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Machine Learning for Human Action Recognition Based on Kinect Skeleton Data

Faculty of Information Engineering, Computer Science and Statistics
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Abstract

This thesis conducts a detailed comparative study of several Machine Learning models, with a focus on their application to Kinect-based data for classifying human movements. The primary aim of this research is to evaluate these models to determine the most effective ones for accurately classifying movements recorded through Kinect sensors.

This study begins with a introduction to Kinect technology, highlighting its ability to capture detailed movement data. Following this, an examination of a range of Machine Learning models, such as Support Vector Machines, Random Forest, Linear Regression, and so on. Each model is tested to evaluate its accuracy, processing efficiency, and robustness in accurately classifying various movements.

The core of this comparative analysis is a diverse dataset consisting of several movements captured through a Microsoft Kinect. The research methodology involves several steps: processing the Kinect data, extracting key features that are characteristic of specific movements, and applying the selected models to this improved data. Performance evaluation of each model using standard metrics like accuracy, precision, recall, and the F1 score, which provide a complete picture of their effectiveness.

Over this study, valuable understandings are gained into the specific strengths and limitations of each model in the context of Kinect-based movement classification. The findings reveal that some models prove enhanced performance in certain situations, which is influenced by factors like the complexity of the captured movements and the characteristics of the dataset.

This thesis acts as a useful guide for researchers and professionals. It helps them pick the best models for similar work and sets the stage for more research in this area. This study contributes to the advancement of accurate and efficient Kinect-based data movement classification using Machine Learning methods, leading to more progress in this field.

Contents

Chapter 1

Introduction

This thesis is structured in the following way: **Chapter** 1 presents the problem statement, literature review, dataset overview and the aims and objectives of the study. **Chapter** 2 presents the data collection methodology, data structure and attributes, participants characteristics, movements visualization and data processing. **Chapter** 3 presents the methodology used in this study, including the models used, data splitting and feature engineering. **Chapter** 4 presents the evaluation metrics used, the results obtained and the discussion of the results. Finally, **Chapter** 5 presents the conclusions of this study and future work.

1.1 Problem statement

Traditionally, movement classification requires high quality sensors and and complicated computer vision algorithms. However, with the advent of the Microsoft Kinect sensor and the release of the Kinect SDK [9], it is now possible to obtain high quality 3D skeleton data with a relatively low cost device and with minimal effort. This opens up the possibility of using this data to classify movements performed by individuals, which can be used in a variety of applications, such as rehabilitation, sports, and fall risk assessment. In this thesis, the focus is on the latter, with the goal of using Kinect skeleton data to classify movements performed by elderly individuals.

1.2 Literature review

Overview of the literature on the topic of movement classification using Kinect data. Organize the papers you want to review and tell for every paper what is the main contribution and how it relates to your work.

1.3 Dataset overview

In this thesis, a dataset of Kinect skeleton data was used, provided by the PsyComp Lab. The dataset is composed of recorded movements performed by a group of 22 individuals. The movements were performed in front of a Kinect sensor, which recorded the movements and saved them as a series of 3D coordinates. The dataset contains 10 different movements, each performed a various number of times by each individual. The movements are listed in Table 1.1.

Table 1.1. Movements used in this study, along with a brief description.

No.	Movement Name	Description
1	Reach Overhead	In a standing position, the subject raises one of their arms above their head.
2	Chair to Chair	Starting from a sitting position, the subject stands up, then sits down on another chair.
3	Cross-Reach Left	In a standing position, the subject using their left arm reaches across their body to the right side.
4	Cross-Reach Right	In a standing position, the subject using their right arm reaches across their body to the left side.
5	Reach Forward	In a standing position, the subject reachs forward with one of their arms.
6	Hoop Walk	Starting from a standing position, the subjects walks inside a hoop placed on the floor and then walks out of it.
7	Right Leg Stand	In a standing position, the subject raises their left leg and holds it in the air for a few seconds.
8	Left Leg Stand	In a standing position, the subject raises their right leg and holds it in the air for a few seconds.
9	Mat Walk	Starting from a standing position, the subject walks over a mat placed on the floor and then off it.
10	TUG Walk	Starting from a sitting position, the subject is asked to stand up, walk 3 meters, turn around, walk back to the chair and sit down while being timed.

1.4 Objectives

In this thesis work the task that was se to be accomplished was to *classify movements using kinect skeleton data*, this task was divided into several objectives that would help to accomplish it. The objectives are described as follows:

1. Visualize and label the Kinect skeleton data using 3D plots animations.
2. Preprocess data to remove noise and outliers for better classification results.
3. Analyze different approaches for handling the data, such as using raw data or applying Feature Engineering techniques.
4. Implement and evaluate various Machine Learning models.
5. Conduct a comprehensive comparative analysis of the perfomance of the models based on evaluation metrics and execution time.
6. Provide insights into the interpretability of selected models, aiding in the understanding of the approaches used by the models to classify movements.

Chapter 2

Dataset analysis

In this chapter, the dataset used in this thesis is analyzed. The data collection methodology is described, along with the recording setup. The data structure and attributes are presented, along with the participants characteristics. Finally, the data processing steps are described.

2.1 Data collection methodology

Data used in this thesis was collected at the Waterford Hospital in Ireland as part of a Fear of Falling study conducted on a group of 22 elderly individuals. A Microsoft Kinect sensor was used to record the movements performed following a recording setup.

2.1.1 Microsoft kinect

Kinect sensor

Kinect skeletal tracking

2.1.2 Recording setup

The patient's data recording setup illustrated in Figure 2.1 consists of consumer-level hardware (a laptop, a Kinect v2 depth camera, an external webcam, and a smartphone) and a dedicated application developed within the project. Once launched, the operator can display a sample stimulus on an external monitor to show the target movements to the patient (*1. Stimulus playback*) so they can repeat (*2. patient performs movement*) them by selecting one of them from a list in the appplication. Then, by pressing the "*record*" button (*3. record/analyse skeleton + rgb + accelerometer*), the recording of the patient's full-body movement can be started. The application stores the recorded patient's movement files in a separate folders, naming them based on their patient ID, movement ID, and repetition ID.

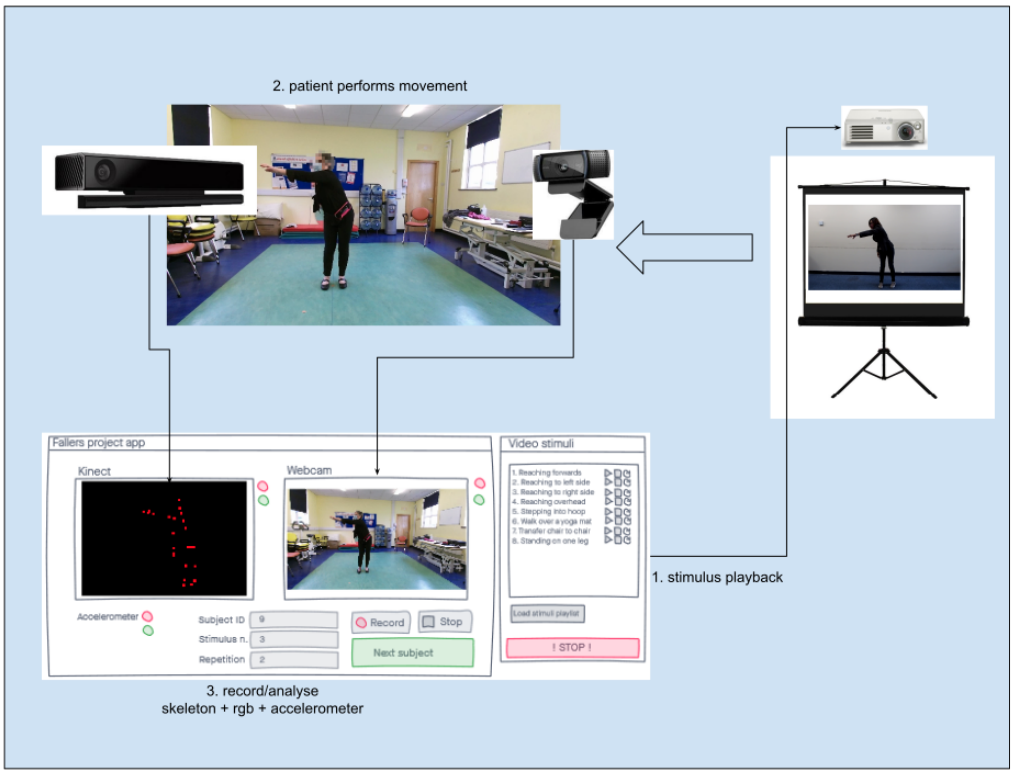


Figure 2.1. Kinect recording setup.

The full-body capture mainly relies on the PyKinect library [1]. The library provides functions for getting the patient's body segment's position and rotation 25 times per second. The application gets the data and stores it as a multi-dimensional time series (one per body segment and coordinate type) in CSV files like the one shown in Figure 2.2.

	A	B	C	D	E	F	G	H
1	timestamp	datetime	Head.state	Head.px	Head.py	Head.pz	Head.rx	Head.ry
2	1.666.953.978.8	2022-10-28_11:4	2.00	2371.34.00	9561.15.00	11735.38.00	0.00	0.00
3	1.666.953.979.2	2022-10-28_11:4	2.00	2783.25.00	9490.54.00	11698.14.00	0.00	0.00
4	1.666.953.979.3	2022-10-28_11:4	2.00	2958.20.00	9435.11.00	11708.02.00	0.00	0.00
5	1.666.953.979.4	2022-10-28_11:4	2.00	3033.29.00	9422.21.00	11713.33.00	0.00	0.00
6	1.666.953.979.4	2022-10-28_11:4	2.00	3144.00.00	9419.49.00	11742.47.00	0.00	0.00
7	1.666.953.979.5	2022-10-28_11:4	2.00	3249.39.00	9413.10.00	11751.10.00	0.00	0.00
8	1.666.953.979.6	2022-10-28_11:4	2.00	3339.20.00	9410.33.00	11758.34.00	0.00	0.00
9	1.666.953.979.6	2022-10-28_11:4	2.00	3415.19.00	9406.38.00	11768.52.00	0.00	0.00
10	1.666.953.979.7	2022-10-28_11:4	2.00	3483.13.00	9407.19.00	11760.25.00	0.00	0.00
11	1.666.953.979.7	2022-10-28_11:4	2.00	3529.38.00	9401.21.00	11753.20.00	0.00	0.00
12	1.666.953.979.8	2022-10-28_11:4	2.00	3569.21.00	9398.26.00	11725.32.00	0.00	0.00

Figure 2.2. Example of a CSV file containing the Kinect skeleton data.

The accelerometer is captured via a smartphone running an app streaming 3D gyroscope data at 50 frames per second. Again, the application on the computer stores it as a multi-dimensional time series (one per rotation axis). The communication between the smartphone and the computer is based on a wireless network and the Open Sound Control (OSC) protocol [15].

2.2 Data structure and attributes

Data used in this thesis consists of a series of CSV files, each containing 3D coordinates of the joints of a participant performing a movement. The total number of csv files is **637**. In Figure 2.3 the distribution of the csv files between the movements is presented with a median of **68** files per movement.

Figure 2.3. CSV files distribution between the movements. *M009* is the only movement with less than 68 files due to it not being performed multiple times by the participants.

Dataset is organized in a directory structure. Each patient has a folder named with their ID (*Patient-ID*) and inside there are 10 folders for each movement, named with the movement ID (*M-XXX*). For every movement folder there is a folder for each repetition of the movement, named with the repetition ID (*R-XXX*). Inside

each repetition folder there is a CSV file that contains the Kinect skeleton data. In Figure 2.4 an example of the directory structure is displayed.

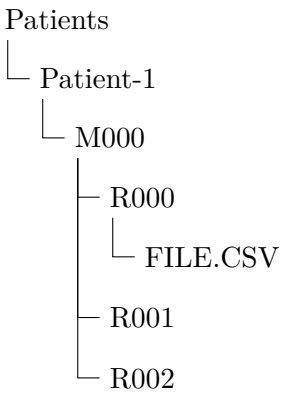


Figure 2.4. Directory structure example using the first patient and first movement in the dataset.

a CSV file is organized as a series of columns, each column represent a joint in Table 2.1 that the Kinect sensor records. Each joint is represented by 4 columns, one for each coordinate (x, y, z) and one for the state. The state column is used to indicate if the joint is trackd or not. Beside the joints columns, there are 2 columns for the timestamp and datetime of the recording.

Table 2.1. Joints recorded by the Kinect sensor.

Joints			
AnkleLeft	AnkleRight	ElbowLeft	ElbowRight
FootLeft	FootRight	HandLeft	HandRight
HandTipLeft	HandTipRight	Head	HipLeft
HipRight	KneeLeft	KneeRight	Neck
ShoulderLeft	ShoulderRight	SpineBase	SpineMid
SpineShoulder	ThumbLeft	ThumbRight	WristLeft
WristRight			

2.3 Participants characteristics

The participants that took part in the study were 22 elderly individuals, in Figure 2.5 the age distribution of the patients is presented, with a median age of 67 years.

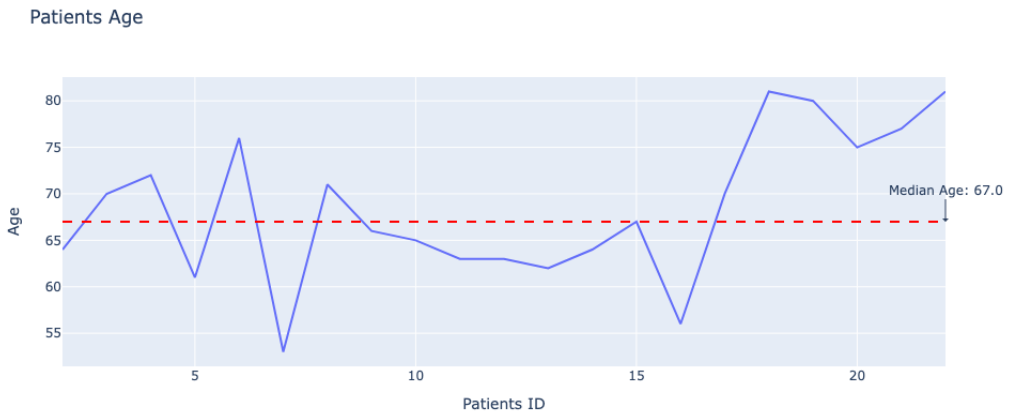


Figure 2.5. Age distribution of the participants.

In Figure 2.6 patients characteristics are presented. Fear of Falling is present in **57%** of the patients, this is a relatively high percentage, due to the study being conducted on a Fear of Falling assessment group. The patients gender is dominated by females with a **95%** of the patients, this is also expected since most studies in the literature had mostly female participants (>50%) [11]. The patients education is also presented, with the majority of the patients having a **Secondary** or **Third Level** education.

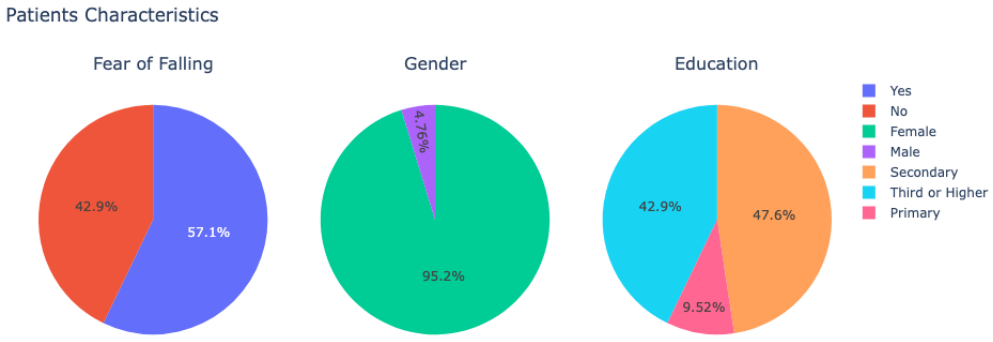


Figure 2.6. Age distribution of the participants.

What is fear of falling ?

The definition of **Fear of Falling** had various interpretations over the years. Initially, it was described as a phobic reaction to standing or walking. However, it was reclassified as a syndrome characterzied by the aftermath of a fall. As understanding developed, this fear was seen as a loss of confidence in one's balance ability. It was also further defined as an ongoing concern about falling, which leads to the avoidance of performing daily activities. Recently, it has been described as continous avoidance of activities due to the concern of falling. [10]

2.4 Movements visualization

Kinect-based data comes as a series of 3D coordinates, which can be visualized in 3D space. In this section, the implementation of the movements visualization is described. The visualization was implemented using the Python programming language and the Plotly library [8].

The first step in the visualization process is to identify the set of joints to be used. In this approach, the dataset contains 25 joints but only 16 joints are used and are shown in Table 2.2.

Table 2.2. Selected kinect joints used for the visualization.

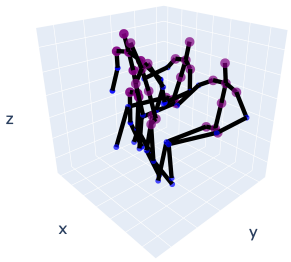
Joints		
Head	Spine Shoulder	Spine Mid
Spine Base	Shoulder Right	Elbow Right
Wrist Right	Shoulder Left	Elbow Left
Wrist Left	Hip Right	Knee Right
Ankle Right	Hip Left	Knee Left
Ankle Left		

The selected joints form toghether a skeleton, which is shown in Figure **??**. The skeleton is used to visualize the movements performed by the participants.

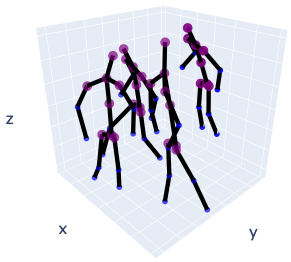
Once the joints are selected, the next step is to transform the data. In its original state the data is organized incorrectly for the 3D visualization, the y and z coordinates are inverted. To fix this, the y and z coordinates are swapped. The data is then transformed into a Pandas DataFrame, which is then used to create the 3D visualization.

```
            for index, row in data_transformed.iterrows():
                x_values = [row[f"{joint}.px"] for joint in joints]
                y_values = [row[f"{joint}.py"] for joint in joints]
                z_values = [row[f"{joint}.pz"] for joint in joints]
                lines = []
                for connection in connections:
                    start, end = connection
                    lines.append(
                        go.Scatter3d(
                            x=[row[f"{start}.px"], row[f"{end}.px"]],
                            y=[row[f"{start}.py"], row[f"{end}.py"]],
                            z=[row[f"{start}.pz"], row[f"{end}.pz"]],
                        )
                    )
```

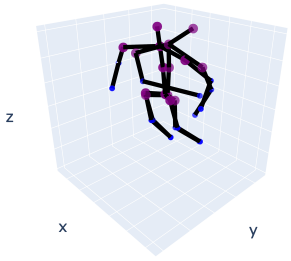
Listing 2.1. Traditional approach to splitting the data into training and testing sets.



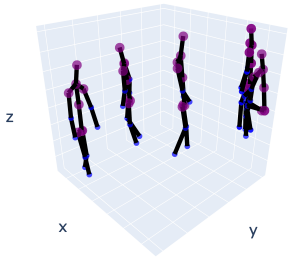
(a) Chair to Chair



(b) Hoop Walk



(c) Cross Reach Left



(d) Tug Walk

Figure 2.7. Main caption

In Figure 2.7 some of the movements performed by the participants are shown. The movements are shown in 3D, with the x, y, and z axes representing the coordinates of the joints.

2.5 Data processing

Original dataset containing the Kinect skeleton data was processed to remove noise and outliers. This process is needed to improve the classification results. The data processing steps are described in the following sections.

2.5.1 Cleaning

From the original dataset a process of cleaning the data was performed. Consisting of removing the columns that contained zero values and the ones that were not needed for the classification task. The columns that were kept are listed in the Table 2.2, only the positional coordinates were kept, the state columns and rotation columns (x, y, z) were removed due to not giving any useful information for the classification task.

2.5.2 Normalization

Pose normalization was performed using the formula described in [12] as follow:

$$P_{n,i}(x,y,z) = P_{n,i}(x,y,z) - P_{spinebase,1}(x,y,z) \tag{2.1}$$

Equation 2.1 is used to normalize the pose of a participant performing a movement. The pose is normalized by subtracting the coordinates of the Spine Base joint in the first frame from the coordinates of all the joints in the dataframe. This is done to remove the effect of the position of the participant in the recording setup and align all the frames to the same position.

2.5.3 Transformation

Once the data cleaning and normalization was performed, the data was transformed into a format that can used for a classification task. The data was transformed using the scikit-learn library [4], **MinMaxScaler** was used to scale the data between 0 and 1 then **StandardScaler** was used to standardize the data. After this process the data was ready to be used for a Machine Learning model.

Chapter 3

Methodology

In this chapter, the methodology used to split the data and train the models is presented. In addition, the fundamental concepts behind the models used are explained.

3.1 Overview of Models Analyzed

In this comparative study a total of ten popular models are selected for analysis of their perfomance on Kinect-based data.

3.1.1 Scikit-Learn

Scikit-Learn is a Python library designed for Machine Learning, it offers a wide range of *state of the art* algorithms for medium scale supervised and unsupervised problems. It emphasizes ease of use, perfomance, and API consistency, targeting non specialists with its high level approach. It stands out for its minimal dependecies and broad accessibility, being distributed under the simplified BSD license. It integrates well with the Python ecosystem, making it highly desirable for both academic and commercial applications [14].

3.1.2 Models Selection

The models presented in Table 3.1 are used for the classification task. Selected on a basis of popularity and performance, these models are widely used in the machine learning community. The models are implemented using the *scikit-learn* library and it's functions for training, testing and evaluating[4].

	Model Name		
1	Support Vector Machine	6	Linear Discriminant Analysis
2	Gaussian Naive Bayes	7	Multi-Layer Perceptron
3	Random Forest	8	K-Nearest Neighbors
4	Gradient Boosting	9	AdaBoost
5	Logistic Regression	10	Decision Tree

Table 3.1. Models selected for use in this thesis.

3.2 Analysis of Top-Performing Models

In this section the models that performed best in the Chapter 4 are analyzed. The models are analyzed in terms of their implementation.

3.2.1 Random Forest

Also known as *random decision forests*, is a method of ensemble learning used for classification, regression, and various other tasks. It involves building numerous decision tress during the training phase. In classification tasks, the class chosen by the majority of trees is the output of the random forest [7].

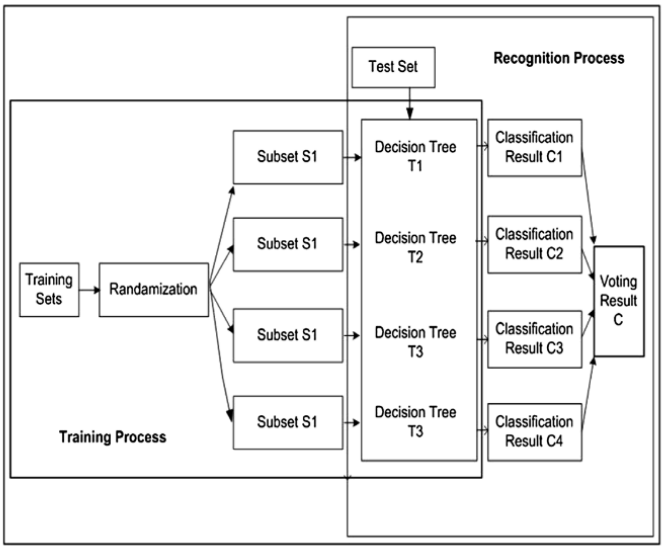


Figure 3.1. Random Forest Classifier architecture [13].

The main steps involved in building a random forest classifier are as follows:

1. Define M as the number of features in each subset.
2. Randomly select a feature subset θ_k from the full set, distinct from proceding subset $\theta_1, ..., \theta_{k-1}$.
3. Train decision trees on each θ_k denoted as $h(X, \theta_k)$.

4. Iteratively select new θ_k subsets and train untill all tress are built.

5. Classify test data by majority vote of all trees in the forest.

Random forests consist of numerous decision trees. Randomization in tree building—through sampling instances and feature subsets via bagging—enhances diversity, reducing overfitting and improving generalization. Feature subsets θ_k are chosen by bagging, and the importance of features is ranked by their impact on the model's accuracy. The "strength" and "correlation" of the forest are influenced by M, with optimal values providing a balance. The random forest's efficiency is due to its parallel structure, accelerating classification significantly [13].

3.2.2 Gradient Boosting

Gradient boosting is a machine learning method that refines predictions iteratively, combining the strengths of simple models, like decision trees, into a more accurate ensemble. Each iteration, represented by $F_m(x)$, improves upon the last by adding a weighted decision tree $\rho_m h_m(x)$ that addresses the previous errors. The process follows the *principle of gradient descent*, where $h_m(x)$ is trained to predict the negative gradient of the loss function, effectively reducin the residual between the predicted and true values. The ensemble begins with a single model $F_0(x)$, which is updated by the formula:

$$F_m(x) = F_{m-1}(x) + \rho_m h_m(x) \tag{3.1}$$

The aim is to minimize the loss function $L(y, F_m(x))$ at each step, ensuring the model's prediction become progressively more accurate [3].

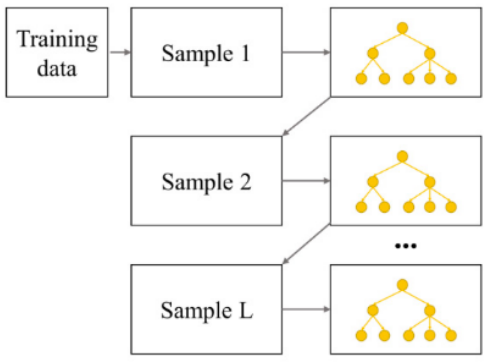


Figure 3.2. Gradient Boosting Classifier architecture [5].

3.2.3 Logistic Regression

Logistic Regression is a statistical method used for binary classification. It predicts the probability of a binary outcome based on one or more predictor variables.

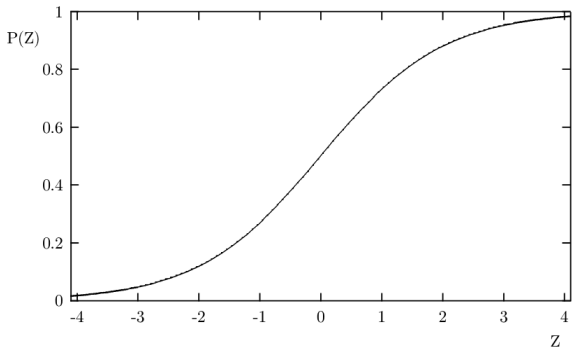


Figure 3.3. Logistic curve P(Z) [6].

3.2.4 Linear-Discriminant Analysis

Linear Discriminant Analysis (LDA) is a method used in statistics and machine learning to find a linear combination of features that separates two or more classes of objects or events. It does so by maximizing the ratio of between-class variance to the within-class variance in any particular data set, thereby ensuring maximum separability.

In the binary class, the goal is to find a linear combination w tjat separates the classes. This involves computing the mean vectors m_1 and m_2 for each class, the within class scatter matrix S_W, and the between class scatter amtix S_B. The linear discriminants are then the eigenvectors of $S_W^{-1} S_B$.

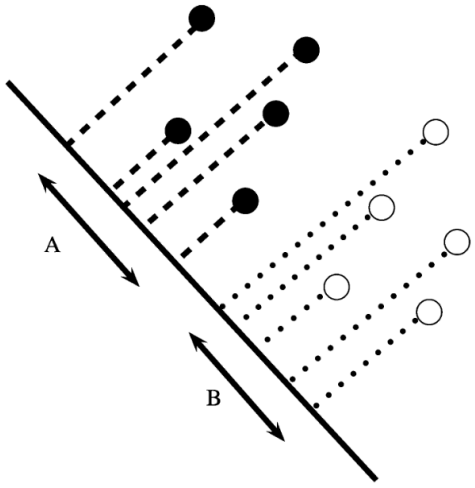


Figure 3.4. Linear Discriminant Analysis [16].

For multi class problems, the same principle applies but extends to multiple classes. The within class scatter matrix S_W and between class scatter matrix S_B are computed considering all classes, and the objective is to find the linear discriminants that maximize the separation among all classes.

The simplicity and effectiveness of LDA, especially under the assumptions of normality and equal class covariances, make it a powerful tool for classification [2].

3.3 Data Splitting Methods

Due to the structure of the data, the traditional approach of splitting the data into training and testing sets is not effective. Two different approaches will be presented, one ineffective and one effective.

3.3.1 Traditional

The data is split into 70% training and 30% testing following the traditional approach used in Machine Learning literature. The code snippet in 3.1 demonstrates this approach.

```
1    def split_data(data: pd.DataFrame) -> tuple:
2        # Extract features (X) and labels (y) from the input data
3        X = data.iloc[:, :-1].values
4        y = data.iloc[:, -1].values
5
6        # Split the data into training and testing sets
7        X_train, X_test, y_train, y_test = train_test_split(
8            X, y, test_size=0.33, random_state=42)
9
10       return X_train, X_test, y_train, y_test
```

Listing 3.1. Traditional approach to splitting the data into training and testing sets.

Figure 3.5 visualization demonstrates why this approach is ineffective. Every row in the dataset is associated with a specific patient. The data is split randomly, so there is a chance that the same patient will appear in both the training and testing sets. This means that the model will be trained on data that it will also be tested on, which will result in a high accuracy score. However, this is not a good indicator of the model's performance on unseen data.

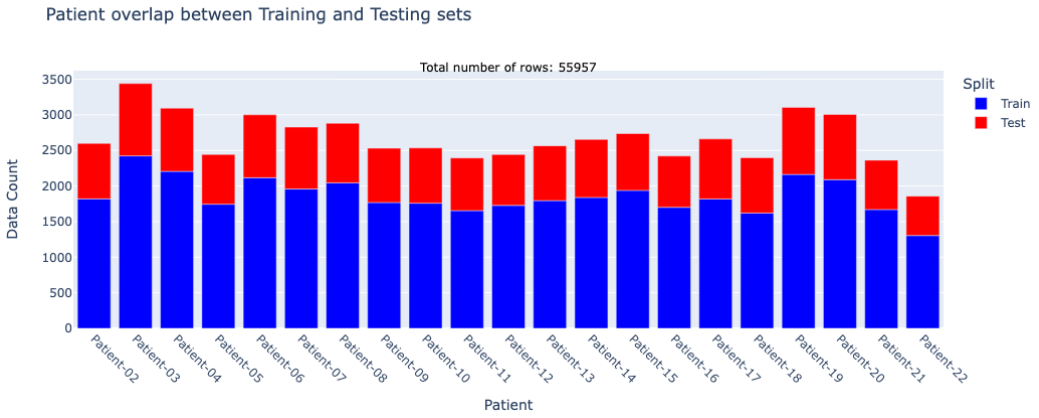


Figure 3.5. Visualization of the ineffective data splitting approach.

3.3.2 Effective

Data is split into training and testing sets based on the patient's unique ids. The patients are split into training and testing sets, and then the data is split based on the patient's unique ids. The code snippet in 3.2 demonstrates this approach.

```
1    def split_data(data: pd.DataFrame) -> tuple:
2        # Patient's unique ids is extracted
3        unique_patients = data['patient'].unique()
4
5        # Patient's unique ids are split into training and testing sets
6        train_patients, test_patients = train_test_split(unique_patients,
             test_size=0.3, random_state=42)
7
8        # Training and testing sets are created
9        train_data = data[data['patient'].isin(train_patients)]
10       test_data = data[data['patient'].isin(test_patients)]
11
12       X_train = train_data.drop(columns=['label', 'patient'])
13       y_train = train_data['label']
14
15       X_test = test_data.drop(columns=['label', 'patient'])
16       y_test = test_data['label']
17
18       return X_train, X_test, y_train, y_test
```

Listing 3.2. Effective approach to splitting the data into training and testing sets.

Figure 3.6 visualization demonstrates why this approach is effective. The data is split based on the patient's unique ids, so the model will be trained on data that it will not be tested on. This means that the model will be tested on unseen data, which is a good indicator of the model's performance.

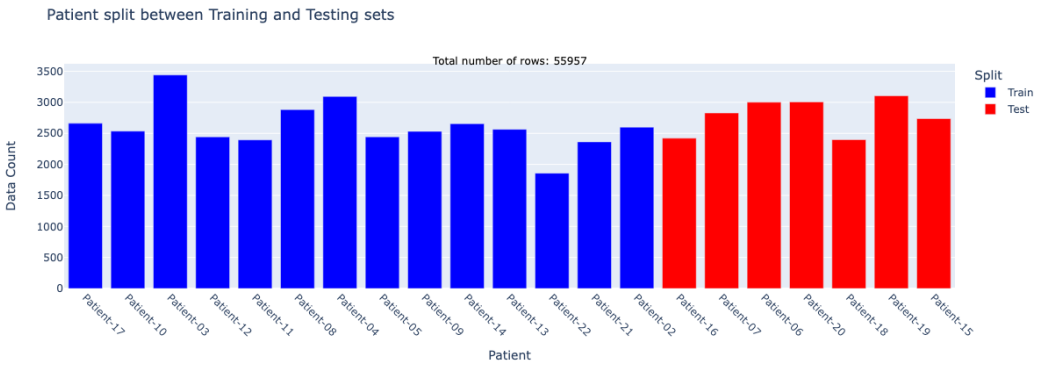


Figure 3.6. Visualization of the effective data splitting approach.

3.3.3 Sequential

Data is split into training and testing sets based on the patient's unique ids, then the sets are split into sequences. Where each sequence represents the stack of frames that make up a movement. The code snippet in 3.3 demonstrates the splitting into sequences of the data.

```
def sequences(df: pd.DataFrame, feature_columns: list,
    sequence_column: str) -> tuple:
    sequences = []
    labels = []
    current_sequence = []
    current_check = None

    for _, row in df.iterrows():
        check = row[sequence_column]
        label = row['label']
        if check != current_check and current_sequence:
            sequences.append(np.array(current_sequence))
            labels.append(label)
            current_sequence = []
        current_sequence.append(row[feature_columns].to_numpy())
        current_check = check

    if current_sequence:
        sequences.append(np.array(current_sequence))
        labels.append(label)

    return sequences, labels
```

Listing 3.3. Effective approach to splitting the data into training and testing sets.

Figure 3.7 visualization shows how for each movement the data is split into sequences for training and testing. However, using only this approach is not enough, as the sequences are of different lengths due to each movement having a variable number of frames. This means that the sequences cannot be used as input for the models since they require a fixed input size.

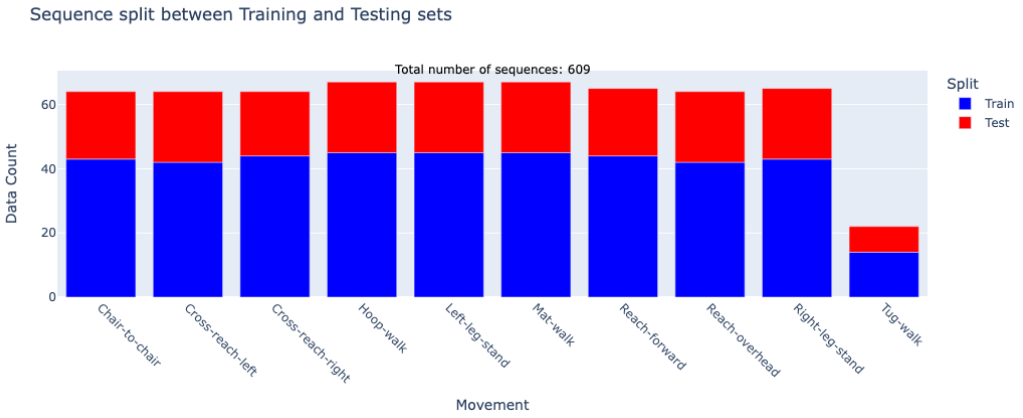


Figure 3.7. Visualization of the sequences splitting approach.

To solve the variable length problem, the sequences are aggregate into a single featurere vector. The code snippet 3.4 demonstrates this approach. In Figure 3.8, the length of the sequences before and after aggregation is visualized. The aggregation is done by calculating the mean of each feature for each frame in the sequence. This results in a single feature vector for each sequence, which can be used as input for the models.

```
1    def aggregate_features(sequences: list) -> np.ndarray:
2            return np.array([np.mean(sequence, axis=0) if sequence.size
                 != 0 else np.zeros(sequence.shape[1]) for sequence in
                 sequences])
```

Listing 3.4. Sequences are aggregated into a single feature vector.

However, there are some drawbacks to this approach. The aggregation results in a loss of information, as the data is no longer represented as a sequence of frames. In addition, the aggregation results in a loss of the temporal information, as the order of the frames is lost. This means that the models will not be able to learn the temporal patterns in the data.

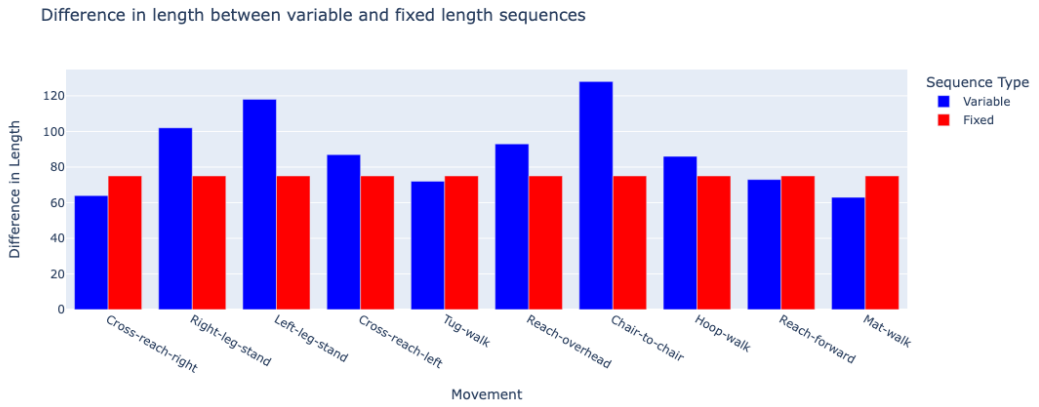


Figure 3.8. Visualization of the length of the sequences before and after aggregation.

3.4 Feature Engineering

Feature Engineering is the process of extracting features from raw data. In this thesis, the raw data is the Kinect Skeleton data, which is a series of 3D coordinates. The features extracted from the Kinect Skeleton data are presented in Table 3.2.

3.4.1 Overview

Features			
1	Duration	2	Area
3	Velocity	4	Distance
5	Displacement	6	Acceleration
7	Energy	8	Power
9	Directional Changes	10	CoM Trajectory
11	Peak Velocity	12	Peak Acceleration
13	Sway	14	Vertical Displacement
15	Forward Displacement	16	Jerk
17	Range of Motion		

Table 3.2. Features extracted from the Kinect Skeleton data.

3.4.2 Calculation Methods

Chapter 4

Results and Discussion

This chapter presents the result obtained from the expirements conducted in the previous chapter. Classification models are evaluated using different approaches and metrics. The results are then discussed and compared to each other.

4.1 Models evaluation

Performed using the *Scikit-Learn* library [4]. It provides a wide range of validation methods and metrics to evaluate the performance of the models. The following sections will present the validation methods and metrics used in this thesis.

4.1.1 Validation

Validation is the process of evaluating the perfomance of the models. The goal of validation is to estimate the performance of the model on new data, not used during the training process. The following validation methods are used:

Hold-Out

This method is widely used for for its simplicity and speed. The dataset is split into two subsets. The Training set is used to train the model, Testing set is used to evaluate the performance of the model. Typically, a common split ratio is:

- **Training set**: 70% of the dataset.
- **Testing set**: 30% of the dataset.

Cross-Validation

This method is used in the literature for its effectiveness and robustness. It can be time consuming for large datasets, but it is the best method to evaluate the performance of the models.

- **K-fold**: The data is divided into K folds, then *K-1* folds are used for training and the remaining fold is used for testing. This process is repeated K times,

with each fold being used exactly once for testing. The fig:kfold shows an example of a k-fold split. Fig 4.1 shows the KFold split.

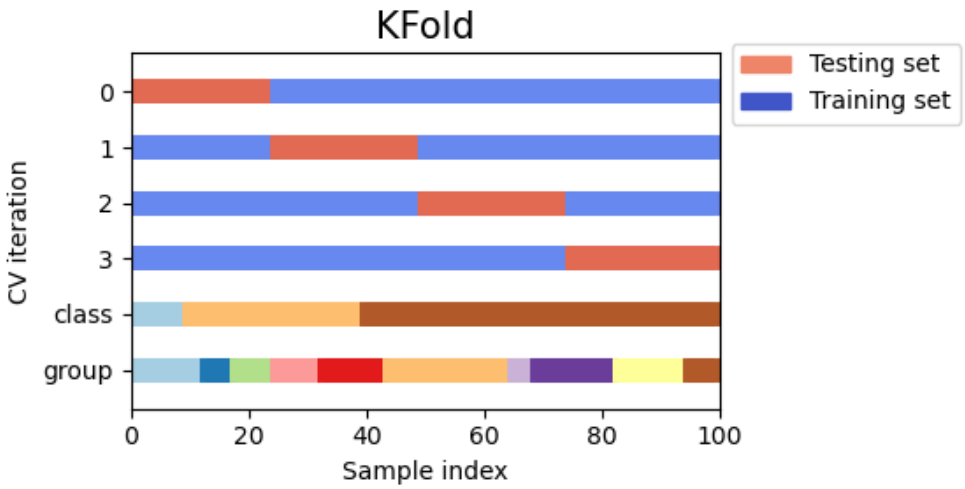


Figure 4.1. KFold Visualization from the scikit-learn documentation [14].

- **Group-k-fold**: Variation of k-fold designed for situations where the data has inherent groupings or dependecies that should be preserved in the train/test split. In this method, the data is divided into K folds, then an additional constraint is imposed to ensure that data point from the same group are in the same fold. Fig 4.2 shows the GroupKFold split.

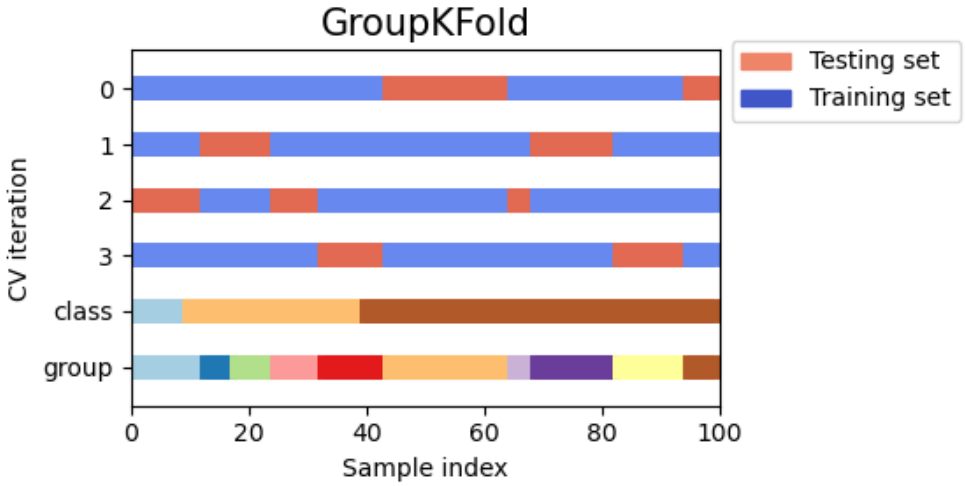


Figure 4.2. GroupKFold Visualization from the scikit-learn documentation [14].

The advantage of using *Cross-Validation* over *Hold-Out* is that all the samples are used for both training and testing, and each sample is used for testing exactly once. This method helps to reduce the variance of the estimated performance of

the model, by averaging the results over a number of trials. The disadvantage of using Cross-Validation is that it is computationally expensive for very large datasets.

In this study, both methods are used to evaluate the performance of the models. The Hold-Out method is used to evaluate the perfomance of the models for the *Wrong approach* and *Sequence approach* datasets due to their large dimension. The Cross-Validation method is used with the Hold-Out method to evaluate the perfomance of the models for the *Correct approach* and *Feature Engineering approach* dataset due to them scoring the best results and being the effective approaches. Confronting the results of the two methods will show the correctness of the evaluation, as the results should be similar.

4.1.2 Metrics

This section will report the metrics used to benchmark the different models used in this study.

Accuracy score

The *accuracy* is the proportion of correct predictions, considering both true positives and true negatives, among the total number of samples. The formula used to calculate the accuracy is the following:

$$\frac{TP + TN}{TP + TN + FP + FN} \tag{4.1}$$

where **TP** is the number of true positives, **TN** is the number of true negatives, **FP** is the number of false positives and **FN** is the number of false negatives.

Precision score

The *precision* is the ability of the classifier not to label as positive a sample that is negative. The formula used to calculate the precision is the following:

$$\frac{TP}{TP + FP} \tag{4.2}$$

Recall score

The *recall* is the ability of the classifier to find all the positive samples. The formula used to calculate the recall is the following:

$$\frac{TP}{TP + FN} \tag{4.3}$$

F1 score

The *F1 score* is the harmonic mean of the precision and recall. The formula used to calculate the F1 score is the following:

$$\frac{2 \times (precision \times recall)}{precision + recall} \tag{4.4}$$

Matthews correlation coefficent

The *Matthews correlation coefficent* (or φ coefficient) takes into account true and false positives and negatives and is regarded as a balanced measure which can be used even if the classes are of very different sizes. The formula used to calculate the φ coefficient is as follows:

$$\frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{4.5}$$

These metrics will be used to show the effectiveness of the approaches proposed in this thesis.

4.2 Results

Combining the validation methods and metrics presented above, the following tables will show the results obtained from the expirements conducted. The results are divided into two categories: **Exploratory** shows two approaches that were tested but did not obtain good results due to wrong implementation or loss of information. **Effective** shows two approaches that obtained good results and are suitable for this task. The results are presented in the following order: *Traditional approach*, *Sequence approach*, *Effective approach* and *Feature Engineering approach*.

4.2.1 Exploratory

The following approaches are included because they are a starting point in this thesis, and show how different implementations can affect the accuracy of the models.

Traditional approach

Pesented in Section 3.3.1, it was the first one to be tested and it got surprisingly good results. Such a simple approach and yet high accuracy raised doubts about the validity of the results, after further investigation it was discovered that the dataset was not properly split into training and testing sets.

Table 4.1. Evaluation results using **Hold-Out** validation method.

Model	Accuracy	F1	Recall	Precision	MCC
Random Forest	**0.99**	**0.99**	**0.99**	**0.99**	**0.99**
K-Nearest Neighbors	0.98	0.98	0.98	0.98	0.98
Decision Trees	0.96	0.96	0.96	0.96	0.96
Support-Vector Machines	0.87	0.86	0.85	0.86	0.86
Logistic Regression	0.82	0.80	0.80	0.80	0.80

In Table 4.1 the results obtained from the Hold-Out method are displayed. High values are obtained for all the metrics, with **Random Forest** obtaining the highest values with a score of **0.99** for accuracy. This confirmed the doubts about the validity of the results, a patient is both present in the training and testing set. This led to the models overfitting the data and obtaining high accuracy.

Sequence approach

Presented in Section 3.3.3, it achieved the lowest results of all the approaches. Tested to see if by concatenating the frames of a movement into a sequence would help the models differentiate between movements and obtain a higher accuracy.

Table 4.2. Evaluation results using **Hold-Out** validation method.

Model	Accuracy	F1	Recall	Precision	MCC
K-Nearest Neighbors	**0.56**	**0.54**	**0.54**	**0.54**	**0.51**
Random Forest	0.55	0.52	0.53	0.53	0.49
Support-Vector Machines	0.52	0.47	0.49	0.46	0.47
Logistic Regression	0.44	0.41	0.42	0.43	0.38
Decision Trees	0.41	0.38	0.39	0.40	0.34

In Table 4.2 the results obtained from the Hold-Out method are displayed. Low values are obtained for all the metrics, with **K-Nearest Neighbor** obtaining the highest values with a score of **0.56** for accuracy. This results are considered low based on other approaches, however in the context of randomly guessing the movement of a patient the accuracy would be **0.10** as there are 10 movements. This means that the models are able to differentiate between movements, but the sequence implementation leads to a loss of information and a high accuracy cannot be obtained.

4.2.2 Effective

The following approaches are the ones that obtained the best results and are suitable for this task. The main difference between the two approaches is the data used to train the models. The *Correct Approach* uses the data as it is from the Kinect sensor, while the *Feature Engineering Approach* uses the data after applying feature engineering techniques.

Correct approach

Presented in Section 3.3.2, considered effective because the raw kinect data is able to obtain a high accuracy. The data is not modified in any way, beside the removal of rotational , state and pre-processing the data to remove noise and outliers.

In Table 4.3 the results obtain from the Hold-Out method are shown. **Random Forest** obtains the highest values for all the metrics, with a score of **0.74** for accuracy. Other models such as *Gradient Boosting*, *Linear Discriminant Analysis*, *Support-Vector Machines*, *K-Nearest Neighbors* obtained great results as well with a score greater than **0.70** for accuracy. This confirms that the data obtained from the Kinect sensor is suitable for the task of movement classification without any major tweaks.

Table 4.3. Evaluation results using **Hold-Out** validation method.

Model	Accuracy	F1	Recall	Precision	MCC
Random Forest	**0.74**	**0.73**	**0.73**	**0.73**	**0.71**
Gradient Boosting	0.73	0.72	0.72	0.72	0.69
Linear-Discriminant Analysis	0.72	0.71	0.71	0.74	0.68
Support-Vector Machines	0.71	0.71	0.71	0.72	0.68
K-Nearest Neighbors	0.71	0.69	0.69	0.70	0.67
Logistic Regression	0.66	0.64	0.64	0.64	0.62
Multi-Layer Perceptron	0.63	0.59	0.62	0.61	0.59
Naive Bayes	0.63	0.60	0.61	0.62	0.58
Decision Trees	0.63	0.60	0.62	0.61	0.58
Ada Boost	0.35	0.22	0.28	0.24	0.32

In Table 4.3 **Hold-Out** validation method was used for all the models, while in Table 4.4 **Cross-Validation** was used with only 3 models to compare the two validation methods and show that there is no major difference between them. The results obtained from the two methods are similar.

Hold-Out method was used for it's speed, with **10 minutes** of training time while cross-validation run for hours without finishing. This is due to the fact that this approaches use the raw Kinect data, that contains over **59000** rows and **100** columns.

Table 4.4. Comparison of obtained results with Cross-Validation and Hold-Out methods. The metrics reported are (from top to bottom): Accuracy, F1, Recall, Precision, MCC.

Model	Cross-Validation	Hold-Out
Linear Discriminant Analysis	0.73	0.72
	0.71	0.71
	0.70	0.71
	0.75	0.74
	0.70	0.68
K-Nearest Neighbors	0.71	0.71
	0.70	0.69
	0.70	0.69
	0.71	0.70
	0.68	0.67
Naive Bayes	0.66	0.63
	0.62	0.60
	0.63	0.62
	0.66	0.61
	0.62	0.58

In Table 4.5 are displayed the results of a final approach, where two movements *Mat-Walk* and *Hoop-Walk* are removed from the dataset one at a time. The results show that the accuracy of the models increased by **4%** to **5%**. This is due to the

fact that the two movements are very similar, and this caused the models to struggle to differentiate between them no matter the features used.
By removing either one of the movements, the models accuracy increased by the same amount. This leaves the decision to the user to choose which movement to remove based on the context of the application.

Table 4.5. Comparison of obtained results with Mat-Walk and Hoop-Walk removed from the dataset. The metrics reported are (from top to bottom): Accuracy, F1, Recall, Precision, MCC.

Model	Hoop Walk Removed	Mat Walk Removed
Random Forest	0.79	0.79
	0.79	0.79
	0.79	0.79
	0.79	0.79
	0.76	0.76
Gradient Boosting	0.78	0.78
	0.78	0.78
	0.78	0.78
	0.78	0.79
	0.74	0.75
Linear-Discriminant Analysis	0.76	0.76
	0.77	0.77
	0.76	0.76
	0.80	0.79
	0.73	0.73

Feature engineering approach

Presented in Section 3.4, considered the most effective because it obtained the highest accuracy of all the approaches and it is the fastest to train. The data is modified by applying feature engineering techniques, this leads to the dataset having less rows and columns.

Table 4.6. Evaluation results using **Cross-Validation** method.

Model	Accuracy	F1	Recall	Precision	MCC
Linear-Discriminant Analysis	**0.82**	**0.82**	**0.83**	**0.84**	**0.81**
Logistic Regression	0.82	0.83	0.83	0.84	0.80
Multi-Layer Perceptron	0.79	0.80	0.80	0.82	0.77
Gradient Boosting	0.78	0.79	0.79	0.82	0.76
Random Forest	0.76	0.77	0.78	0.80	0.74
Support-Vector Machines	0.75	0.75	0.76	0.78	0.72
K-Nearest Neighbors	0.73	0.73	0.74	0.75	0.70
Decision Trees	0.67	0.67	0.69	0.69	0.64
Naive Bayes	0.66	0.65	0.68	0.69	0.63
Ada Boost	0.36	0.27	0.35	0.29	0.31

In Table 4.6 the results obtained from the Cross-Validation method are displayed. High values are obtained for all the metrics, with **Linear Discriminant Analysis** and **Logistic Regression** obtaining the highest values with a score of **0.82** for accuracy. Other models such as *Multi-Layer Perceptron*, *Gradient Boosting*, *Random Forest*, *Support Vector Machines*, *K-Nearest Neighbors* obtained great results as well with a score greater than **0.70** for accuracy.

Table 4.7. Comparison of obtained results with Cross-Validation and Hold-Out methods. The metrics reported are (from top to bottom): Accuracy, F1, Recall, Precision, MCC.

Model	Cross-Validation	Hold-Out
Linear Discriminant Analysis	0.82	0.81
	0.82	0.81
	0.83	0.81
	0.84	0.82
	0.81	0.79
Logistic Regression	0.82	0.78
	0.83	0.79
	0.83	0.79
	0.84	0.79
	0.80	0.75
Gradient Boosting	0.78	0.76
	0.79	0.77
	0.79	0.78
	0.82	0.79
	0.72	0.73

This confirms that the feature engineering techniques applied to the data are suitable for the task of movement classification. This approach is also the fastest to train, with a training time of **1 minute**.

Table 4.7 shows the results obtained from the Hold-Out validation method. Similar to the ones obtained with Cross-Validation method, with a lower training time of **10 seconds**. However, Cross-Validation is preferred over Hold-Out because it is more used in the literature and robust.

In Table 4.8 are displayed the results of the final approach used in the Correct approach. The results show that the accuracy of the models increased by **8%** to **12%**. This is a larger increse than the one obtained in the Correct approach, this is due to the fact that the feature engineering techniques applied are more informative than the raw Kinect data. Leading to the models being able to differentiate between the two movements more easily.

Table 4.8. Comparison of obtained results with Mat-Walk and Hoop-Walk removed from the dataset. The metrics reported are (from top to bottom): Accuracy, F1, Recall, Precision, MCC.

Model	Hoop Walk Removed	Mat Walk Removed
Linear Discriminant Analysis	0.94	0.93
	0.94	0.93
	0.94	0.93
	0.95	0.94
	0.93	0.93
Logistic Regression	0.90	0.90
	0.91	0.90
	0.91	0.90
	0.92	0.92
	0.89	0.89
Multi-Layer Perceptron	0.90	0.89
	0.90	0.90
	0.91	0.90
	0.92	0.91
	0.89	0.88

4.3 Discussion

This section will discuss the results obtained from the expirements conducted in the previous chapter. The difference between the approaches, the best performing models and the similarity between movements will be the topic of discussion.

Differences between approaches

Four approaches were tested in this thesis, each one with a diffrent implementation. It was presented that *Feature engineering* obtained the best results in terms of accuracy and training time. However, the *Correct approach* also obtained great results but it was laking in training time. These two approaches were considere the most effective and suitable for the task of movement classification. Nevertheless, their implementation is completely different, with one using the raw Kinect data containing a very large number of rows and columns, while the other uses the data after applying feature engineering techniques transforming the data into a more informative dataset. This demonstrates how the approach used to solve a problem can affect the results obtained. The others two approaches *Wrong approach* and *Sequence approach* prove that an incorrect data splitting method and a loss of information can lead to low accuracy. Their implementation is not suitable for this task but were a crucial step in the development phase to better understand why the models were not performing well.

Best performing models

The models listed below obtained the best results in the two approaches considered effective.

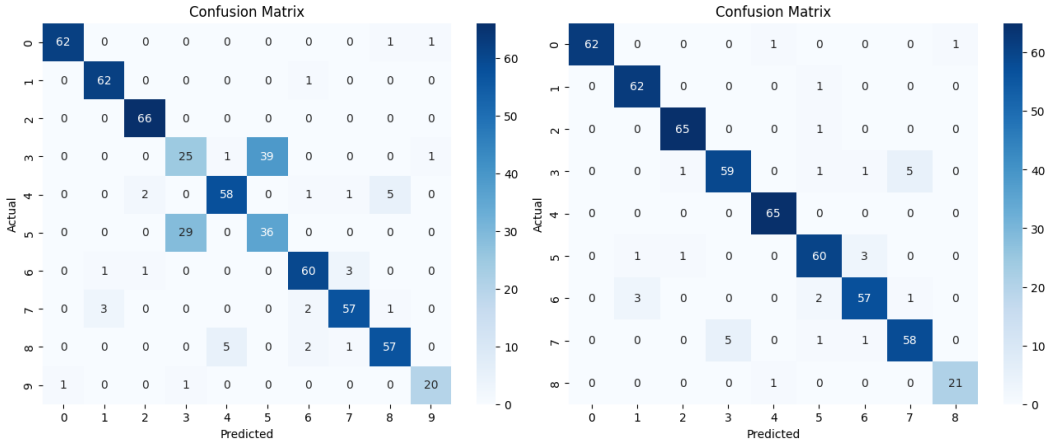
1. **Random Forest** and **Gradient Boosting** are the two best performing models in the *Correct approach* with a **0.74** and **0.73** accuracy score respectively.
2. **Linear Discriminant Analysis** and **Logistic Regression** are the two best performing models in the *Feature engineering approach* with both scoring a **0.82** accuracy score.

The results above demonstrate how the models perform differently depending on the approach used, due to the fact that the used to train the models is of different dimension and information.

Movements similarity

It was demonstrated in Table 4.5 and Table 4.8 that by removing *Mat-Walk* and *Hoop-Walk* from the dataset, the accuracy of the models increased.

This problem was first noticed when the confusion matrix was plotted for the *Feature enginerring* approach using the *Linear-Discriminant Analysis* model. In Figure 4.3a the Confusion Matrix of all 10 movements is displayed, the model is struggling to differentiate between movement 3 and 5 (Mat-Walk and Hoop-Walk). In Figure 4.3b one between Mat-Walk and Hoop-Walk is removed, the model does not struggle anymore to differentiate between the two movements.



(a) 10 Movements. **(b)** 9 Movements.

Figure 4.3. Confusion Matrix of Linear-Discriminant Analysis model using Feature Engineering approach.

To confirm this, *3D Visualization* of the movements used in Section 2.4 was used. A random sample of *Mat-Walk* and *Hoop-Walk* was plotted, in Figure 4.4a and Figure 4.4b the two movements are displayed. The two movements are very similar due to the fact that they are both walking movements, the only difference is that in *Mat-Walk* the patient is walking on a mat while in *Hoop-Walk* the patient is walking in a hoop. This is the reason why the models struggle to differentiate between the two movements.

(a) Hoop-Walk Movement. **(b)** Mat-Walk Movement.

Figure 4.4. 3D Visualization plots of the two similar movements.

Chapter 5

Conclusions

This chapter presents the key findings of the thesis, highligthing its limitations and review potential approaches for future research to improve the results and develop more effective models.

5.1 Discoveries

Presented below are the key findings of this thesis:

1. *Preprocessed raw data* obtained from the Kinect sensor is suitable for the task of movement classification. However, it alone does not provide enough information for the models to obtain a high accuracy.

2. *Feature engineering* is a crucial process of creating new features from the raw data with the goal of improving the accuracy and training time of the models.

3. *Linear Discriminant Analysis* is the best perfoming model for this task, with a score of **0.82** using 10 movements and **0.94** using 9 movements after removing one of the similar movements and using a feature engineering approach.

4. *Data splitting* tecniques are an essential step in the process of training the models, an incorrect split can lead to overfitting and an incorrect evaluation. Using the "Patient-ID" as a split criteria is the best approach to avoid any data leakage between the training and testing sets.

5. *Sequence of frames* is not a good approach to take for this type of data, due to every movement having a variable number of frames and Machine Learning models need a fixed length input. Transforming the data into fixed length sequences will lead to a loss of information and a decrease in accuracy.

6. *3D visualization* of the movements allow to visually identify and label them. It was found that "Mat-Walk" and "Hoop-Walk" movements are very similar, with the only difference being the object that the patient is walking over. This led to the models struggling to differentiate between these two movements and by removing one of them from the dataset the accuracy of the models improved.

5.2 Limitations

Limitations encountered in this work will be presented, along with an exploration of their impact and the strategies used to overcome them.

A list of 10 movements names was provided with the dataset, however the movements were not labeled accordingly to the list and only a unique ID has been assigned to each one. This led to the need of updating the labels after visually identifying them with the help of the 3D visualization.
While the data was collected an unknown number of movements have not been performed correctly by the patients. It was not possible to develop a tecnique that would identify and remove them, so they have been kept in the dataset. This limitation may have affected the accuracy of the models due to the noise introduced.

The dataset dimensions is relatively small, with only 10 movements and 21 patients. This led to only using the Training and Testing sets for the evaluation of the models, as the dataset was too small to split it into Training/Validation/Testing sets. A larger dataset is needed to split it into these sets and evaluate the models better.
Features calculated in the feature engineering step are not accurate to literature due to only using positional data from the Kinect sensor. However, they still provide enough information for the models to obtain a high accuracy.

5.3 Future work

Kinect-based data is suitable for the task of movement classification, this leads to the possibility of implementing new tecniques and approaches to improve the accuracy of the models.

Feature engineering approach obtains a high accuracy and reduce the training time of the models by reducing the dimension of the original dataset. It is recommended to use it if the dataset is going to be scaled up to include more movements and patients, as the training time will increase exponentially.
The number of features have been reduced but it was not possible to tell which ones contribute the most to the accuracy of the models. In future work it is recommended to calculate the importance of each feature and remove the ones that do not contribute to the accuracy of the models. With the help of domain experts it is possible to calculate new and more meaningful features that can help the models differentiate between movements.
As stated before two movements (*Mat-Walk* and *Hoop-Walk*) are very similar. It is suggested to remove one of them from the dataset to obtain a realistic evaluation of the models, this will help to differentiate between movements that are very similar.

This thesis only used Machine Learning models from the *Scikit-Learn* library. It is possible to implement new models from the *TensorFlow* library, such as *Convolutional Neural Networks* and *Long Short-Term Memory* networks. These models

are more complex and require a larger dataset to train on, but they can obtain a higher accuracy than the models used in this thesis with a correct implementation. It is crucial to acquire new data from the Kinect sensor, add new movements and patients. This will allow to scale up the dataset and study how the models perform on more classes and patients.

The possibles approaches for future work on this task are endless, above are only a few suggestions that can be implemented. The goal of this thesis was to study the feasibility of using Kinect-based data for movement classification, and provide a baseline for future research with this type of data.

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