Lower Limb Disorder Identification

Subjects: Computer Science, Artificial Intelligence

Contributor: Hafeez Ur Rehman Siddiqui , Adil Ali Saleem , Muhammad Amjad Raza , Santos Gracia Villar , Luis Alonso Dzul Lopez , Isabel de la Torre Diez , Furqan Rustam , Sandra Dudley

A novel approach for the classification of lower limb disorders, with a specific emphasis on the knee, hip, and ankle. The research employs gait analysis and the extraction of PoseNet features from video data in order to effectively identify and categorize these disorders. The PoseNet algorithm facilitates the extraction of key body joint movements and positions from videos in a non-invasive and user-friendly manner, thereby offering a comprehensive representation of lower limb movements.

lower limb disorder | PoseNet | gait analysis | machine learning

1. Introduction

Lower extremity disorders have been identified as a significant factor contributing to disability and reduced quality of life on a global scale [1][2]. Osteoarthritis of the knee, hip, and ankle is a commonly observed disorder affecting the lower limbs [3][4]. These conditions, commonly resulting from trauma, degenerative diseases, or bio-mechanical abnormalities, can give rise to discomfort, a restricted range of motion, and diminished functionality [5][6]. The prompt and precise classification of these conditions is crucial for effective treatment planning, individualized rehabilitation, and the prevention of further consequences. Clinical trials, subjective patient testimonials, and diagnostic imaging modalities such as X-rays and magnetic resonance imaging (MRI) have conventionally served as the predominant approaches in ascertaining the existence and extent of lower limb issues [7][8]. Although these techniques have proven to be valuable, they often require the utilization of specialized equipment, entail significant time investments [9][10], and may not fully capture the comprehensive dynamics of joint movement observed during typical activities. In recent years, advancements in technology have enabled the objective and continuous monitoring of the bio-mechanics in the lower extremities using gait data [11][12].

Gait analysis is employed in a wide variety of domains, including medical diagnostics [13][14][15], osteopathic medicine [16][17], comparative bio-mechanics [18][19][20], and sports-related bio-mechanics [21][22][23]. The application of gait analysis has exhibited considerable promise in the identification and assessment of lower limb disorders [24]. Gait analysis encompasses the evaluation of an individual’s walking pattern, including diverse elements such as stride length, step width, joint angles, and the temporal coordination of movements. Through the examination of these gait parameters, medical professionals and scholars can detect irregularities or deviations from typical gait patterns, which may serve as indicators of the existence of a lower limb disorder [25][26][27]. The objective of the study is to investigate the potential application of PoseNet features in the classification of lower limb disorders. PoseNet is a real-time pose estimation model developed by Google, which employs deep learning techniques to accurately assess human poses from both photos and videos [28][29]. Refs. [30][31][32] used PoseNet for in-home rehabilitation, and [33][34] used PoseNet for batsman stroke prediction. These features are capable of capturing the spatial positions and movements of key body joints. PoseNet was chosen by the authors because of its better attributes in the domain of real-time human pose estimation. This is due to its real-time capabilities, user friendliness, and versatility. The model's ability to perform efficiently with just one video feed, together with its minimal preprocessing requirements and smooth integration into widely used deep learning frameworks, makes it an excellent choice for a wide range of applications. The researchers aimed to establish a dependable and precise classification system for the identification of particular disorders in the hip, ankle, and knee by means of analyzing gait patterns and movements extracted from videos.

PoseNet offers a non-invasive and user-friendly approach to extracting human pose data from videos, obviating the necessity for dedicated apparatus or body-attached markers. This facilitates a more authentic and unimpeded evaluation of gait patterns in real-world contexts. The application of deep learning in PoseNet enables the extraction of complicated and detailed features from videos, resulting in a comprehensive depiction of movements in the lower limbs. The characteristics effectively capture the complex variations and fluctuations in an individual's gait, which have the potential to serve as indicators for particular disorders affecting the lower limbs. This methodology presents the potential for improved accuracy in diagnosis.

2. Lower Limb Disorder Identification

In recent years, there has been growing interest in the field of gait analysis and the categorization of joint abnormalities. This attention is driven by the desire to enhance the accuracy of diagnosis and treatment methods. Various studies employ ML and deep learning techniques to automatically categorize joint abnormalities using gait data. Each study in the field of gait analysis is centered around a particular condition or aspect and employs a range of methodologies and evaluation metrics. The research conducted by [35] centers on the diagnosis of knee osteoarthritis using the automated analysis of walking data obtained from both diagnosed persons and symptom-free controls. Ground reaction force features are extracted using force plates and piezoelectric sensors, and these values are then associated with the severity of osteoarthritis using random forest regression models. The attained accuracy of 72.61% in the five-fold cross-validation indicates a decent level of performance, leaving space for potential improvement.

In [36], the researchers use supervised classifiers and an RGB-D camera to diagnose gait problems in osteoarthritis patients. The researchers categorize gait disorders with 97% accuracy using fourteen gait measures, demonstrating its potential for osteoarthritis diagnosis. Another work [37] proposes a novel method of detecting gait abnormalities using a single 2D video camera. Video analysis with a support vector machine (SVM) classifier determines biomechanical gait parameters with 98.8% accuracy. The research in [38] presents a cost-effective and user-friendly gait data acquisition and analysis system. This technique quantifies osteoarthritis-related walking irregularities. The hybrid prediction model, combining manual and automated characteristics, achieves 98.77% accuracy. Meanwhile, Ref. [39] uses deep learning to classify abnormal gait patterns by integrating 3D skeletal data and plantar foot pressure readings. The multimodal hybrid model achieves 97.60% accuracy by utilizing pressure and skeletal data effectively.

The aim of [40] was to develop an automated framework for knee osteoarthritis (KOA) classification utilizing radiographic imaging and gait analysis, with a Kallgren-Lawrence grading system. A support vector machine and deep learning features from Inception-ResNet-v2 classified KOA based on gait and radiographic data, showing strong relationships between gait characteristics and radiological severity. The AUC varied from 0.93 to 0.97 for KL grades 0–4. Moreover, Ref. [41] intended to evaluate gait symmetry in unilateral ankle osteoarthrosis (AOA) patients and identify variables affecting post-surgery asymmetry. They compared 46 gait metrics in 10 healthy people with 10 AOA patients using 3D inertial sensors and pressure insoles. They found significant differences in 23 impacted-side and 20 non-impacted-side variables. In particular, 14 metrics exhibited differences during bilateral AOA patient comparisons, notably in the toe area, and in forefoot mobility during walking.

In [42], the researchers use ground reaction force (GRF) measurements to automate the diagnosis of functional gait disorders (GDs). They evaluate GRF parameterization methods for GD identification and establish a reference for automatic classification. The study divides 279 GD patients and 161 healthy controls into hip, knee, ankle, and calcaneus impairment groups using GRF data. It tests GRF and PCA-based parameterization approaches. The evaluation of discriminative power uses linear discriminant analysis. The study classifies normal walking patterns and multiclass GD categories. The study in [43] focuses on categorizing gait disorders, with an emphasis on ground reaction force (GRF) analysis. The study preprocesses GRF signals and extracts and selects features from the GaitRec and Gutenberg databases with data from gait problem patients and healthy participants. The K-nearest neighbor (KNN) model outperforms conventional machine learning approaches in four experimental schemes categorizing gait disorders. The study contrasts vertical and three-dimensional GRF, with the latter performing better. Meanwhile, Ref. [44] develops an automated, accurate knee osteoarthritis (KOA) diagnosis method. The study uses RQA, fuzzy entropy, and statistical analysis to analyze dynamical characteristics collected from gait kinematic data. Discriminant analysis on these characteristics evaluates shallow classifiers like SVM, KNN, NB, DT, and Adaboost. SVM distinguishes KOA patients and healthy controls with the maximum accuracy of 92.31% and 100%, proving its KOA diagnostic efficacy.

Previous research studies provide evidence of the efficacy of ML and deep learning methodologies in the automated categorization of joint abnormalities using gait data. The utilization of diverse modalities, including RGB-D cameras, 2D video, and ground reaction force measurements, exemplifies the multifaceted nature of these methodologies. Nevertheless, certain studies demonstrate limitations in terms of moderate accuracy, the necessity for supplementary evaluation metrics, and comparatively limited sample sizes. This research introduces a novel approach to categorizing lower limb disorders, focusing on ankle, knee, hip, and normal subjects. The proposed method involves the utilization of PoseNet features extracted from video data. The approach centers on utilizing PoseNet, a pose estimation model based on deep learning, to extract significant features from the video recordings. The primary objective of the proposed methodology is to improve the precision and effectiveness of diagnosing lower limb disorders through the utilization of video data. This approach capitalizes on the abundance of valuable information pertaining to subjects' movements and joint positions that can be extracted from video recordings. The application of this methodology holds promise in assisting healthcare practitioners in the identification and classification of distinct lower limb disorders, thus facilitating the implementation of suitable treatment and rehabilitation approaches.

References

1. Fatima, S.Z. Life of an amputee: Predictors of quality of life after lower limb amputation. Wiener Medizinische Wochenschrift 2022, 1–5.
2. Grimmer, M.; Riener, R.; Walsh, C.J.; Seyfarth, A. Mobility related physical and functional losses due to aging and disease-a motivation for lower limb exoskeletons. J. Neuroeng. Rehabil. 2019, 16, 1–21.
3. Pirani, H.; Noori, S.; Shahmoradi, D. Examining the prevalence of lower body disorders among male lower-secondary education students in Kermanshah. Int. J. Health Life Sci. 2019, 5, e85033.
4. Leggit, J.; Carey, P.M.; Alisangco, J.B. Disorders of the Lower Extremity. In Family Medicine: Principles and Practice; Paulman, P.M., Taylor, R.B., Paulman, A.A., Nasir, L.S., Eds.; Springer International Publishing: Cham, Switzerland, 2017; pp. 1489–1513.
5. Osteoarthritis. Available online: https://www.mayoclinic.org/diseases-conditions/osteoarthritis/symptoms-causes/syc-20351925 (accessed on 17 August 2023).
6. Musculoskeletal Health. 2022. Available online: https://www.who.int/news-room/fact-sheets/detail/musculoskeletal-conditions (accessed on 17 August 2023).
7. Khalid, H.; Hussain, M.; Al Ghamdi, M.A.; Khalid, T.; Khalid, K.; Khan, M.A.; Fatima, K.; Masood, K.; Almotiri, S.H.; Farooq, M.S.; et al. A comparative systematic literature review on knee bone reports from mri, x-rays and ct scans using deep learning and machine learning methodologies. Diagnostics 2020, 10, 518.
8. Heidari, B. Knee osteoarthritis diagnosis, treatment and associated factors of progression: Part II. Casp. J. Intern. Med. 2011, 2, 249.
9. Hamza, A.; Khan, M.A.; Alhaisoni, M.; Al Hejaili, A.; Shaban, K.A.; Alsubai, S.; Alasiry, A.; Marzougui, M. D2BOF-COVIDNet: A framework of deep bayesian optimization and fusion-assisted optimal deep features for COVID-19 classification using chest X-ray and mri scans. Diagnostics 2022, 13, 101.
10. Devereux, R.B.; Pini, R.; Aurigemma, G.P.; Roman, M.J. Measurement of left ventricular mass: Methodology and expertise. J. Hypertens. 1997, 15, 801–809.
11. Weygers, I.; Kok, M.; Konings, M.; Hallez, H.; De Vroey, H.; Claeys, K. Inertial sensor-based lower limb joint kinematics: A methodological systematic review. Sensors 2020, 20, 673.

12. Picerno, P. 25 years of lower limb joint kinematics by using inertial and magnetic sensors: A review of methodological approaches. Gait Posture 2017, 51, 239–246.
13. Balaji, E.; Brindha, D.; Elumalai, V.K.; Umesh, K. Data-driven gait analysis for diagnosis and severity rating of Parkinson’s disease. Med Eng. Phys. 2021, 91, 54–64.
14. Van Deventer, K.A.; Seehusen, C.N.; Walker, G.A.; Wilson, J.C.; Howell, D.R. The diagnostic and prognostic utility of the dual-task tandem gait test for pediatric concussion. J. Sport Health Sci. 2021, 10, 131–137.
15. Beyrami, S.M.G.; Ghaderyan, P. A robust, cost-effective and non-invasive computer-aided method for diagnosis three types of neurodegenerative diseases with gait signal analysis. Measurement 2020, 156, 107579.
16. Hill, C.N.; Romero, M.; Rogers, M.; Queen, R.M.; Brolinson, P.G. Effect of osteopathic manipulation on gait asymmetry. J. Osteopath. Med. 2021, 122, 85–94.
17. Terrell, Z.T.; Moudy, S.C.; Hensel, K.L.; Patterson, R.M. Effects of osteopathic manipulative treatment vs. osteopathic cranial manipulative medicine on Parkinsonian gait. J. Osteopath. Med. 2022, 122, 243–251.
18. Martins, J.S.; Sabino, G.; Nascimento, D.H.; Machado, G.M.; Vimieiro, C.B. Biomechanical model for Dynamic Analysis of the Human Gait. In Proceedings of the International Symposium on Computer Methods in Biomechanics and Biomedical Engineering, New York, NY, USA, 14–16 August 2019; pp. 362–370.
19. Silva, M.P.; Ambrósio, J.A. Sensitivity of the results produced by the inverse dynamic analysis of a human stride to perturbed input data. Gait Posture 2004, 19, 35–49.
20. Ruiz, D.V.; Magluta, C.; Roitman, N. Experimental verification of biomechanical model of bipedal walking to simulate vertical loads induced by humans. Mech. Syst. Signal Process. 2022, 167, 108513.
21. Song, Y.; Biro, I. The Evolution of Marker-based Motion Analysis and the Integration of Advanced Computational Methods: Application to Human Gait Biomechanics. In Proceedings of the 2022 2nd International Conference on Bioinformatics and Intelligent Computing, Harbin, China, 21–23 January 2022; pp. 201–205.
22. Li, J.; Du, H. Research on the sports biomechanics modeling of the human motion technical movements. In Cyber Security Intelligence and Analytics; Springer: Berlin/Heidelberg, Germany, 2020; pp. 243–248.
23. Meng, Y.; Bíró, I.; Sárosi, J. Markerless measurement techniques for motion analysis in sports science. Analecta Tech. Szeged. 2023, 17, 24–31.

24. Fouasson-Chailloux, A.; Menu, P.; Dauty, M. Lower-Limb Arthropathies and Walking: The Use of 3D Gait Analysis as a Relevant Tool in Clinical Practice. Int. J. Environ. Res. Public Health 2022, 19, 6785.
25. Klöpfer-Krämer, I.T.; Augat, P. Functional Capacity Evaluation and Quantitative Gait Analysis: Lower Limb Disorders. In Handbook of Human Motion; Müller, B., Wolf, S.I., Brueggemann, G.P., Deng, Z., McIntosh, A., Miller, F., Selbie, W.S., Eds.; Springer International Publishing: Cham, Switzerland, 2017; pp. 1–17.
26. Shin, J.; Yoo, J.; Jung, T.; Goo, H. Comparison of lower extremity motor score parameters for patients with motor incomplete spinal cord injury using gait parameters. Spinal Cord 2011, 49, 529–533.
27. Schmid-Zalaudek, K.; Fischer, T.; Száva, Z.; Lackner, H.K.; Kropiunig, U.; Bittner, C.; Höcker, K.; Winkler, G.; Peternell, G. Kinetic Gait Parameters in Unilateral Lower Limb Amputations and Normal Gait in Able-Bodied: Reference Values for Clinical Application. J. Clin. Med. 2022, 11, 2683.
28. Fernandez, J. MediaPipe Pose Estimation Documentation. Available online: https://github.com/google/mediapipe/blob/master/docs/solutions/pose.md (accessed on 17 August 2023).
29. Chen, Y.; Shen, C.; Wei, X.S.; Liu, L.; Yang, J. Adversarial posenet: A structure-aware convolutional network for human pose estimation. In Proceedings of the IEEE International Conference on Computer Vision, Venice, Italy, 22–29 October 2017; pp. 1212–1221.
30. Chua, J.; Ong, L.Y.; Leow, M.C. Telehealth using PoseNet-based system for in-home rehabilitation. Future Internet 2021, 13, 173.
31. Li, Y.; Wang, C.; Cao, Y.; Liu, B.; Tan, J.; Luo, Y. Human pose estimation based in-home lower body rehabilitation system. In Proceedings of the 2020 International Joint Conference on Neural Networks (IJCNN), Glasgow, UK, 19–24 July 2020; pp. 1–8.
32. Cordella, F.; Di Corato, F.; Zollo, L.; Siciliano, B. A robust hand pose estimation algorithm for hand rehabilitation. In Proceedings of the New Trends in Image Analysis and Processing–ICIAP 2013: ICIAP 2013 International Workshops, Naples, Italy, 9–13 September 2013; pp. 1–10.
33. Siddiqui, H.U.R.; Younas, F.; Rustam, F.; Flores, E.S.; Ballester, J.B.; Diez, I.d.l.T.; Dudley, S.; Ashraf, I. Enhancing Cricket Performance Analysis with Human Pose Estimation and Machine Learning. Sensors 2023, 23, 6839.
34. Devanandan, M.; Rasaratnam, V.; Anbalagan, M.K.; Asokan, N.; Panchendrarajan, R.; Tharmaseelan, J. Cricket Shot Image Classification Using Random Forest. In Proceedings of the 2021 3rd International Conference on Advancements in Computing (ICAC), Colombo, Sri Lanka, 9–11 December 2021; pp. 425–430.

35. Kotti, M.; Duffell, L.D.; Faisal, A.A.; McGregor, A.H. Detecting knee osteoarthritis and its discriminating parameters using random forests. Med. Eng. Phys. 2017, 43, 19–29.

36. Cui, X.; Zhao, Z.; Ma, C.; Chen, F.; Liao, H. A gait character analyzing system for osteoarthritis pre-diagnosis using RGB-D camera and supervised classifier. In Proceedings of the World Congress on Medical Physics and Biomedical Engineering 2018, Prague, Czech Republic, 3–8 June 2018; Springer: Berlin/Heidelberg, Germany, 2019; Volume 1, pp. 297–301.

37. Verlekar, T.T.; Soares, L.D.; Correia, P.L. Automatic classification of gait impairments using a markerless 2D video-based system. Sensors 2018, 18, 2743.

38. Chen, F.; Cui, X.; Zhao, Z.; Zhang, D.; Ma, C.; Zhang, X.; Liao, H. Gait acquisition and analysis system for osteoarthritis based on hybrid prediction model. Comput. Med Imaging Graph. 2020, 85, 101782.

39. Jun, K.; Lee, S.; Lee, D.W.; Kim, M.S. Deep learning-based multimodal abnormal gait classification using a 3D skeleton and plantar foot pressure. IEEE Access 2021, 9, 161576–161589.

40. Kwon, S.B.; Han, H.S.; Lee, M.C.; Kim, H.C.; Ku, Y. Machine learning-based automatic classification of knee osteoarthritis severity using gait data and radiographic images. IEEE Access 2020, 8, 120597–120603.

41. Chopra, S.; Crevoisier, X. Preoperative gait asymmetry in end-stage unilateral ankle osteoarthrosis patients. Foot Ankle Surg. 2019, 25, 298–302.

42. Slijepcevic, D.; Zeppelzauer, M.; Gorgas, A.M.; Schwab, C.; Schüller, M.; Baca, A.; Breiteneder, C.; Horsak, B. Automatic classification of functional gait disorders. IEEE J. Biomed. Health Inform. 2017, 22, 1653–1661.

43. Shuzan, M.N.I.; Chowdhury, M.E.; Reaz, M.B.I.; Khandakar, A.; Abir, F.F.; Faisal, M.A.A.; Ali, S.H.M.; Bakar, A.A.A.; Chowdhury, M.H.; Mahbub, Z.B.; et al. Machine learning-based classification of healthy and impaired gaits using 3D-GRF signals. Biomed. Signal Process. Control 2023, 81, 104448.

44. Zeng, W.; Ma, L.; Zhang, Y. Detection of knee osteoarthritis based on recurrence quantification analysis, fuzzy entropy and shallow classifiers. Multimed. Tools Appl. 2023, 1–22.