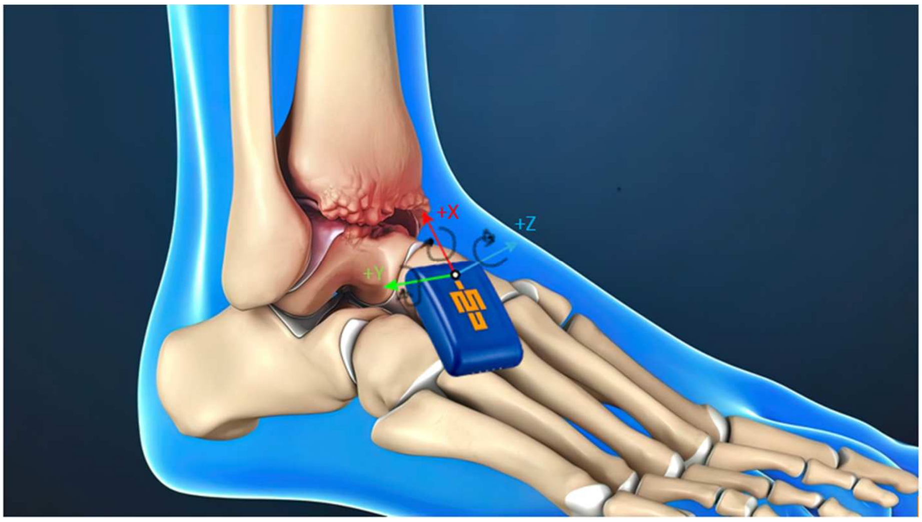

Figure 3. IMU (Nexus, Trident) attached to the midfoot, tri-axial linear accelerations and angular velocities indicated by arrows. X is anterior-posterior axis, Y is Medio-lateral and Z is the vertical.

As illustrated in Figure 3, IMU (Nexus, Trident) was attached to the mid-foot section to record various foot-segment based kinematic data (200Hz) but for the current study, tri-axial linear accelerations (AccX, AccY,AccZ) and angular velocities (GyroX, GyroY, GyroZ) were obtained for machine learning application. The overall goal of the study was to predict in which category (Table 1) upcoming MFC would be classified based on the 5 consecutive frames from toe-off comprising 0.025s kinematic information from toe-off. MFC categories employed in the current study are described in Table 1, determined by the previous studies indicating the average MFC for young adults to be about 1.5cm (R1), slightly above the average up to 2cm, (R2) and minimum risk of tripping (R3) as above 2cm [22, 45, 20, 21].

Table 1. MFC Categories.

R1	**R2**	**R3**

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Below average	Safe	Well-above safety limit
MFC < 1.5cm	1.5cm < MFC < 2cm	MFC > 2.0cm

3.2. Data Exploration

The selected features (i.e. tri-axial linear accelerations, angular velocities) were plotted with Seaborne pair plot [46] and showed non-linearly separable classes. The average values are indicated in Table 2

Table 2. Data from IMU sensor showing mean and standard deviation (5 frames from toe- off; 0,025s) of feature variables and number of counts per category of the 18,490 datasets collected.

Category		Average value of corresponding feature variables						Total
		AccX (m/s^2)	AccY (m/s^2)	AccZ (m/s^2)	GyroX $(rads/s)$	GyroY $(rads/s)$	GyroZ $(rads/s)$	
R1	Mean	10.54	-3.85	4.18	0.02	-1.64	0.55	7235
	STD	5.92	5.81	4.79	2.75	1.91	2.11	
R2	Mean	9.89	-2.00	0.16	0.09	-0.69	0.10	3738
	STD	4.40	5.34	4.08	1.51	1.12	1.84	
R3	Mean	8.43	-0.23	8.09	2.34	-3.22	1.83	7517
	STD	7.06	3.94	7.28	2.00	2.10	2.01	

Zoomed Z-axis component of the acceleration and angular velocity on the three categories of the MFC heights, distinctive patterns illustrated in Figures 2a and 2b argues to the range of our classification

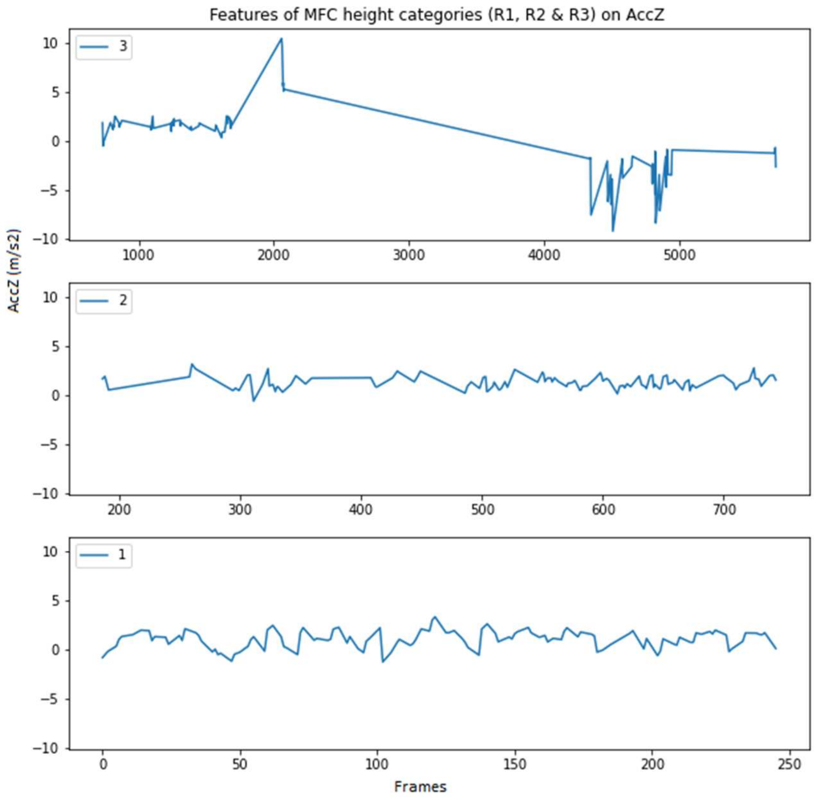

Figure 2. a: Zoomed Z-axis of linear acceleration on R1, R2 and R3 graphically compared.

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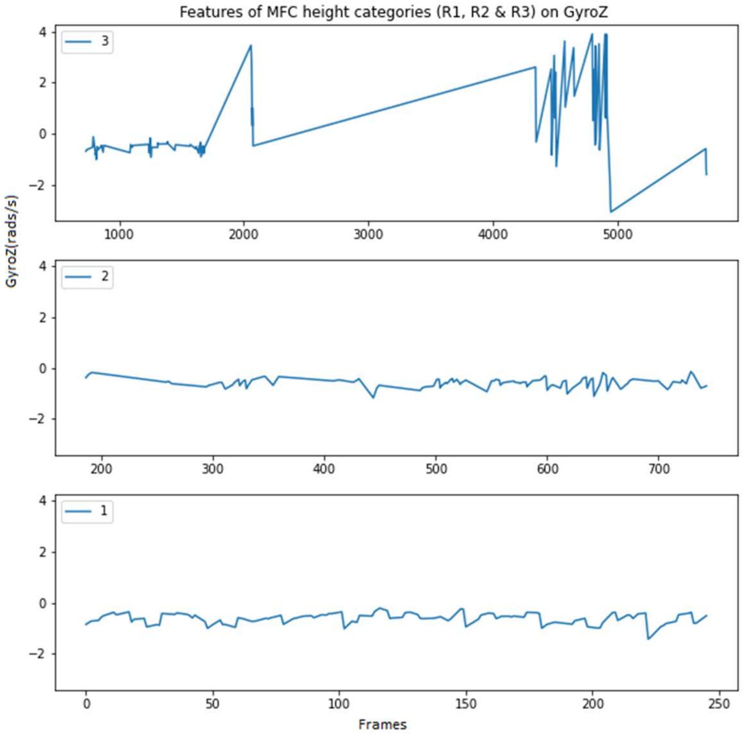

Figure 2. b: Zoomed Z-axis of angular velocity on R1, R2 and R3 graphically compared.

3.3. Model Selection and Algorithm Design

K-Nearest Neighbour (KNN) and Random-Forest were selected because our dataset variables are non-linearly separable as can be seen in Figure 3. Additionally, the characteristic attributes of each data point in Figure 3 formed a category that is assigned a class and the data points of any particular class are neighbors of each other.

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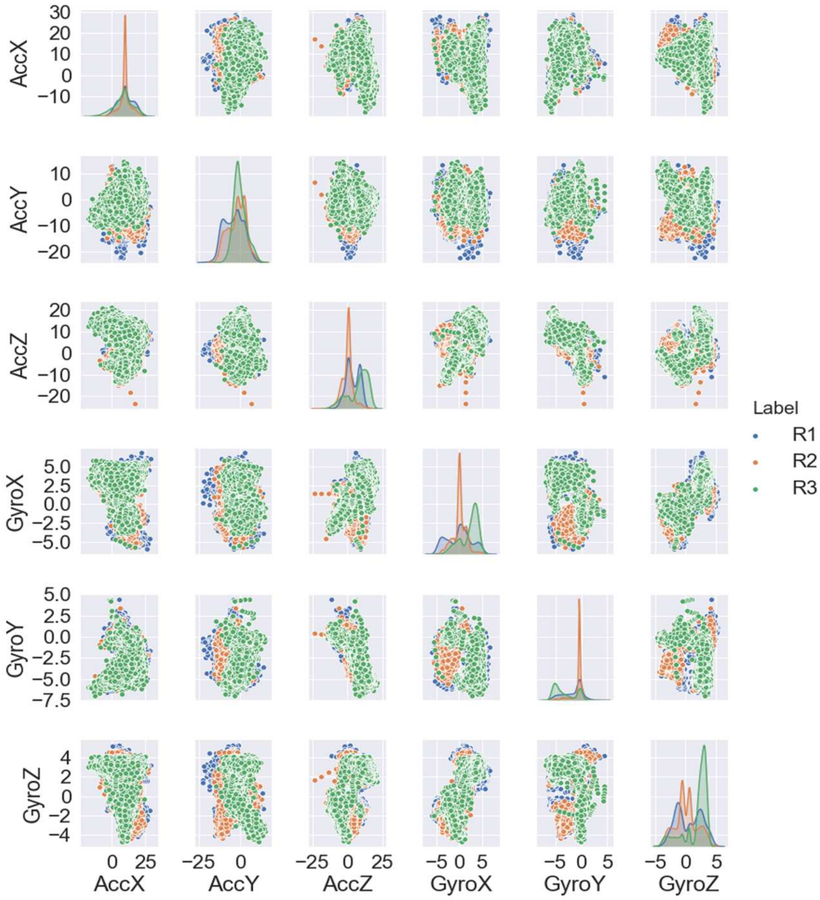

Figure 3. Pair plot correlation of the feature variables (linear acceleration and angular velocity) on R1 (blue), R2 (orange) and R3 (green).

In KNN, each instance is categorised as a vector of numbers in an n-dimensional Euclidean space. To find the class to which an unknown data point is a neighbor the Euclidean distance is measured as the true straight-line between two points. All instances, therefore, correspond to points in an n-dimensional Euclidian space and the distance between instances $d(p,q)$ is

$$d(p,q)=\sqrt{(q_1-p_1)^2+(q_2-p_2)^2+\ldots+(q_n-p_n)^2}$$

$$=\sqrt{\sum_{i=1}^{n}(q_i-p_i)^2}$$

Given k nearest neighbours, the optimum value is picked for best prediction of either R1, R2 or R3 MFC height category. In Random-Forest, an ensemble of many decision trees is designed to overcome overfitting problems associated with decision trees by bootstrap aggregation or bagging. Given a random-forest tree T_b *(for b = 1 to B)* to the bootstrap sample Z^* of size *N* from training data,

To make a prediction at a new point x :

Regression: $$\hat{f}_{rf}^{\,B}(x)=\frac{1}{B}\sum_{b=1}^{B}T_b(x)$$

Classification:

$$\hat{C}_{rf}^{\,B}(x)=\textit{majority vote}\ \{\hat{C}_b(x)\}_1^B$$

where $\hat{C}_b(x)$ is the class of prediction of the b^{th} random-forest tree.

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These methods have proven success in several use cases in gait classification and identification [47-49]. Both KNN and Random-Forest were, therefore, selected for our study and as both were useable for regression or classification problems and belonged to supervised machine learning algorithms

3.3.1. Hyper Parameter Tuning and Optimization

Each variable data (Table 2) was reshaped for scaling, using RobustScaler. GridSearch cross validation was used to determine the optimal list of parameters for our machine learning problem. Fitting 5 folds and iterating for 28 candidates, totalling 140 fits, the best parameters for KNN was tested with 7 neighbours 2 distances, 2 weights and 5 cross validations, and the best parameters proposed were ({'n_neighbors': 13, 'p': 2, 'weights': 'distance'}). Similarly, Random-Forest best parameters suggestion with GridSearach was ({'criterion': 'gini', 'max_depth': 8, 'max_features': 'sqrt', 'n_estimators': 400, 'random_state': 42}).

The feature variables (accelerometer and angular velocity) were separately investigated to determine individual contribution to the prediction of the MFC heights. The results are shown in table 4a and 4b.

4. Results

Figure 2 depicted the Z-axis variables of the critical MFC heights. MFC height in the range of the critical threshold based on the young population's lower end of the normal range (i.e. mean – SD) indicated the Z-axis component of the kinematic variable is highly unstable with increased tripping risk at MFC. Figure 3 is the correlation plot that helped us visualise the relationship between the variables. Figure 4a and 4b are adapted from the confusion matrix for KNN and Random-Forest with close matched accuracies. Higher accuracies are prioritised in ML modelling, while precision and recall rate are more valuable for better data classification. For example, high recall signifies good coverage, i.e. the percentage of tags the classifier predicted for a given label out of the total number of tags it should have predicted for that given label [50]. Both precision and recall are at acceptable levels supported by the F1 Score.

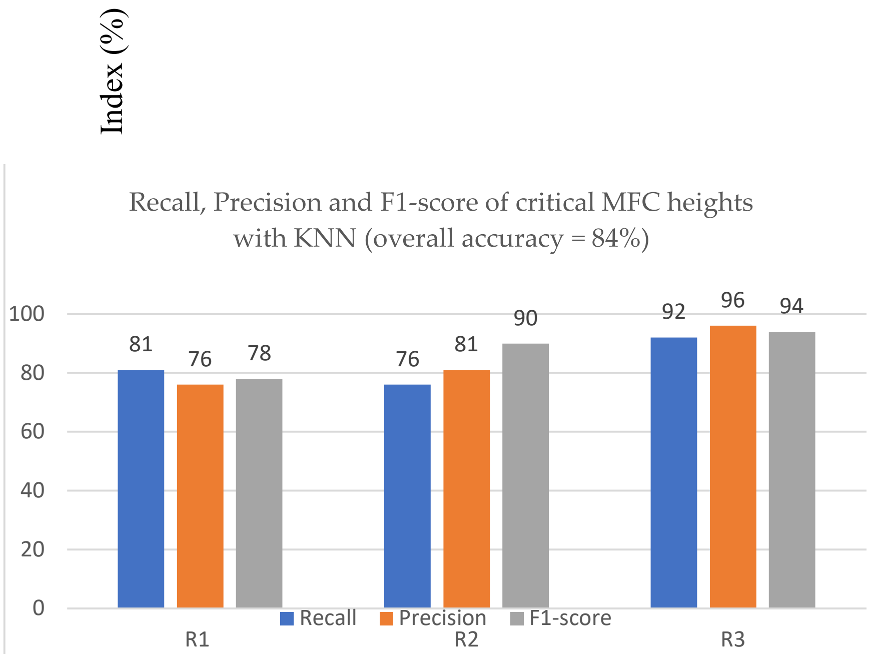

Figure 4. a. Performance evaluation of KNN algorithm showing average accuracy of 84 percent with high recall and F1-scores.

A particular MFC height is predictable with 84 percent accuracy, suitability for business case related by high recall rate of 92 percent on R3 which has the highest risk of fall.

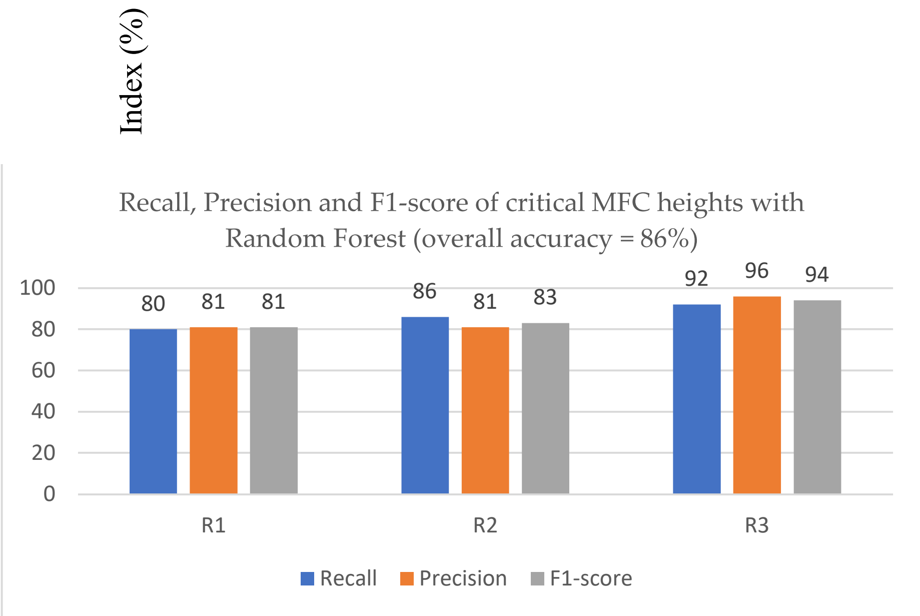

Figure 4. b. Performance evaluation of Random-Forest with average accuracy of 86 percent with high recall and F1-scores.

Performance result with Random-Forest is similar to the KNN algorithm with slight improvement in overall accuracy and recall. Random-Forest randomly selects a subset of features that are used as candidates at each split. This protocol automatically prevents the multitude of decision trees from relying on the same set of features, solving problems of overestimated correlations by avoiding a correlation of the individual trees. Each tree then draws a random sample of data from the training dataset when generating its splits, which further introduces an element of randomness and prevents the individual trees from overfitting the data. The uniformly generated weighted average on R1, R2 and R3 with both algorithms showed that each class was equally considered in its calculation of the metrics and had equal impact on the average score for each of those metrics (Table 3)

Table 3. Performance Summary of KNN and Random-Forest.

Algorithm	Accuracy score (%)	Weighted average (%)	Run time
KNN	84	83	0.39 seconds, at K =12
Random Forest	86	86	13.98 seconds, with 800 estimators and max depth of 8

Table 4. a. Comparison of prediction accuracies using linear acceleration and angular velocity as separate features on Random Forest and KNN.

Feature Variables	Random Forest (% accuracy)	KNN (% accuracy)
Acceleration (X,Y,Z)	67	65
Gyro meter(X,Y,Z)	75	74
Combined Acceleration and Gyro meter (X,Y,Z)	86	84

Table 4. b. Comparison of individual axial features (acceleration and angular velocity) on prediction with Random Forest and KNN.

ML Algorithm	Percentage accuracies of individual features to predict MFC height					
	AccX (%)	AccY (%)	AccZ (%)	GyroX (%)	GyroY (%)	GyroZ (%)
Random Forest	40	43	51	51	46	48
KNN	41	45	55	56	51	55

Table 4a showed the angular velocity had more positive effect on the predicted MFC heights than the linear acceleration and MFC height are best predicted with multiple features. Table 4b indicated that the vertical acceleration and the x and z axis of the angular velocities are more significantly related to the MFC height than the other kinematic variables.

4. Discussion

Minimisation of tripping risks has been one of the central issues for falls prevention and providing sufficient swing foot-ground clearance at MFC has been a key consideration while applying an intervention. For the real-time technology as part of the intelligent system, one effective approach is to use feed-forward prediction of upcoming MFC as early as the initiation of swing phase at toe-off. For healthy young adults, MFC usually takes place approximately around 50% of the swing phase, 0.2s-0.3s after toe-off [51]. It can be interpreted that 'prediction and actuation' should, in this example, occur within that time limit. In the current study, KNN successfully classified MFC into the three categories at 84% accuracy within 0.025s, suggesting the sufficient reliability and feasibility of our machine learning outputs to be incorporated into intelligent assistive device. Previous methods for MFC height estimation based on double-integration of vertical acceleration [24] is useful for measurement outside the laboratory environments, but our machine learning based prediction is the first attempt to devise intelligent active exoskeletons to increase MFC height. We have previously demonstrated toe-off kinematics can be used to predict MFC timing [38] – in this research we have applied toe-off kinematics for the real-time feedforward prediction of MFC heights.

Machine learning approaches are the emerging technique to classification and evaluation of gait patterns based on large data volumes, considered to be the mainstream analytical method in future and replacing conventional complex manual customised mathematical programming. The prediction of a future gait event can be incorporated into assistive device to become intelligent real-time systems to augment human ambulation. In machine learning use cases, we have employed KNN and Random

Forest for gait classification. Both of our models successfully classified MFC height into the three subcategories from toe-off information at high accuracies. Nevertheless, a caution is required for machine learning algorithms to provide feedforward control for a powered assistive device in a timely manner. While Random-Forest showed better performance in accuracy, KNN may be the preferred option considering the time taken for prediction to activate assistive device at MFC based on a preceding toe-off event. High recall and high precision cannot be compromised to ensure correct classification of MFC heights for the populations at critically high and moderate tripping risks, respectively [50]. Further collection of the data is essential in feeding the developed algorithms to improve performance before equipping it into assistive device for people.

In addition to the essential data feeding, there are some other fundamental concerns to overcome for practical application into assistive device as intelligent system. In the current proof-of-concept research, data of healthy young participants were selected to build the algorithms but, prediction of the tripping risk is more useful for vulnerable populations such as older adults, stroke survivors, people with Parkinson's disease and other pathological conditions. Gait patterns of the high tripping risk are often clearly different from the healthy young, implying that the currently developed algorithms need fine-tuning accounting for each gait pathology. MFC classification requires reconsideration in that further sub-divisions of the lower end (e.g. less than 0.5cm, 1cm etc) should be tested to examine the hazardous risk rather than MFC below 1.5cm categorisation.

After data feeding from various populations to achieve certain reliability in recognising hazardous MFC heights, the developed intelligent systems can be incorporated into ankle active exoskeleton devices to directly control ankle motion to increase MFC and prevent the risk of tripping falls. Kubota et al. [52] introduced the active ankle exoskeleton based on hybrid assistive limb (HAL) technology, which operates ankle dorsiflexion-plantarflexion motion based on efferent neural signals. In another word, HAL technology utilises intention to make movements to precisely control exoskeletons and reproduce intended movements, known to enhance motor control functions and improve neurological disorders [53, 54]. Ankle-HAL technology was developed for rehabilitation to focus on joint motion training by users' own neuro-signals, therefore not designed to directly assist active walking [55, 56]. Using our attempts to incorporate ML algorithm, however, feedforward actuation to reduce the tripping risk could be possible by operating exoskeletons by kinematic inputs. If ankle control is not based on neuro-signals, rehabilitation effects on motor control may be lower but in return, wearers can be expected to learn the optimum ankle motion during the swing phase and acquire less trip-prone walking patterns. Such application is one of the fruitful directions of the current research outcomes for practical rehabilitation settings, while continuous research efforts are essentially required.

5. Conclusions

Tri-axial linear accelerations and angular velocities data obtained from a single IMU sensor attached to the mid-foot successfully classified MFC into the three sub-categories including (i) less than 1.5cm, (ii) 1.5-2.0cm and (iii) higher than 2.0cm. As the data were collected only from the six healthy young adults, the next phase of development requires larger data volume from different population groups including individuals with higher risk of tripping-related falls such as older adults, stroke survivors and people with pathological conditions (e.g. Parkinson's disease, dementia). In conclusion, the current study has provided important implications about predicting MFC heights and KNN has provided high accuracy (i.e. 84%) and quick computation time. While MFC prediction performance needs to be tested using other machine learning algorithms and populations, the results of this research provide support for application into control of movement assistive devices. Secondly, that vertical acceleration and the 'x' and 'z' components of the angular velocities are mostly related to the minimum foot clearance height.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.
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