A Rapid Detection of Parkinson's Disease using Smart Insoles: A Statistical and Machine Learning Approach

Luigi D'Arco
School of Computing
Ulster University
Belfast, Northern Ireland, UK
darco-l@ulster.ac.uk

Haiying Wang
School of Computing
Ulster University
Belfast, Northern Ireland, UK
hy.wang@ulster.ac.uk

Huiru Zheng*
School of Computing
Ulster University
Belfast, Northern Ireland, UK
h.zheng@ulster.ac.uk

Abstract*—Determining whether a subject has a gait impairment due to a disease or to the loss of muscularity due to advancing age is fundamental for an early diagnosis of musculoskeletal diseases. Parkinson's is the second most common neurodegenerative disease. The disease's most prevalent symptom is slow movement or sluggish gait, which can adversely impact the individual's quality of life. Generally, the gait analysis is carried out on long test sessions, which include for example long periods of walking, that cause inconvenience when the subjects under test have marked gait impairments. To help the diagnosis of Parkinson's disease, in this study we investigated the classification of Parkinson's disease by analysing only a few seconds of walking data using smart insoles, statistical analysis and machine learning techniques. The data from the smart insoles was assessed using correlation analysis. By creating pressure groups and analysing their values, it was found that the number of sensors could be reduced from 16 to 7. Furthermore, a feature vector representing the subject's gait was created by applying on the data a time windowing segmentation of 5 seconds and extracting six statistical features (mean, variance, skewness, kurtosis, energy and entropy). Four different models have been compared in terms of classification performance, reaching an F1-Score in the classification of patients with Parkinson's against healthy subjects, considering adult and elderly subjects as two separate classes, of 97.04% using the Random Forest. Such metric increased to 98.89%, using the K-Nearest Neighbours when healthy subjects were considered as a single class. The models' performance for each experiment was determined to be statistically equivalent, demonstrating the potential of this approach to provide the groundwork for the rapid detection of Parkinson's disease. Although the performance obtained is promising the number of subjects included in the study was fairly low, with a high bias towards the number of healthy subjects. Hence, in future work, the proposed solution will be tested on a larger cohort to ascertain its robustness.

***Index Terms*—Gait Analysis, Parkinson's Disease, Machine Learning, Smart Insole**

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I. INTRODUCTION

Human gait analysis is the study that assesses a person's locomotion, with the aim of understanding the effectiveness of the mechanisms of movements in individuals. Lower-limb muscles are activated during a person's stride, coordinated by the brain and neurons that allow the individual to maintain balance and move through space [1]. Gait analysis has historically been limited in its range of applications since it required a specialised laboratory and expensive equipment. However, recent advancements in technology have led to reliable, affordable, and compact sensors for gait analysis, enabling its application outside of a laboratory setting. Gait analysis has been applied in several sectors, including healthcare [2], security [3], and fitness [4] domains. According to the type of sensors involved and the methodologies chosen for assessing the gait, the available techniques can be classified into three main categories: image processing-based [5], floor sensors-based [6], and wearable sensors-based [7]. The image processing-based systems analyse the subject's gait using devices, such as cameras, infrared sensors and laser scanners. The floor sensors-based systems exploit pressure sensors placed on the floor or biomechanical devices, such as force plates that measure the force generated by the subject during a standing or a walking activity. The wearable sensors-based systems involve the use of small sensors located on the subject's body, such as inertial sensors. The most diffused solutions are the image processing based and the floor sensors-based, since the former is non-invasive and provides the expert a clear visualisation of events, and the latter provides high fidelity data about pressure applied to each anatomical region of the foot. However, these systems are generally very expensive and bulky which makes it impossible to integrate into real-time scenarios. Wearable sensors have been preferred to overcome these problems, as they allow high performance with a minimum cost and footprint, becoming the first choice in everyday life applications [8].

The locomotion of an individual can be influenced by accidents, ageing and neurological impairments. Pathological gait can significantly reduce the quality of life in terms of mobility and other psychological factors, especially in neurodegenerative disorders, which affect the motor neuron and lead to a loss of balance and movement ability [9].

Parkinson's disease (PD) is the second most common neurodegenerative disease after Alzheimer's Disease [10]. It causes a loss of the neuronal cell in the mid-brain substantia nigra pars compacta region and dopamine depletion in the striatum. It is characterised by hypokinetic movement, tremor, bradykinesia, and freezing, resulting in a decreased walking speed, stride length, and swing time, whereas, an increase in stride cadence and double support time [11].

As they age, people tend to develop problems related to walking, leading them to a lower level of quality of life with a consequent predisposition to falls. The main cause can be traced back to the loss of muscle mass and reduction of perception, such as vision and skin receptors. Reduced mobility mainly manifests itself in slow movements, swaying walking, and reduced stance phases and stride lengths [12].

The relationship between PD and ageing has been highly studied over the years, as the number of patients with PD grows exponentially with increasing age. There is currently no cure for PD and although a loss of neural cells in the substantia nigra has been identified for both PD and elderly patients, there is still no clear relationship between the two [13]. In terms of gait analysis, both according to the severity, present similar disorders. Therefore it is necessary to identify a baseline to distinguish the two pathologies starting from the gait impairments, in order to provide a correct classification.

Identifying a gait-related disease is a time-consuming practice. A doctor must analyse the patient's medical history, determine the tests to undergo and assess him/her visually. Gait-related disorders are more widespread as a result of an increase in life expectancy, which has led to a high workload for doctors [14]. Therefore, the goal of this research is to find automatic solutions that might make the diagnosing process easier for the doctor. In this regard, the introduction of machine learning for the analysis of patient data has rapidly gained research attention, because it can process large amounts of information, and it can determine patterns between similar patients by creating a baseline of the disease [15].

In this paper, we propose a machine learning and statistical approach for the differentiation of abnormal gait patterns from normal gait. Three groups of subjects have been included: Parkinson's patients (PD), Elderly subjects (ES) and Adult subjects (AS). Although PD and ES individuals, as well as ES and AS individuals, may occasionally overlap in terms of gait, the objective is to establish a baseline that enables them to be distinguished. A pair of smart insoles have been used for collecting data, which consists of sixteen pressure sensors, a tri-axis accelerometer and a tri-axis gyroscope. With the objective of identifying a fast and cost-effective solution, that can simplify the workload of a doctor, statistical analysis and machine learning have been employed to classify those conditions only by taking into account a few seconds of gait data. The following questions are addressed: Can machine learning-based classifiers accurately discriminate Parkinson's patients among healthy subjects? Can gait abnormalities be rapidly detected during a short walk, such as a few seconds? Can statistical features perform as well as gait parameters or perhaps better while taking much less time?

The remainder of the paper is organised as follows: the existing solutions in literature have been examined in Section II, which is followed by the strategy employed in this study in Section III. The findings are presented in Section IV. The paper concludes with a discussion of results and future work.

II. Related Work

The analysis of gait patterns for the recognition and treatment of neurodegenerative diseases has received a great deal of attention in recent years.

Alkhatib et al. [16] presented an approach to the early detection of Parkinson's disease. They extracted the ground vertical ground reaction forces (VGRFs) from 16 pressure sensors underneath the feet, eight per foot. Combining VGRFs with the age and speed of participants spatial and time analysed of data were analysed to distinguish gaits as balanced and unbalanced by using a linear decision boundary. The unbalanced gaits were referred to the subjects with Parkinson's disease and the balanced gaits were classified, in turn, into normal and disease subjects. A total of 47 participants were included in the study, 18 normal subjects and 29 Parkinson-affected patients. The overall accuracy achieved was 95%, stating that the proposed solution could provide the basis for designing real-time early detection of Parkinson's disease.

Açıcı et al. [17] exhibited an algorithm for the diagnosis of Parkinson's by exploiting ground reaction force sensors worn under the foot. Sixteen time-domain features were extracted from each sensor and 7 frequency-domain features. A Random Forest algorithm was employed to classify the data. Walking on a flat surface for two minutes was defined as the test set, and 166 participants were included in the study, including 93 Parkinson's disease patients and 73 healthy control subjects. The accuracy obtained by the proposed solution was 98.04%.

Mehra and Mittal [18] proposed an algorithm for the diagnosis of Parkinson's by utilising gait data generated from IoT-based wearable sensors. Three datasets were involved individually for the identification of healthy against Parkinson's patients, one consisting of recordings about subjects walking on level ground, one about subjects walking on a treadmill and one about moving at a comfortable place with RAS. A total of 73 healthy subjects and 93 subjects affected by Parkinson's have been evaluated. Eight pressure sensors have been included in a shoe as the only device for gait analysis. From each gait cycle, time, length, frequency temporal and force features were extracted and selected by applying a correlation analysis using the Spearman correlation coefficient and a reduction in data dispersion utilising the 95% confidence level. Random Forest has been used for classification. A five-fold cross-validation method was applied to achieve an Accuracy for each dataset of 95.54%, 98.80% and 94.52%, respectively, using the feature selection approach.

Li and Li [19] analysed the use of baseline machine learning models for the classification of Parkinson's patients. Including 306 participants, 214 Parkinson's disease patients and 92 healthy control subjects, they extracted the ground reaction forces (GRFs) from a two-minute level ground walking. The GRFs were extracted from eight pressure sensors placed underneath each foot. The data from the walking test were segmented using a window size of 80 seconds. Two machine learning models were developed, including a Logistic Regression model and a Support Vector Machine with radial basis function kernel, using the coefficients of variation extracted from the data collected. The accuracy achieved by the proposed solutions was 85% for the SVM and 81% for LR.

Carvajal-Castaño et al. [20] developed a novel framework to evaluate Parkinson's gait patterns using state-of-the-art deep learning algorithms. Three groups of subjects were involved in the study, for a total of 134 participants, including 45 Parkinson's disease patients (PD), 44 Young Healthy Controls (YHC), and 45 Elderly Healthy Controls (EHC). Three deep learning architectures were developed for the comparison analysis, a Convolutional Neural Network (CNN), a Gate Recurrent Unit (GRU) and a combination of them in which energy information are processed by the CNN and the temporal information by the GRU. The system was developed using only IMU Sensors, which involved a 3-axis accelerometer and a 3-axis gyroscope. Considering the pairs of groups, the CNN best accuracy achieved in classifying PD versus YHC was 82.7% and EHC was 82.4%. The GRU achieved an accuracy of 82.7% in classifying PD versus EHC, and 92.7% with YHC. The combination of both architectures provided almost the same performance with an accuracy of 83.7% and 92.7%, in the classification of PD versus EHC and YHC, respectively.

Despite these solutions producing excellent results, they demand extensive data collection, which may be impractical for individuals with severe mobility issues who cannot carry out a long-session test. This research aims to develop a classification method that only requires a smaller sample of data. Furthermore, these solutions heavily rely on the usage of pressure sensors, which are susceptible to errors when the surfaces or dynamics of data collection change. For this reason, inertial sensors were included in this study together with pressure sensors to produce more reliable results.

III. Methodology

A. Dataset

The dataset included in this study is the "Smart Insole v1.0 Dataset" provided by Chatzaki et al. [21]. The dataset comprised data collected from 29 participants from three separate groups, including Parkinson's disease patients, elderly people, and adult subjects. A smart insole was the only wearable device included for the collection of data, which was composed of 16 pressure sensors, a 3-axis accelerometer and a 3-axis gyroscope. Each participant had to complete two types of tests for data collection purposes: a Walking Straight and Turn test, and a modified version of the Timed Up and Go test [22]. Each session was recorded and evaluated by a neurologist specialised in movement disorders. The neurologist rated the performance of the participants using four items of the MDS-Unified Parkinson's Disease Rating Scale (MDS-UPDRS) [23]. The four items were arising from a chair, gait, freezing of gait and global spontaneity of movement.

To analyse and distinguish the various patterns that represent the unique conditions of the participants, in this study the attention was focused only on the walking activity. The walking data was taken from the Walking Straight and Turn test, but the different walking speeds (slow, normal, and fast) were treated as a single activity to offer a categorisation that did not take into account the user's walking speed. Two PD subjects were excluded from this study because they did not complete the Walking Straight and Turn Test. Table I summarises the number of participants, their demographic information, and their evaluated UPDRS gait score. which were reduced from the original dataset to 27 participants.

B. Dataset Analysis

The dataset used is made up of 44 different sensors, of which 22 per foot, divided into 16 pressure sensors and 6 inertia sensors. Selecting only the independent features that provide useful information for the classification of the conditions of the subjects, is a vitally important operation as it allows to eliminate those redundant features that can compromise the correct functioning of the algorithm. To meet this need, a statistical analysis of the correlation between the various features was defined. The analysis was carried out involving the Pearson correlation coefficient [24] which is a measure of linear correlation between two sets of data. Given a pair of samples generated by the sensors, the Pearson correlation coefficient (ρ) can be expressed as:

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} \tag{1}$$

where $cov(X,Y)$ is the covariance between the samples X and Y, and σ_X, σ_Y the standard deviations of X and Y, respectively. The value of ρ, can range between 1 and -1. If ρ is close to 1 then X and Y are positively correlated (high values of X are associated with high values of Y), instead, if ρ is close to -1 then X and Y are negatively correlated (high values of X are associated with low values of Y, and low values of X are associated with high values of Y). An evaluation criterion of ± 0.8 was set to assess the features that showed a strong correlation. By combining the various correlations, it was possible to discover the groups of features that had a high degree of similarity, and an approach based on the arithmetic mean between the samples of each group was used to reduce the number of features and eliminate the redundant ones.

Considering the objective of developing a rapid, cost-effective system and preserving the temporal spatiality of the data, a time window-based segmentation technique was used with a time window of 5 seconds.

This decision was made with the assumption that a completed gait cycle would be sufficient to reveal the subject's con-

TABLE I
PARTICIPANT DEMOGRAPHY

Group	No. Person	Age	Height (cm)	Weight (Kg)	Shoe Size (EU)	"MDS-UPDRS-3.10" Gait
Elderly (ES)	9	74 ± 12	172 ± 6	80 ± 8	42 ± 1	0.22 ± 0.42
Adult (AS)	13	38 ± 12	176 ± 6	81 ± 10	42 ± 1	0.15 ± 0.36
Parkinson (PD)	5	71 ± 6	175 ± 5	80 ± 6	42 ± 1	1.83 ± 0.90

*All the values are expressed as mean (μ) $\pm$ standard deviation (σ).

dition. Additionally, this decision was made after a thorough review of the literature on similar subjects, such as activity recognition, where data segmentation is frequently utilised. In order to lower the cost of the system and improve the classification rate while preserving the necessary amount of information for the classification, the size of the window is typically lowered to a smaller size, such as 2 seconds, while processing data from wearable sensors [25]. Aware of this, and that a person can complete a gait cycle in about 2.5 seconds, we concluded that 5 seconds was the ideal window size for including data from patients with disabilities who need additional time to perform such a task. In support of this hypothesis, different window sizes have been compared ranging from 3 to 7 seconds, finding that no statistical differences can be identified between them ($p_{value} > 0.05$ using the ANOVA analysis).

Generally, in literature, when a gait signal has to be flattened in a vectorise form the gait parameters are extracted (such as stride length, stride cadence, and single support percentage). Although these parameters have shown high reliability and performance [26], their use requires long data collection sessions and only with multiple strides can have valuable insights. Set the time window for this study to 5 seconds, we chose to use statistical features which, according to our hypothesis, can reach the same level of reliability as gait parameters. The statistical features are widely used for the analysis of data coming from the lower limbs and have allowed obtaining high performance in related research such as in human activity recognition applications [27]. Two kinds of features have been extracted, time-domain features and frequency-domain features. Time-domain features included mean, variance, skewness, and kurtosis, whereas, the frequency-domain features included energy and entropy which are extracted by converting the time-domain signal into frequency-domain by the use of the Fourier Transform.

Defined X as the independent variable vector, N as the number of samples in X, and F_i as the i-th Fourier transform coefficient, the statistical features can be described as follows:

- **Mean**: it represents the average of the samples; it is expressed as:

$$\mu(X) = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{2}$$

- **Variance**: it is a measure of the dispersion of how far the samples are spread out from their average value; it is expressed as:

$$\sigma^2(x) = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2 \tag{3}$$

- **Skewness**: it is a measure of the asymmetry of a distribution around its mean; it is expressed as:

$$s(x) = \frac{1}{N\sigma^3}\sum_{i=1}^{N}(x_i - \mu)^3 \tag{4}$$

- **Kurtosis**: it is a measure of how different a distribution's tails are from the tails of a normal distribution; it is expressed as:

$$k(x) = \frac{1}{N\sigma^4}\sum_{i=1}^{N}(x_i - \mu)^4 \tag{5}$$

- **Energy**: it is a measure of the strength of the sample; it is expressed as:

$$energy(x) = \sum_{i=1}^{N/2} F_i^2 \tag{6}$$

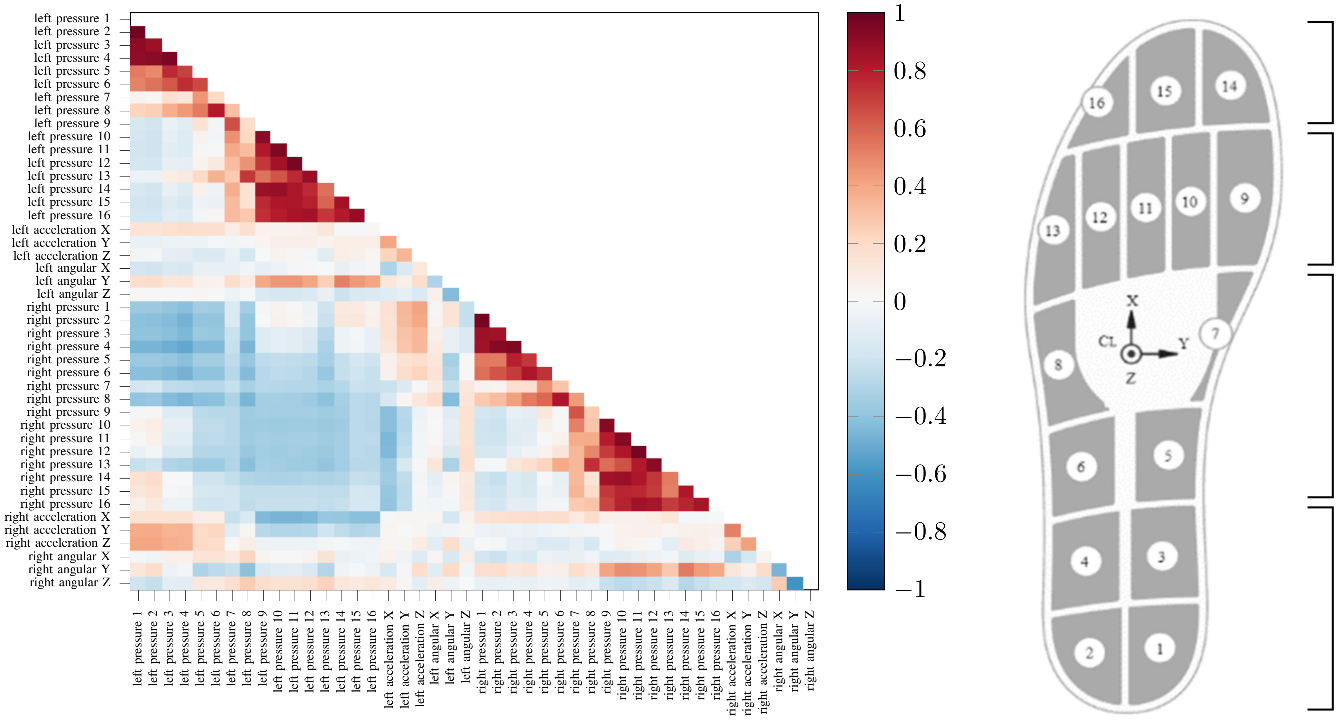
- **Entropy**: it is a measure of the average level of uncertainty; it is expressed as:

$$entropy(x) = -\sum_{i=1}^{N/2} F_i \log_2 F_i \tag{7}$$

C. Machine Learning Model

Machine learning and deep learning solutions for gait analysis in patients suffering from neurodegenerative diseases are the preferred ones in recent years as they allow to achieve, especially in classification, very high performance with very reliable results. However, by analysing the state-of-the-art solutions available, simple machine learning models produce better results than deep learning ones, as also stated by Tăuţan et al. in [28].

In this study, a total of four machine learning models (K-Nearest Neighbours, Linear Discriminant Analysis, Random Forest, and Support Vector Machine) have been evaluated to identify the optimal model for the classification of Parkinson's disease patients among healthy individuals, including elderly and adult subjects. The K-Nearest Neighbours (KNN) uses feature similarity to predict the values of new data points. The Euclidean Distance was used as the similarity function and the number of neighbours used was set to five. The Linear Discriminant Analysis (LDA) is a linear model used for classification and dimensionality reduction. It projects the



(a) (b)

Fig. 1. Analysis results for the reduction of the number of redundant sensors using the Pearson correlation coefficient. (a) Correlation matrix (b) Pressure sensors groups. The original pressure sensors map figure has been extracted from [21].

input data into a lower-dimensional vector space in a way to maximise the variability between the classes and reduces the variability within the classes. The Random Forest (RF) is an ensemble learning algorithm that classifies entities based on the majority votes across all the trees in the forest. The number of trees in the forest was set to 100 with no limitation on the depth of trees and the Gini function was used to measure the quality of the split. The Support Vector Machine (SVM) is a kernel-based algorithm that is remarkable for its ability to deal with high dimensional data making it suitable for pattern recognition. The kernel used in this study was the radial basis function (RBF).

To evaluate the performance of the classifiers and their robustness a stratified 10-fold cross-validation [29] has been used, which partitions the data into ten parts while maintaining the proportion of the samples belonging to the respective classes in the original dataset. One part is reserved for testing, while, the others are used for training. In addition, a set of metrics were identified to evaluate the solutions, including Accuracy (*Acc*), Precision (*Pr*), Sensitivity (*Se*), F1-Score (*F1*) and Area Under the Receiver Operating Characteristic Curve (*AUC*).

IV. Results and Discussion

This study proposed an effective and cost-effective solution for the early detection of Parkinson's disease patients along with adult and elderly people by using smart insoles.

Initially, 16 pressure sensors and 6 inertial sensors per foot were included to collect data and provide gait information. However using an analysis based on the Pearson correlation coefficient several sensors were found to be redundant with each other, as reported in Fig. 1a, and different groups were formed in which the values were more correlated. The results showed that the most correlated sensors are pressure sensors, so the analysis on reducing the number of sensors is mainly focused on the latter. Four areas of the foot have been identified: the front, the mid-high and mid-low and the back, as shown in Fig. 1b. The data coming from these areas have been merged using an average between them, except for the one belonging to the medium-low group which had low correlation values and therefore it was considered appropriate to leave them unchanged. In summary, the number of pressure sensors has been reduced from 16 to 7 for each foot, however, as regards the inertia sensors, no changes have been made.

Once the sensor redundancy analysis has been completed, the data in the dataset have been divided into segments of five seconds to preserve the spatio-temporal structure of the data and the statistical features have been extracted. Each segment and therefore each sample created using the statistical features included both the left and right foot, favouring a simultaneous analysis of both feet. The total number of features extracted was 156, which is given by the number of features (6) for each pressure sensor (7) and inertial sensor (6), for both feet.

Four machine learning models have been trained and tested

TABLE II
PREDICTION RESULTS FOR THE CONDITION CLASSIFICATION PROBLEM INCLUDING THREE COHORTS OF PARTICIPANTS: ELDERLY (ES), PARKINSON'S PATIENTS (PD), AND ADULT SUBJECTS (AS)

Model	Acc (%)	F1 (%)	ES			PD			AS		
			Pr (%)	Se (%)	AUC (%)	Pr (%)	Se (%)	AUC (%)	Pr (%)	Se (%)	AUC (%)
KNN	95.04	95.03	96.14	91.81	98.83	97.18	95.78	99.91	93.86	97.50	99.25
LDA	94.66	94.65	95.07	92.79	97.53	95.50	93.89	96.65	94.49	96.67	98.74
RF	97.05	97.04	96.89	95.71	99.31	99.00	96.89	99.93	96.90	98.33	99.64
SVM	96.69	96.63	96.49	96.14	99.57	97.33	91.67	99.93	97.24	99.17	99.78

*The performance metrics have been extracted from a stratified 10-fold cross-validation and averaged.

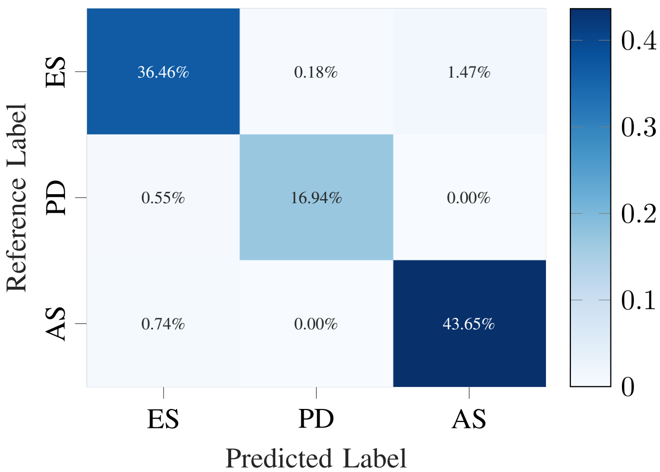


Fig. 2. Cumulative confusion matrix (expressed in percentage) obtained from the evaluation of Random Forest algorithm employing the stratified 10-fold cross-validation.

employing the stratified 10-fold cross-validation.

The performance of each model is reported in Table II. The Random Forest has been identified as the best model, with an accuracy of 97.05% and an F1-Score of 97.04%. Although RF is raised above other models, the models' performance is not statistically significant ($p_{value} > 0.05$ using ANOVA analysis), and their variations are solely dependent on random probabilities. These findings highlight the dependability of the dataset created and lay the groundwork for the definition of a rapid algorithm for the recognition of Parkinson's disease based on machine learning and smart insoles, which requires only 5 seconds of measurements.

A closer examination of the results presented in Table II and of the cumulative confusion matrix obtained from the Random Forest evaluation (shown in Fig. 2), reveals that the Parkinson's patients were correctly classified in nearly all the cases with a limited number of type I and type II errors reflected by the high values of Precision, 97.18%, and Sensitivity, 95.78%. Analysing the misclassifications of Parkinson's patients, the incorrect predictions mainly concern two patients whose ages are 76 and 79, respectively, whose severity grade when assessing the gait was identified as 1 on the UPDRS scale by neurologists specialised in movement disorders. Although both subjects are comparable to elderly subjects in both age and gait impairments, the proposed solution was able to correctly classify these patients, whose number of total samples for each one was on average 15, except for a sample which requires further investigation to ascertain the causes. The proposed solution encountered challenges while distinguishing the data from elderly individuals and adult subjects. The challenge was discovered, in particular, in elderly people who did not have gait impairment symptoms. However, for both the classes elderly and adult subjects, the precision and sensitivity were above 91%.

Taking into account these considerations, a new experiment has been carried out to assess the validity of the proposed solution for the classification of Parkinson's subjects against healthy subjects. Since the elderly and adult people can be considered as the same group that differ only in their age, they were treated as a single class for the sake of this experiment, the control subjects (CS). The findings of the experiment have been reported in Table III. The KNN model, which had an F1 score of 98.89% and an accuracy of 98.90%, turned out to be the best model, nevertheless, as in the previous experiment, the performance of the models is not statistically different ($p_{value} > 0.05$ using ANOVA analysis), reaffirming what was previously defined, namely that the dataset is robust and lays the groundwork for the creation of a rapid algorithm for the detection of Parkinson's disease. In this experiment, the separation between the classes has been increased, reducing the number of errors, however, there are still some misclassifications between PD and CS, that tracked refer to patients with Parkinson's disease whose gait disturbances were assessed in a range between 1 and 2 using the UPDRS scale by neurologists. Only one sample belonging to a control subject was misidentified as having Parkinson's, which had been determined to have a gait impairment grade of 1 on the UPDRS scale by neurologists. Overall, the proposed solution's error rate is low when compared to the number of samples per user, which require further investigation to determine the reasons.

In the original dataset paper [21], the results highlighted that with the use of the walking ratio parameter, namely the relationship between stride length and stride frequency, it is possible to distinguish between the various classes. The proper usage of this parameter, however, necessitates a prolonged data collection session; as a result, it cannot be employed in this study because it would violate the study's guiding principle, which is to minimise the amount of data required for classification.

The proposed solution has therefore proved to be reliable in

TABLE III
PREDICTION RESULTS FOR THE CONDITION CLASSIFICATION PROBLEM INCLUDING TWO COHORTS OF PARTICIPANTS: CONTROL SUBJECTS (CS), AND PARKINSON'S PATIENTS (PD)

Model	Acc (%)	F1 (%)	AUC (%)	CS		PD	
				Pr (%)	Se (%)	Pr (%)	Se (%)
KNN	98.90	98.89	99.86	99.13	99.56	97.98	95.78
LDA	97.05	97.07	98.33	98.23	98.21	92.34	91.89
RF	96.49	96.30	99.71	96.61	99.33	96.66	82.78
SVM	97.06	96.90	99.90	96.81	99.78	98.75	84.56

*The performance metrics have been extracted from a stratified 10-fold cross-validation and averaged.

recognising Parkinson's patients, and in differentiating them from both adult and elderly subjects. However, it is worth highlighting the limitations encountered during the study. First of all, the number of subjects included was low, with an imbalance towards adult and elderly subjects, since there were five patients with Parkinson's disease compared to thirteen adults and nine elderly subjects. The initial hypothesis of limiting the segment length to 5 seconds, so that at least a completed gait cycle was considered, has been proven to be effective and provided accurate results, however, the study could be extended to recognise a full gait cycle early and extract the statistical characteristics from that segment, which would favour the analysis of subjects that take longer to complete a gait cycle. Cases of misclassification were discovered to be related to elderly people and Parkinson's patients whose gait characteristics overlapped and had minor impairments. This emphasises the need to take into account in a future study the severity of the included subjects in the algorithm definition, in order to reduce errors. The number of statistical features extracted was the same for each signal produced by the smart insoles, however, a detailed analysis of the impact each feature has on the classifier will be carried out in future work to improve its performance.

V. CONCLUSION

Determining impairments in the normal locomotion of individuals provides objective insights from which a medical expert can design a treatment plan in situations such as neuromusculoskeletal diseases, traumas or ageing. In this research, a machine learning and statistical approach have been proposed to support gait analysis in the classification of Parkinson's patients against healthy subjects, by using data from a short walking session. Four machine learning models have been compared for the classification of Parkinson's disease. The Random Forest resulted to be optimal in the classification of the three subject groups (Parkinson's patients, elderly subjects and adult subjects) achieving an F1-Score of 97.04%. Considering the elderly and adult subjects as a single class, the performance obtained increased, identifying the K-Nearest Neighbours as the best one with an F1-Score of 98.89%. In conclusion, the presented solution is comparable and in some cases surpasses existing state-of-the-art solutions with the advantage of requiring only 5 seconds of data for classification. From the statistical analysis of the performance of machine learning models, it was possible to identify that their performances are comparable and that they differ only in terms of random fluctuations, which lays the foundation for the creation of a rapid and inexpensive Parkinson's disease recognition algorithm by means of smart insoles. Future research will make an effort to build a newer dataset with a large participant population while maintaining a balance between the cohorts. To evaluate each participant only on a completed gait cycle without concern for their length, dynamic estimation of the gait cycle length will be added. Eventually, a feature importance analysis will be performed to determine the influencing factors in the classification.

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REFERENCES

[1] R. Das, S. Paul, G. K. Mourya, N. Kumar, and M. Hussain, "Recent trends and practices toward assessment and rehabilitation of neurodegenerative disorders: Insights from human gait," *Frontiers in Neuroscience*, vol. 16, 4 2022.

[2] T. Zhu, Y. Wang, F. Tian, W. Wang, R. Zhong, H. Zhai, and S. Wang, "Clinical assessments and gait analysis for patients with trimalleolar fractures in the early postoperative period," *BMC Musculoskeletal Disorders*, vol. 23, no. 1, 2022.

[3] B. Mathivanan and P. Perumal, "Gait recognition analysis for human identification analysis-a hybrid deep learning process," *Wireless Personal Communications*, vol. 126, no. 1, p. 555 – 579, 2022.

[4] D. Xu, W. Quan, H. Zhou, D. Sun, J. S. Baker, and Y. Gu, "Explaining the differences of gait patterns between high and low-mileage runners with machine learning," *Scientific Reports*, vol. 12, no. 1, 2022.

[5] X. Wang, S. Feng, and W. Q. Yan, "Human gait recognition based on self-adaptive hidden markov model," *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 18, no. 3, p. 963 – 972, 2021.

[6] E. Panero, U. Dimanico, C. A. Artusi, and L. Gastaldi, "Standardized biomechanical investigation of posture and gait in pisa syndrome disease," *Symmetry*, vol. 13, 12 2021.

[7] Y. Saito, T. Ishida, Y. Kataoka, R. Takeda, S. Tadano, T. Suzuki, K. Nakamura, A. Nakata, S. Osuka, S. Yamada, M. Samukawa, and H. Tohyama, "Evaluation of gait characteristics in subjects with locomotive syndrome using wearable gait sensors," *BMC Musculoskeletal Disorders*, vol. 23, 12 2022.

[8] S. Subramaniam, S. Majumder, A. I. Faisal, and M. J. Deen, "Insole-based systems for health monitoring: Current solutions and research challenges," *Sensors*, vol. 22, 1 2022.

[9] J. Nonnekes, R. J. Goselink, E. Růzicka, A. Fasano, J. G. Nutt, and B. R. Bloem, "Neurological disorders of gait, balance and posture: a sign-based approach," *Nature Reviews Neurology*, vol. 14, pp. 183–189, 1 2018.

[10] A. A. Citarella, F. De Marco, L. Di Biasi, M. Risi, and G. Tortora, "Padd: Dynamic distance-graph based on similarity measures for go terms visualization of alzheimer and parkinson diseases.," *J. Vis. Lang. Comput.*, vol. 2021, no. 1, pp. 19–28, 2021.

[11] S. Chen, J. Lach, B. Lo, and G. Z. Yang, "Toward pervasive gait analysis with wearable sensors: A systematic review," *IEEE Journal of Biomedical and Health Informatics*, vol. 20, pp. 1521–1537, 11 2016.

[12] A. H. Snijders, B. P. Van De Warrenburg, N. Giladi, and B. R. Bloem, "Neurological gait disorders in elderly people: clinical approach and classification," *The Lancet Neurology*, vol. 6, no. 1, pp. 63–74, 2007.

[13] T. J. Collier, N. M. Kanaan, and J. H. Kordower, "Aging and parkinson's disease: different sides of the same coin?," *Movement Disorders*, vol. 32, no. 7, pp. 983–990, 2017.

[14] D. E. Lilienfeld and D. P. Perl, "Projected neurodegenerative disease mortality in the united states, 1990–2040," *Neuroepidemiology*, vol. 12, no. 4, pp. 219–228, 1993.

[15] Z. Obermeyer and T. H. Lee, "Lost in thought: the limits of the human mind and the future of medicine," *The New England journal of medicine*, vol. 377, no. 13, p. 1209, 2017.

[16] R. Alkhatib, M. O. DIab, C. Corbier, and M. E. Badaoui, "Machine learning algorithm for gait analysis and classification on early detection of parkinson," *IEEE Sensors Letters*, vol. 4, 6 2020.

[17] K. Açıcı, Ç. B. Erdaş, T. Aşuroğlu, M. K. Toprak, H. Erdem, and H. Oğul, "A random forest method to detect parkinson's disease via gait analysis," in *International conference on engineering applications of neural networks*, vol. 744, pp. 609–619, Springer Verlag, 2017.

[18] N. Mehra and P. Mittal, "Design and implementation of ml model for early diagnosis of parkinson's disease using gait data analysis in iot environment," *IJACSA) International Journal of Advanced Computer Science and Applications*, vol. 13, p. 2022, 2022.

[19] A. Li and C. Li, "Detecting parkinson's disease through gait measures using machine learning," *Diagnostics*, vol. 12, p. 2404, 10 2022.

[20] H. A. Carvajal-Castaño, P. A. Pérez-Toro, and J. R. Orozco-Arroyave, "Classification of parkinson's disease patients—a deep learning strategy," *Electronics (Switzerland)*, vol. 11, 9 2022.

[21] C. Chatzaki, V. Skaramagkas, N. Tachos, G. Christodoulakis, E. Maniadi, Z. Kefalopoulou, D. I. Fotiadis, and M. Tsiknakis, "The smart-insole dataset: Gait analysis using wearable sensors with a focus on elderly and parkinson's patients," *Sensors*, vol. 21, no. 8, 2021.

[22] D. Podsiadlo and S. Richardson, "The timed "up & go": A test of basic functional mobility for frail elderly persons," *Journal of the American Geriatrics Society*, vol. 39, no. 2, pp. 142–148, 1991.

[23] C. G. Goetz, B. C. Tilley, S. R. Shaftman, G. T. Stebbins, S. Fahn, P. Martinez-Martin, W. Poewe, C. Sampaio, M. B. Stern, R. Dodel, *et al.*, "Movement disorder society-sponsored revision of the unified parkinson's disease rating scale (mds-updrs): scale presentation and clinimetric testing results," *Movement disorders: official journal of the Movement Disorder Society*, vol. 23, no. 15, pp. 2129–2170, 2008.

[24] J. Benesty, J. Chen, Y. Huang, and I. Cohen, "Pearson correlation coefficient," in *Noise reduction in speech processing*, pp. 1–4, Springer, 2009.

[25] G. Wang, Q. Li, L. Wang, W. Wang, M. Wu, and T. Liu, "Impact of sliding window length in indoor human motion modes and pose pattern recognition based on smartphone sensors," *Sensors*, vol. 18, no. 6, 2018.

[26] H. Zheng, M. Yang, H. Wang, and S. McClean, "Machine learning and statistical approaches to support the discrimination of neuro-degenerative diseases based on gait analysis," in *Intelligent patient management*, pp. 57–70, Springer, 2009.

[27] L. D'Arco, H. Wang, and H. Zheng, "Assessing impact of sensors and feature selection in smart-insole-based human activity recognition," *Methods and Protocols*, vol. 5, no. 3, 2022.

[28] A. M. Tăuţan, B. Ionescu, and E. Santarnecchi, "Artificial intelligence in neurodegenerative diseases: A review of available tools with a focus on machine learning techniques," *Artificial Intelligence in Medicine*, vol. 117, 7 2021.

[29] X. Zeng and T. R. Martinez, "Distribution-balanced stratified cross-validation for accuracy estimation," *Journal of Experimental & Theoretical Artificial Intelligence*, vol. 12, no. 1, pp. 1–12, 2000.