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A Proposal for the Recognition of Gait Pathologies in Individuals based on Multimodal Features

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Abstract. This work focuses on developing a gait pathology diagnosis system using machine learning with multimodal features. The methodology combines inertial sensors and RGB-D cameras to understand gait patterns and identify movement pathologies in humans. The process begins with creating a controlled environment for data collection, using inertial sensors placed at key body points, such as the ankles, knees, and hips, along with strategically positioned RGB-D cameras. Data acquisition involves recording accelerations, rotations, images, and depth data during participants' gait. Subsequently, this data is preprocessed through cleaning, normalization, and noise removal, ensuring high-quality information. Key gait features, such as phase durations, range of motion, and oscillation frequencies, are extracted and used to apply multimodal classification algorithms like Random Forest, SVM, and CNN. These algorithms classify and diagnose gait pathologies based on temporal, spatial, and frequency characteristics. The methodology will be supported by publicly accessible databases such as the Daphnet Freezing of Gait Dataset, GaitRec Dataset, and Murooka Gait Dataset, which provide diverse data to validate and improve diagnostic models.

Keywords: Gait analysis, machine learning, multimodal features.

1 Introduction

Human gait is a cyclical process that allows human locomotion, characterized by a series of repetitive and coordinated movements of the lower limbs. Normal gait involves a precise sequence of biomechanical and neuromuscular events that ensure stability, balance, and energy efficiency during locomotion.[19]. According to Perry and Burnfield [26], gait can be defined as a dynamic and complex process that involves the coordinated interaction of multiple body systems and is divided into two main phases: the stance phase and the swing phase, critical events that ensure stability, balance, and energy efficiency in the movement of people.

Gait problems in individuals are conditions that decrease the ability to walk normally and smoothly [27]. Gait pathologies, which refer to deviations from the normal pattern of locomotion, result from various neurological, musculoskeletal, and other disorders. According to Perry[26], these pathologies can be classified into several types, such as antalgic gait, Trendelenburg gait, hemiplegic gait, spastic gait, ataxic gait, neuropathic gait, parkinsonian gait, and foot drop gait. Kirtley emphasizes the importance of detailed and quantitative analysis to diagnose and treat these conditions, highlighting how gait pathologies can result from neuromuscular disorders, musculoskeletal injuries, and balance and coordination problems [19].

The development of technology to detect gait disorders offers significant advantages for patients, such as diagnosing with initial symptoms, continuous monitoring, objective evaluation, personalization, and assessment of treatment or therapy[6]. various technologies are used for gait analysis in individuals, some of the most common being force platforms, inertial sensors, electromyography, videography and image analysis, motion capture systems, and pressure insoles. The information from these systems is used in clinical research, evaluation, and analysis settings, allowing for the identification of abnormal patterns, performance assessment, and the design of rehabilitation interventions [9, 3, 11].

In gait analysis research, several studies have used innovative techniques with sensors and machine learning methods. Ionescu and Moga [17] present a gait recognition approach based on multiple projections and machine learning algorithms, highlighting the improvement in accuracy by combining different projections. Panwar and Gupta [25] review various gait recognition techniques using the Kinect sensor, discussing their effectiveness and challenges in capturing and analyzing gait data. Wang, Tan, Ning, and Hu [30] propose a gait recognition method based on silhouette analysis, applying machine learning algorithms for human identification. Chen, Jafari, and Kehtarnavaz [10] explore the fusion of depth and inertial sensor data for human action recognition, including gait, highlighting the improvement in recognition accuracy. Eskofier [13] discusses recent advances in the use of deep learning for sensor-based mobility analysis, emphasizing the integration of multimodal data for fall risk assessment. Zhang and Tao [33] introduce slow feature analysis for human action recognition, applicable to detailed gait analysis and capturing movement dynamics. These studies demonstrate the potential of multimodal technologies and machine learning to transform the analysis and evaluation of human gait.

The proposal in this work aims to achieve significant advantages over traditional approaches by integrating multiple data modalities, such as video images and inertial sensor data. This integration improves analysis accuracy

Table 1. Studies on Human Gait.

Autor-Published	Technology
Buffanti,2020	Camera RGB-D
Bijalwan,2021	IMU, Camera RGB-D
Palermo,2022	IMU, Camera RGB-D
Yamamoto,2022	IMU, Camera RGB-D
Cai,2023	IMU, Binocular Camera
Alanazi,2022	Camera RGB-D, Micro-Dopler
D'Antonio,2021	IMU, 3-WebCam
Albert,2020	Camera RGB-D
vanKersbergen,2021	Camera RGB-D

by providing a more comprehensive and detailed representation of human gait, mitigating individual errors from each sensor or modality. The combination of features captured by different sensors enables the detection of patterns to adapt to various conditions and environments. Altogether, the multimodal approach will capture subtle movement patterns and offer model adaptability in clinical, sports, and rehabilitation applications.

2 Background

2.1 Human Gait Parameters

Gait parameters are defined as quantitative measures used to describe and analyze human movement during locomotion. These parameters include kinematic, kinetic, and temporal variables that provide detailed information on how a person moves. Kinematic data describe the position and movement of joints and body segments in three-dimensional space during gait. This includes joint angles, range of motion, and movement patterns of each joint. Kinetic parameters quantify the forces and moments applied through the joints during ground contact, evaluating ground reaction forces, load distribution, and joint moments.

Finally, temporal parameters describe the duration of specific gait phases, such as stance time and swing time, providing information on the sequence and coordination of movement. These parameters are fundamental for understanding both normal gait and pathological alterations, allowing for a detailed analysis that guides the diagnosis and treatment of clinical conditions related to gait[19, 26]. Table 1 shows a summary of works related to gait analysis and the technology used.

Buffanti et al. demonstrate that non-invasive and cost-effective systems based on depth cameras can recover relevant features of human gait patterns. Gait data recordings were taken using multiple depth sensors. Time-domain analysis includes joint excursions across gait phases, range of motion (ROM), measures of central tendency and dispersion, spatial variables, and center of mass (COM) position. Spectral analysis examines dominant frequency, magnitude, and phase shift during gait. Only features showing significant gender differences were used to train a Support Vector Machine (SVM) classifier [16].

Bijalwan et al. work on the biomechanics of pelvic, hip, knee, and ankle joint movements using a Kinect sensor and an inertial measurement unit (IMU) during normal walking. They present a cost-effective gait analysis system based on Microsoft Kinect v2 and an IMU device. The Kinect sensor is used to acquire 3D skeleton data (camera (x, y, z), depth (x, y), orientation (x, y, z, w), color (x, y)) with 25 human body joints. For their analysis, they consider lower limb joints, namely the spine joint, hip, knee, and ankle of both left and right legs [5].

Palermo et al. collect a multi-camera and multimodal dataset from patients walking with a robotic walker equipped with wheels and a pair of cameras. Depth data were acquired at 30 fps and synchronized with inertial data from Xsens MTw Awinda sensors and kinematic data from Xsens biomechanical model segments, acquired at 60 Hz [24].

Yamamoto et al. demonstrate the capability of markerless gait analysis using posture estimation based on a single RGB camera via OpenPose (OP) and an inertial measurement unit (IMU) on the foot segment to measure ankle joint kinematics under various walking conditions. Their proposed method has the potential to measure spatiotemporal gait parameters and lower limb joint angles, including ankle angles, as an assessment tool for gait in clinical environments [31].

Cai et al. present a procedure for joint angle estimation assisted by binocular camera to acquire initial orientations of the lower limb segment using a human pose estimation algorithm based on images and then estimate joint angle with kinematic constraint. The alignment procedure requires only a sitting posture and does not need any functional movement. Ten healthy participants were recruited for validation experiments, including standing up, turning around, and walking. The accuracy and efficiency of their alignment procedure were validated against optical motion capture (OMC) [7].

Alanazi et al. propose the use of millimeter-wave (MMW) radar as a promising solution for gait applications due to its low cost, improved privacy, and resilience to ambient light and weather conditions. They present a novel method of human gait analysis that combines micro-Doppler spectrogram and skeletal posture estimation using MMW radar, complemented by 3D coordinates extracted from 25 joints via Kinect V2 sensor [1].

D'Antonio et al. characterize the performance of a low-cost markerless system, consisting of the open-source OpenPose library, two web cameras, and a linear triangulation algorithm. The system was validated in terms of 3D gait kinematic analysis, compared with inertial sensors. They recorded synchronized videos of six healthy subjects in three webcam configurations, in walking and running sessions on a treadmill. They also compared sagittal joint angles between the two systems to assess the kinematic performance of the markerless system [12].

Albert et al. evaluate the motion tracking performance of the latest generation Microsoft Kinect camera, Azure Kinect, compared to its predecessor Kinect v2 in treadmill walking using a reference multicamera motion capture system Vicon and the Plug-in Gait model with 39 markers. Five young and healthy subjects walked on a treadmill at three different speeds while data were simultaneously recorded with all three camera systems. They used an easy-to-manage camera calibration method developed here to spatially align 3D skeleton data from both Kinect cameras and the Vicon system [2].

Van Kersbergen et al. studied the use of a depth camera to capture changes in the gait characteristics of Parkinson's patients. The dataset consisted of 19 patients (tested in both defined OFF and ON phases) and 8 controls, performing the "Timed-Up-and-Go" test multiple times while being recorded with the Microsoft Kinect V2 sensor. Derived features from the camera were step length, average walking speed, and mediolateral sway. Motor signs were clinically assessed using the Unified Parkinson's Disease Rating Scale by the Movement Disorder Society [18].

2.2 IMU Systems

Inertial systems are advanced technologies used to accurately capture and analyze parameters of gait and other human movements. These systems rely on sensors that measure linear acceleration and angular velocity of body segments. A typical architecture of an inertial system includes multiple sensors strategically distributed on the body, connected to a central processing unit that records and processes the data. Inertial sensors are small and lightweight, allowing comfortable and unrestricted data capture during gait. These systems provide precise measurements of kinematic parameters such as joint angles and movement trajectories, as well as temporal parameters like cadence, step length, and stance and swing times. This capability makes inertial sensors versatile tools in clinical settings for evaluating musculoskeletal disorders and in sports applications for performance analysis and functional biomechanics [28].

The optimal placement of inertial sensors for gait parameter recording depends on the biomechanical factors of human gait and joint movement, which affect the accuracy and reliability of collected data. Generally, it is recommended to mount sensors on body segments that undergo significant movements during gait, such as thighs, shins, and feet (Fig. 1). For example, placing sensors on the lumbar region or legs allows for direct capture of relevant joint angles and movement patterns. Moreover, precise placement at specific anatomical points, such as the anterior superior iliac spine for the pelvis or the knee center for knee joint flexion, ensures more accurate measurements of kinematic parameters. This strategy not only facilitates detailed assessment of gait biomechanics but also minimizes the risk of external interferences and motion artifacts, thus ensuring data quality for clinical analysis and sports applications [8].

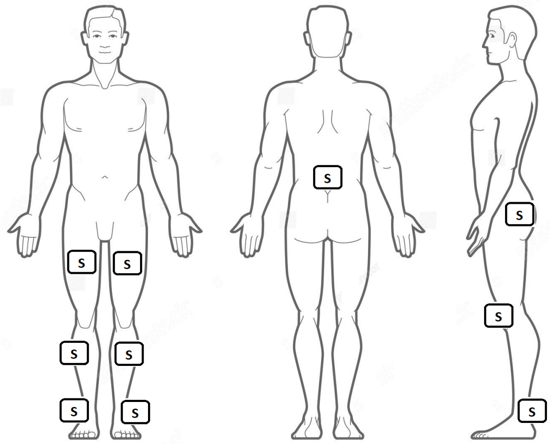

Fig. 1. Proposed placement of inertial sensors.

2.3 Camera with Depth

The use of RGB-D depth cameras, such as the Microsoft Kinect system, has revolutionized gait analysis by providing three-dimensional data capture that combines RGB sensors with depth sensors. This technology is known for its ease of use, minimal invasiveness, and cost-effectiveness, making it accessible in both clinical and research settings. Depth cameras allow for precise evaluation of kinematic and kinetic parameters without needing body-worn markers, thereby enhancing subject comfort. Their application in biomechanical research and rehabilitation has been extensively documented, highlighting their advantages and limitations compared to traditional motion capture systems. While they present challenges such as limited accuracy and dependence on lighting conditions, depth cameras offer a valuable tool for detailed and accessible analysis of human gait [29].

Proper placement of the capture system is crucial for obtaining accurate and reliable gait analysis data. The camera's location and angle determine the quality and precision of the measured kinematic and kinetic parameters. To achieve optimal motion capture, the camera should be positioned at an appropriate height and distance from the subject, typically at waist height and approximately 2-3 meters away (Fig.2). This positioning ensures that the subject's entire body is within the camera's field of view throughout the complete gait cycle. Additionally, adjusting the camera's tilt angle is important to maximize the visibility of body segments and minimize marker occlusion [14].

3 Datasets

In the context of gait analysis, the use of established databases such as GaitRec, MotionSense, and the CMU Graphics Lab Database is fundamental

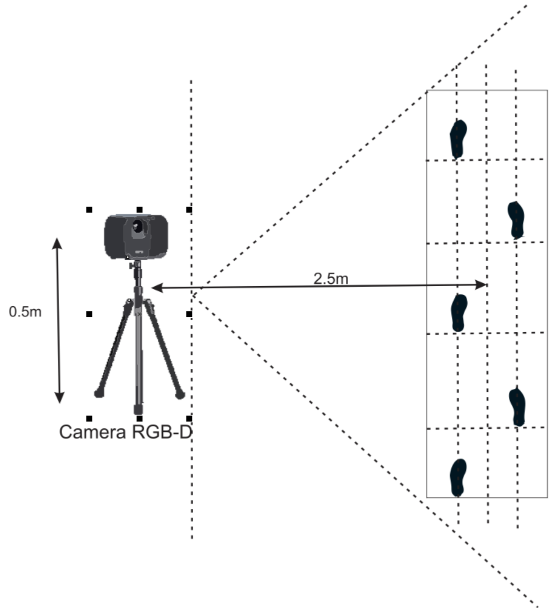

Fig. 2. Proposal for camera placement.

to ensure the validity and reliability of the obtained results. These databases have been collected with rigorous methodologies and have been widely used in the scientific literature, allowing direct comparison of results and validation of new analysis approaches. Furthermore, access to a wide variety of data allows for the consideration of multiple variables and a more comprehensive and detailed analysis of gait patterns. By basing the use of these databases, transparency and reproducibility of the research are guaranteed[19, 26, 21].

Using established databases in gait analysis is essential to ensure the validity and reliability of the obtained results. Table 2 shows a brief description of databases such as GaitRec[20], MotionSense[22], CMU Graphics Lab Database[15], OU-ISIR Gait Database[21], and CASIA Gait Database [32], allowing direct comparison of results and validation of new analysis approaches. Additionally, access to a wide variety of data allows for the consideration of multiple variables and a more comprehensive and detailed analysis of gait patterns. By basing the use of these databases, transparency and reproducibility of the research are guaranteed.

4 Multimodal Machine Learning

Multimodal machine learning refers to the ability of models to process and relate multiple modalities from sensors, images, text, audio, and video. This field focuses on building models that can jointly interpret multimodal signals,

Table 2. Data base gait parameters.

Data base	Description	Adquisition	Subjets
GaitRec[20]	Data for the evaluation of gait recognition algorithms. Includes multiple subjects and conditions	Inertial sensors, RGB-D cameras	744
MotionSense[22]	Data from mobile sensors for real-time analysis of IoT systems, including gait data captured by wearable devices.	Accelerometers and gyroscopes in smartphones	24
CMU Graphics Lab Motion Capture Database[15]	Motion capture database that includes various activities, including gait, collected with high-speed cameras.	Motion capture cameras	25
OU-ISIR Gait Database[21]	Treadmill gait dataset, captured under multiple conditions and with different subjects.	Video cameras	34
CASIA Gait Database[32]	Gait recognition database, which includes multiple views and recording conditions.	Video cameras	124

leveraging available data to enhance understanding and performance across various tasks. Characteristics of multimodal learning include integrating data from different sources, the ability to learn joint representations, and the capability to translate and align information across modalities [4]. Among the advantages of multimodal machine learning are increased robustness and accuracy in pattern recognition and classification, as well as improved capability to capture complex contexts and nuances that would be challenging to understand from a single modality [23].

The proposal presented in this work adopts a multimodal system for gait analysis that integrates data from multiple sensory sources such as RGB cameras, depth cameras, and inertial sensors, enabling precise and comprehensive three-dimensional motion capture. This integration enhances the analysis by providing combined kinematic and kinetic data, allowing for a deep understanding of gait and its disorders. It highlights the potential of multimodal systems to significantly improve the understanding and treatment of gait disorders.

4.1 Multimodal Gait Parameters

The identification of parameters is essential for understanding and evaluating specific aspects of human gait, considering that they come from the combination of inertial sensors and depth cameras. Table 3 groups the parameters that can

Table 3. Multimodal Machine Learning comparison.

Parameter	RGB-D Cameras	Inertial Sensors	Common References
Position and joint angles	Yes	No	[20][21][32]
Speed and acceleration of movement	Yes	Yes	[20][21][32][22]
Body segment trajectories	Yes	No	[20][21][32]
Distances and step lengths	Yes	No	[20][21][32]
Area of movement	Yes	No	[20][21][32]
Detection of joint points	Yes	No	[20][21][32]
Linear and angular acceleration	No	Yes	[22]
Angular velocity	No	Yes	[22]
Orientation and posture	No	Yes	[22]
Step frequency	No	Yes	[22]
Duration of gait phases	No	Yes	[22]
Variability in movement patterns	No	Yes	[22]

be identified by each of the technologies used, facilitating the analysis and understanding of gait movement.

When using inertial sensors to record accelerations and rotations during gait analysis, various features can be extracted that are crucial for understanding and evaluating human movement. These features not only provide a quantitative description of movement during gait but can also serve as inputs for machine learning algorithms aimed at identifying specific patterns, recognizing anomalies, or classifying different gait conditions. The appropriate selection of these features depends on the study or clinical application's objectives and the type of biomechanical analysis desired.

RGB and depth camera systems are known for their ability to capture three-dimensional data using structured light technology, making them useful for gait analysis and other human motion studies.

Table 3 provides a clear and concise comparison of the features recorded by RGB-D cameras and inertial sensors in gait analysis. By identifying the overlaps and differences in the parameters measured by both technologies, the selection of appropriate tools for specific human gait studies is facilitated. This comparison also highlights the complementarity of both technologies, suggesting that a multimodal integration can offer a more comprehensive and accurate view of gait analysis, improving the detection and treatment of pathologies.

4.2 Machine Learning Algorithms

Studying the algorithms used in gait analysis is crucial for several reasons. Firstly, different algorithms may offer varying levels of precision and efficiency,

Table 4. Multimodal Machine Learning Algorithms.

Reference	Algorithm	Features	Evaluation Metric (%)	Database
Perry, J., & Burnfield, J. M. (2010)	SVM	Temporal and spatial gait analysis	85%- accuracy	GaitRec
Kirtley, C. (2006)	Random Forest	Acceleration and gyroscope features	88%- accuracy	Daphnet
Umphred, D. A., et al. (2013)	CNN	Images and depth sequences	90%- specificity	Murooka
O'Sullivan, S. B., et al. (2019)	Decision Trees	Frequency and time parameters	82%- accuracy	GaitRec
Buczek Jr., F. L., et al. (Year)	LSTM	Temporal movement sequences	87%- perplexity- accuracy	Daphnet
Webster, J., & Murphy, D. (2018)	KNN	Joint angle analysis	80%- log loss	Murooka
Journal of Biomechanics	Naive Bayes	Kinematic parameters	83%- recall- accuracy	GaitRec
Journal of Biomechanical Engineering	AdaBoost	Combination of temporal and spatial features	89%-F1Score	Daphnet

allowing the selection of the most suitable algorithm for specific study or application needs. Additionally, some algorithms are better suited for integrating and analyzing data from multiple sources, such as inertial sensors and RGB-D cameras, optimizing multimodal analysis. Advanced algorithms, such as neural networks and machine learning models, can identify complex patterns in gait data that may not be detectable using traditional methods, which is essential for the diagnosis and treatment of gait pathologies. In clinical settings, choosing the correct algorithm can significantly improve the diagnosis, monitoring, and treatment of patients, providing more reliable and replicable results. Understanding the algorithms used also drives research and the development of new technologies and methods, contributing to the advancement of the field.

Table 4 provides a comparative overview of various studies employing machine learning algorithms for gait pathology detection, highlighting their importance in validation and methodology comparison. The cited references ensure the validity of the results, while the diversity of algorithms such as SVM, Random Forest, and CNN, demonstrates the breadth of applicable approaches. The utilized features, including temporal and spatial analysis, acceleration

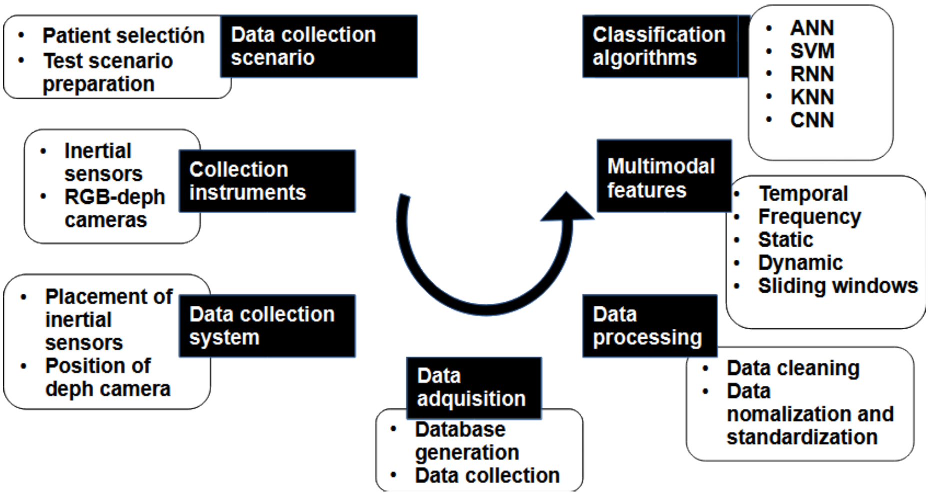

Fig. 3. Proposed architecture.

and gyroscope data, images, and depth sequences, are crucial for capturing relevant signals. The accuracy evaluation, ranging from 80% to 90%, allows for comparison of approach effectiveness. Additionally, databases like GaitRec, Daphnet, and Murooka ensure result validity and generalizability.

4.3 Proposed Approach

The proposed methodology for the multimodal integration of inertial sensors and RGB-D cameras is shown in Fig.3, where a detailed structure for gait analysis is presented. This approach utilizes technologies common to the previously reviewed works, supplemented with preprocessing techniques and machine learning algorithms. The multimodal approach allows for a deep understanding of gait patterns and facilitates the identification of pathologies in human locomotion.

The first step in the gait analysis methodology is to develop an appropriate testing environment. This environment must be controlled and standardized to ensure consistent and reproducible testing conditions. A sufficiently large and flat area should be selected to allow for natural walking, with specific distances marked for participants to walk. It's important to consider lighting and the absence of obstacles that could interfere with walking.

The selection of data collection instruments is crucial for obtaining accurate and useful measurements. In this methodology, inertial measurement units (IMUs) and RGB-D cameras will be used. IMUs are useful for measuring accelerations and rotations, while RGB-D cameras capture images and depth data, providing detailed information about body movement and position in space.

Proper sensor placement is essential for obtaining accurate data. IMUs should be placed at key points on the body such as ankles, knees, hips, and the lower back to capture limb and trunk movement. RGB-D cameras should be positioned around the testing environment to cover multiple angles and ensure that the entire gait sequence is captured without obstructions. Ideal placement is typically at mid-height and at the ends of the walking area to maximize coverage and data depth accuracy.

Once sensors are placed, data acquisition proceeds. Participants walk along the testing environment while IMUs and RGB-D cameras record their movements. It's important to conduct multiple trials for each participant to obtain a robust dataset and better represent natural variations in gait. Data should be properly stored and labeled to facilitate subsequent processing and analysis.

Data preprocessing is a critical step to ensure that the obtained data are of high quality and suitable for analysis. This process includes cleaning data to remove noise, synchronizing data between different sensors, and normalizing data to adjust for differences in measurement scale. Data can also be segmented into individual gait cycles to facilitate specific analysis of each phase of gait.

Once preprocessed, the data are analyzed to extract relevant features. Temporal features include parameters such as gait cycle duration and individual phases (stance and swing). Spatial features include measures such as step length, step width, and pelvic tilt. Frequency-domain features are obtained through spectral analysis, identifying dominant frequencies in motion signals that may be related to specific gait patterns or pathologies.

The final step is the application of multimodal classification algorithms to analyze the extracted features and classify gait patterns. Machine learning algorithms such as Support Vector Machines (SVM), Random Forest, and neural networks (e.g., LSTM for temporal data) are trained using features extracted from IMU and RGB-D data. These algorithms can identify and classify different types of gait, including normal and pathological patterns, enabling precise and detailed assessment of participants' gait.

5 Conclusions

In the study of human gait, technologies such as inertial sensors and Kinect cameras have been used, and various methodologies and applications in machine learning and biomechanics have been explored. It has been reviewed how inertial sensors capture acceleration and gyroscope data, which are crucial for analyzing parameters such as speed, cadence, and abnormal gait movement patterns. On the other hand, Kinect has proven useful for recording three-dimensional joint positions, enabling a detailed analysis of human movement kinematics and dynamics.

In terms of machine learning algorithms, the potential of Convolutional Neural Networks (CNNs) to process images captured by Kinect has been noted, as well as Recurrent Neural Networks (RNNs) for modeling the temporal dynamics of inertial sensor data. Multimodal neural networks and other methods like Support Vector Machines (SVMs) have been considered to integrate and classify data from multiple sources.

Finally, it is envisaged how these technologies and methodologies can significantly contribute to medical diagnosis, rehabilitation, and diagnostic improvement, providing the capability to predict the onset of gait problems in individuals.

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