Machine Learning Driven Classification of Neurological Disorders Affecting Human Gait: A Comparative Study

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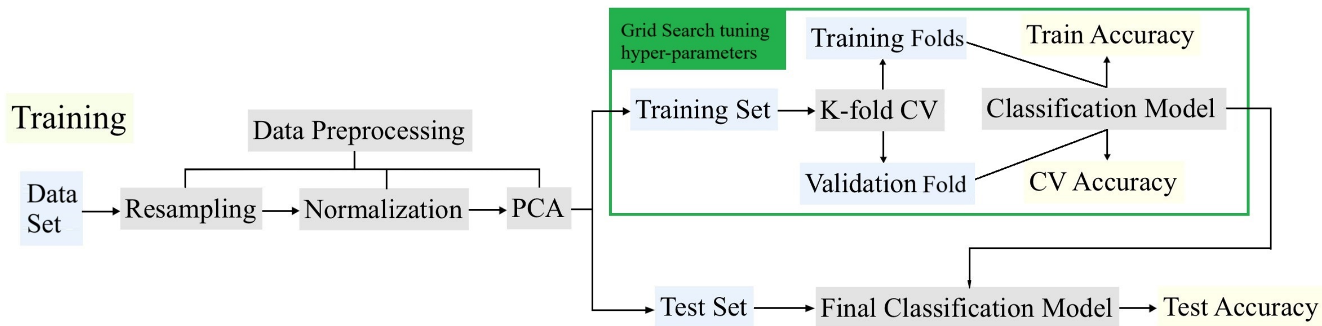

Figure 1: Training and Testing Framework of Gait Classifications Models.

1 Introduction

In a 2016 survey, mobility-related disabilities were found to be the most prevalent type, affecting 13.7% of non-institutionalized U.S. adults, with a particularly significant impact on the elderly population [9], which is a severe problem. Cerebellar Ataxia (CA) [3], Hereditary Spastic Paraplegia (HSP) [6], and Parkinson's disease (PD) [4] are 3 significant causes of damaged gait and mobility. However, diagnosing these diseases remains challenging, and it is widely agreed that analyzing gait characteristics offers a promising solution [3, 5, 6, 13]. A elementary part of it is identifying and distinguishing the gait patterns of these diseases, essentially a classification problem.

Currently, gait assessment in clinical settings primarily relies on subjective rating scales. However, instrumented gait analysis techniques and algorithms provide a more precise quantification of subtle gait characteristics that may go unnoticed during standard clinical examinations [3], which may help uncover deeper levels of gait information. Thus, machine learning driven classification algorithms can be applied with their advantages in feature extraction, flexibility, sensor integration and efficiency [7].

The aim of this project is to compare performance of different machine learning driven classification algorithms applied to gait analysis. In this project, gait classification is performed using different machine learning driven method, such as K-nearest neighbors (KNN), Support Vector Machines (SVM), Artificial Neural Networks (ANN), Random Forests (RF), and Ensemble methods, to categorize gaits into healthy, CA, HSP and PD. The inputs to the gait classifiers are 22 gait parameters of individuals, including anthropometric characteristics along with gait spatiotemporal and joint kinematics parameters. The output are corresponding labels of gait types.

2 Related Work

Recent advancements in gait analysis for PD and other neurodegenerative disorders have leveraged machine learning and deep learning techniques, showcasing significant improvements in classification accuracy and diagnostic potential across various methodologies.

Ajay et al. [1] propose a sensor-free deep learning system for automated Parkinsonian gait analysis using videos captured by everyday devices like smartphones, webcams, and surveillance cameras, achieving 93.75% accuracy in detecting Parkinsonian gait and 100% accuracy for healthy gait. Procházka et al. [11] present a novel method for classifying gait disorders, particularly PD, using MS Kinect image and depth sensors combined with Bayesian classification techniques, achieving a classification accuracy of 94.1%. Wahid et al. [14] used a multiple regression normalization strategy to account for patient physical properties and improve the classification of PD gait, achieving 92.6% accuracy with RF, and enhancing diagnosis and treatment using spatial-temporal gait data. Wan S. et al. [15] propose a deep multi-layer perception (DMLP) classifier for analyzing speech and movement patterns from smartphone data to estimate PD progression. Bilgin [2] uses Compound Force Signal (CFS) and Discrete Wavelet Transform (DWT) to extract features for classifying gait patterns of individuals with Amyotrophic Lateral Sclerosis (ALS), PD, Huntington Disease (HD), and healthy subjects, identifying key frequency bands for ALS discrimination through Linear Discriminant Analysis (LDA) and Naïve Bayesian Classifier (NBC). Ye et al. [16] presents an adaptive neuro-fuzzy inference system (ANFIS) optimized with particle swarm optimization (PSO) for identifying gait patterns in neuro-degenerative disease patients, demonstrating its effectiveness in characterizing gait dynamics with competitive classification results across ALS, PD, HD patients, and healthy controls (HCs). A Loya et al. [8] propose a machine learning-based approach for designing individualized gait rehabilitation devices by integrating gait classification, prediction, and generative synthesis of single-degree-of-freedom linkage mechanisms. Although they have done some comparison between different classification algorithms, they did not try Ensemble algorithm that works well [10] in classifying activities of daily living (ADLs), which may further leverage the strengths of different models and improve the accuracy of classification. That is what this project aims at.

3 Datasets/Environments

The dataset [12] contains gait parameters and lower limb joint kinematics from individuals affected by three types of degenerative neurological diseases: CA, HSP and PD. In addition, it includes a control group of healthy subjects, matched by gender, age, and walking speed. The dataset consists of 142 subjects in total: 77 patients (19 individuals with CA, 26 individuals with HSP and 32 individuals with PD) and 65 HCs. Each subject performed multiple walking trials (at least five per person), resulting in a substantial dataset with high variability.

The data contains 22 kinds of key elements, including spatio-temporal gait parameters such as step length, speed, cadence (number of steps per minute), step width, stance duration (time interval between two consecutive heel strikes of the same lower limb), swing duration (time interval between toe off and the next heel strike of the same lower limb), and double support duration (time interval with both feet on the floor). It also includes joint kinematic data for the hip, knee, and ankle joints in the sagittal plane, focusing on the range of motion during the gait cycle. Alongside these measurements, anthropometric characteristics, such as gender, age, weight, height, and specific diagnostic details for each patient, are provided. The data was collected using an opto-electronic motion capture system, ensuring accurate and high-quality recordings of each trial.

This dataset is well-suited for my gait classification task, as it contains an abundant and diverse set of gait patterns from both diseased and healthy individuals.

The dataset is divided into training and test set. The models are trained on the training set and the performance of the trained models is evaluated on the test set.

In summary, All 142 subjects with their respective 22-body and gait parameters form the input for our model. Given the input gait parameters, the problem is that of multi-class classification predicting the output class as CA, HSP, PD, or HC.

4 Methodology

4.1 Preprocessing

Since the dataset had an imbalance in the number of samples across different classes, a resampling technique should be applied by repeating the samples for classes with minimum frequencies. This method helped to balance the dataset by increasing the sample sizes of underrepresented classes, ensuring that each class had a roughly equal number of samples. Then an $n \times 22$ gait feature input matrix should be obtained, where n is the overall sample quantity. The output for the problem is a scalar label of n samples and is therefore of size $n \times 1$.

Following this, the input features are normalized using the L-2 norm. This normalization process ensured the models to weight them equally. To further reduce the necessary dimension of the data, Principal Component Analysis (PCA) is applied, still capturing most of the original variance in the top eight principal components. This reduction will improve the efficiency and performance of the learning algorithms.

4.2 Classification Models

The classification models used in the study should include 5 different machine learning approaches: K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Artificial Neural Networks (ANN), Random Forests (RF) and Ensemble methods.

(1) The KNN model classifies a data point by finding its K closest points in the training set and assigning it to the class most common among those neighbors.
(2) The SVM model employs a soft-margin approach with a radial basis function kernel to handle non-linear separability between classes.
(3) The ANN model uses a feed-forward structure and is trained using back-propagation and cross-entropy loss. After tuning, an optimal ANN structure should be selected, achieving enough accuracy.
(4) The RF model, an ensemble learning technique, uses enough decision trees with a maximum depth selected.
(5) Finally, other ensemble models can be applied by combining the predictions of multiple models to improve overall accuracy. For example, in a voting classifier, models like KNN, SVM and RF each make predictions, and the final prediction is based on the majority vote (or weighted vote) of these models. Since the dataset is not as abundant as that of some other research field, some learning methods may not have good performance, so different combinations might be beneficial.

The hyper-parameters of the models should be tuned through grid search, achieving enough validation accuracy. Grid search method can be applied since it is complete and the problem does not demand significant computational resources.

The overall training and testing framework is shown in Figure 1.

5 Evaluation

As shown in Figure 1, the evaluation metrics are determined through a systematic cross-validation approach, specifically using k-fold cross-validation. In this process, the training set is divided into 10 equal folds, where each fold is used as a validation fold while the remaining folds serve as the training folds, ensuring that each data point is tested exactly once. The model of each type achieving the highest accuracy across the cross-validation folds is selected. After hyper-parameter optimization and model selection, the final evaluation is conducted on a separate test set that was never used during cross-validation. Accuracy, defined as the ratio of correctly classified gait patterns to the total number of samples, serves as the primary performance metric.

The interested outcome of the evaluation part is the accuracy comparison between different classification algorithms.

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