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GAITCLOUD-EVGS: CLOUD PLATFORM PROJECT FOR AUTOMATIC ANALYSIS OF GAIT VIDEOS

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Postural analysis is a powerful technique for assessing work-related activities. Posture and gait analysis are also important in assessing medical recovery after neurological injuries (*e.g.*, stroke), neurodegenerative diseases (Alzheimer's, Parkinson's, etc.), or traffic or work accidents. In this respect, the Edinburgh Visual Gait Score (EVGS) is a widely used observational clinical tool for the qualitative assessment of human gait. Its traditional determination is based on manual analysis of video recordings by clinicians, a process that is time-consuming, susceptible to inter- and intra-evaluator variability, and strongly dependent on the quality of the available video material. In this context, the present work proposes the conceptual design of a cloud-based service for automated video-based gait analysis and EVGS computation. Within the proposed architecture, the resulting scores and reports would be delivered and visualized through a dedicated web interface.

1. INTRODUCTION

Gait analysis focuses on evaluating movement patterns, joint kinematics, and muscle activity during locomotion [1]. Clinically, it provides valuable insights into musculoskeletal and neurological function and is widely used to assess patients with neurological, orthopedic, or developmental disorders [2]. The Edinburgh Visual Gait Score (EVGS) is one of the most widely used tools for standardized observational gait evaluation. Robinson et al. [3] defined a minimal clinically important difference (MCID) of 2.4 points on the EVGS, corresponding to a 1-point improvement on the Functional Assessment Questionnaire (FAQ), thereby establishing a meaningful threshold for post-surgical and rehabilitative outcomes.

Aroojis et al. [4] proposed a smartphone-based approach to EVGS scoring in 30 children with spastic cerebral palsy. Similarly, Pantzar-Castilla et al. [5] validated a low-cost, markerless gait analysis system using a single RGB-Depth camera that quantified sagittal-plane kinematics and spatiotemporal parameters in children with bilateral cerebral palsy. Building on these innovations, pose estimation techniques now allow fully automated extraction of gait parameters from standard video, enabling scalable and objective analysis.

Stenum et al. [6] reviewed applications of pose estimation in healthcare, highlighting its potential to make quantitative movement analysis more accessible beyond laboratory settings. Algorithms such as OpenPose and DeepLabCut can automatically extract human body keypoints from standard video, enabling clinical applications in physical therapy, gait assessment, and movement disorders.

Building on this line of research, Ramesh et al. [7] proposed a smartphone-based system using the OpenPose BODY25 model to automate gait event detection and compute the EVGS, achieving strong correlations ($r > 0.8$) with manual scoring. Somasundaram et al. [8] later enhanced this method with improved gait event detection and stride segmentation, reaching accuracies above 90% for parameters such as hip and knee flexion in patients with cerebral palsy. However, these systems were limited to controlled or offline settings, lacked cloud deployment, and required substantial computational resources. To address these limitations, integrating pose estimation with cloud-based architecture offers a scalable and accessible solution for automated gait analysis and EVGS computation.

2. PROPOSED SOLUTION

The system is designed as a modular pipeline, composed of four main stages: (i) uploading and managing video files in the cloud; (ii) an automatic filtering module, which verifies the fulfillment of the minimum requirements for EVGS analysis (presence of a single person in the frame, complete visibility of the subject's body, stability of the sagittal/coronal filming plane); (iii) a processing module that uses the estimation of key points of body segments to derive the necessary parameters and calculate the EVGS; (iv) delivering the analysis report to the client.

The solution places special emphasis on the filtering module, which is considered essential to ensuring the robustness and reliability of the entire system. For this purpose, quantitative quality indicators are defined and extracted from the person and keypoint detection information (using the OpenPose application, which proved to behave better), which are subsequently compared with pre-established thresholds. Only videos that meet these criteria are accepted for automatic analysis, while inappropriate recordings are rejected and accompanied by explicit feedback messages explaining the reasons for non-acceptance. The automatic filtering stage is particularly important because the accuracy of markerless pose estimation strongly depends on the quality of the input video. Incomplete body visibility, multiple persons in the frame, poor illumination, camera instability, or an inadequate filming plane may lead to erroneous keypoint detection and, consequently, to unreliable EVGS computation. By introducing a preliminary validation step, the proposed system reduces the risk of propagating low-quality data through the processing pipeline. This approach increases the reproducibility of the analysis and provides the user with clear feedback regarding the acquisition conditions that must be improved before a new recording is submitted.

A markerless and nonintrusive framework was implemented using the OpenPose BODY25 model, an open-

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source, real-time pose estimation system that extracts 25 anatomically relevant keypoints from standard video clips [9]. The use of the OpenPose BODY25 model is relevant in this context because the extracted keypoints correspond to anatomical landmarks that can be associated with clinically meaningful gait parameters. Distances, angles, and temporal variations derived from these landmarks allow the system to approximate deviations in trunk position, pelvic alignment, knee progression, foot orientation, and other parameters included in the EVGS. This comprehensive keypoint set provides a detailed spatial representation of all major body segments (Fig. 1 b,c).

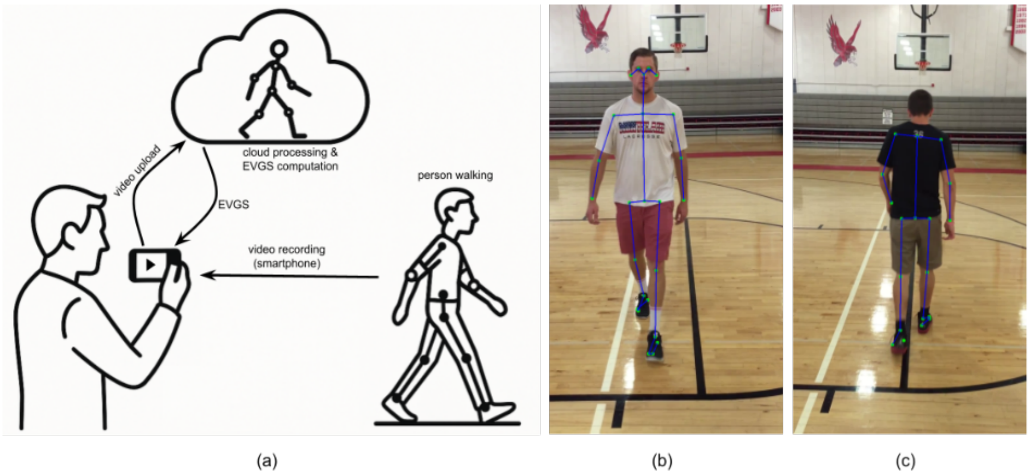


Fig. 1 – (a) Keypoints extracted using the OpenPose BODY25 model for (b) a healthy person and (c) an injured person.

The gait cycle was segmented into four canonical phases: initial contact (IC), midstance (MST), terminal stance (TST), and midswing (MSW). For each detected stride, the EVGS parameters computed from the coronal view were derived based on Euclidean distances and angular relationships between the BODY25 keypoints. The evaluated parameters are lateral trunk shift, pelvic obliquity, knee progression angle, foot rotation, and hindfoot valgus/varus.

The algorithm computes within the coronal view EVGS parameters for each step and then averages the results across all detected strides. Each parameter is scored according to EVGS standards: 0 for normal gait, 1 for mild-to-moderate deviation, and 2 for severe abnormality. The overall EVGS score is obtained by summing all 34 parameters, covering both coronal and sagittal plane evaluations [9].

Table 1

Functional components of the proposed solution.

Component	Role
Mobile application / frontend	It allows video capture of gait, user authentication, data transmission to/from the cloud and display of results.
Posture estimation module	It uses OpenPose or MoveNet to detect anatomical body keypoints from video frames.
Cloud infrastructure	It ensures data storage and processing, running algorithms, and saving results.
Backend / API	It receives data from the mobile application, coordinates processing, and sends the computed scores back to the user.
Scoring module	EVGS computing
Database	It stores the history of analyses, the scores obtained and the data necessary to monitor the patient's progress.

After extracting the initial parameters on the mobile device, the data are transmitted to a cloud backend, where objective indicators of gait quality (i.e. EVGS) are automatically calculated. The result is then transmitted back to the mobile application in the form of a numerical score, a synthetic interpretation or a comparison with previous assessments, using a dedicated web interface for the user.

Table 1 presents the functional components of the proposed cloud-based digital platform for automated and quantitative assessment of human gait. Several cloud computing options suitable for implementing such a mobile platform are presented in Table 2. Among the analyzed deployment options, GCP/Firebase is particularly suitable for the prototyping stage because it provides integrated services for authentication, storage, database management, serverless execution, and mobile application synchronization. This ecosystem allows rapid development of a functional prototype while maintaining the possibility of later scaling the processing components through services such as Cloud Run, Pub/Sub, Firestore, and BigQuery. At the same time, the use of managed cloud services reduces the need for local infrastructure maintenance, although careful configuration of access permissions, storage policies, and cost-control mechanisms remains essential.

In parallel, Amazon Web Services (AWS) represents a compelling alternative for both prototyping and production deployment, especially for computation-intensive video processing. Its rich portfolio of services, including Amazon EC2 for scalable compute, AWS Lambda and Fargate for serverless execution, S3 for durable object storage, and DynamoDB or Aurora for managed databases, facilitates gradual scaling from a single experimental instance to a highly available, clinically robust platform. The mature ecosystem of security and monitoring tools (e.g., IAM, CloudWatch, and Cost Explorer) further supports fine-grained access control, auditability, and cost management, making AWS a suitable long-term infrastructure choice.

Table 2

Cloud computing platforms.

Platform	Role	Main advantages	Restriction
Amazon Web Services (AWS)	Cloud processing, data storage, backend API and automatic score calculation.	High scalability; numerous services; suitable for	More complex setup; costs increase with video volume

		intensive processing.	and processing time.
Google Cloud Platform (GCP) / Firebase	Mobile app, authentication, database, storage and cloud backend.	Good integration with mobile applications; suitable for prototyping and data processing.	It requires careful control of costs and security rules.
On-premises	Local server in university, hospital or laboratory.	Direct control over data; useful for sensitive information.	High initial cost; requires maintenance and technical staff.
Hybrid cloud	Sensitive data kept locally, and analysis or scaling can be done in the cloud.	Good compromise between security, flexibility and computing power.	More difficult to manage architecture; requires clear data transfer policies.

Figure 2 shows the proposed architecture for cloud-based human motion analysis. The Angular/TypeScript client is responsible solely for acquiring the video and uploading the raw recording to the backend. The video file is transmitted via HTTP to the Python web server hosted on the AWS EC2 instance, where it enters the analysis pipeline. In this configuration, the web client functions primarily as an acquisition and communication interface with the cloud-hosted backend.

On the server side, the standard Python web server and routing layer receive the uploaded video and enqueue it for analysis within the same EC2 environment. A dedicated preprocessing and validation module decomposes the video into frames, applies the multi-stage keypoint filtering pipeline, and discards frames or entire videos that do not satisfy the minimum quality and completeness criteria required for robust EVGS computation. The validated frames are then passed to the OpenPose core engine, which extracts body keypoints and forwards them to a Python worker responsible for computing joint angles, gait parameters, and the Edinburgh Visual Gait Score for each limb and plane.

After the cloud pipeline calculates the EVGS and generates the analysis report, the results are stored as structured JSON in the internal database layer with EBS-backed persistence and made available to a clinician-facing dashboard. Within this interface, the clinician can track the patient's progress over time, compare scores across sessions, and interpret the degree of recovery using detailed sagittal and coronal subscores. In parallel, a lightweight client application can retrieve the processed EVGS values and a simplified report, either through periodic polling of the backend API or via an event-driven notification mechanism that automatically delivers the results as soon as processing is complete, without requiring the user to explicitly check job status.

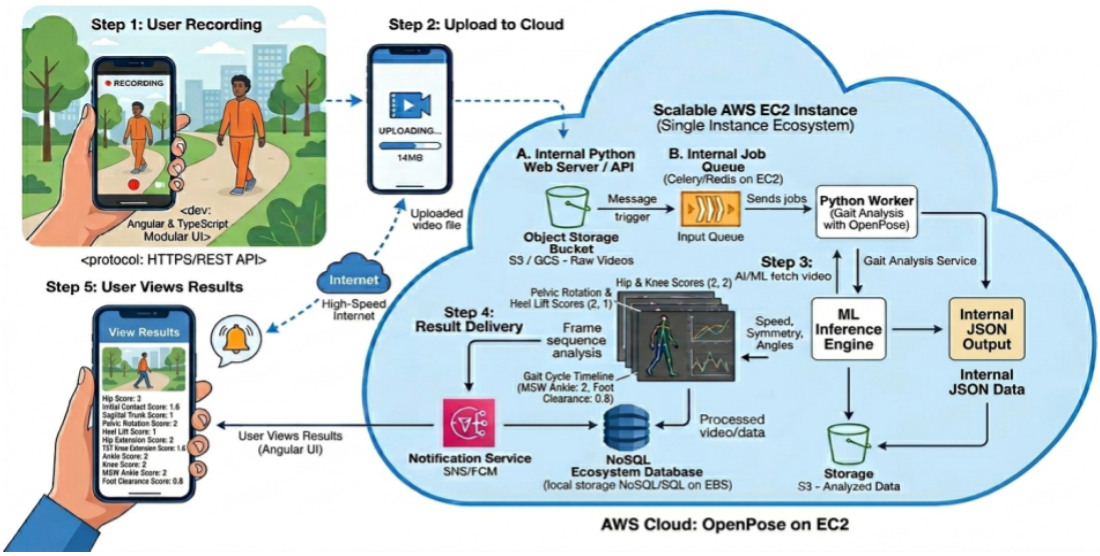


Fig. 2 – Cloud-based (AWS) gait analysis framework

Given the potentially sensitive nature of gait recordings and clinical assessment results, data security and privacy are considered core requirements of the framework. Video files, extracted coordinates, EVGS scores, and longitudinal patient histories are transmitted over protected communication channels and stored in access-controlled cloud services, with role-based access control used to differentiate permissions for patients, clinicians, researchers, and administrators.

Overall, this architecture balances the usability requirements of clinical practice with the computational demands of automatic pose estimation and EVGS scoring. By centralizing the multi-stage preprocessing, OpenPose inference, and scoring logic on a single AWS EC2 instance, while exposing them through a lightweight web client, the system remains easy to deploy, simplifies maintenance, and can be incrementally scaled as the number of patients and recordings increases.

3. IMPLEMENTATION DETAILS

The developed system employs a decoupled, high-performance architectural paradigm divided into a modular client-side frontend and a consolidated, cloud-based backend ecosystem, as illustrated in Fig. 3. This structural topology ensures high resource availability, minimal network latency, and automated, clinically reliable computer vision inference.

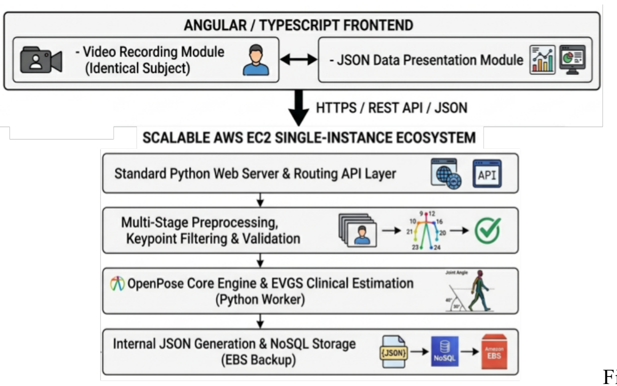
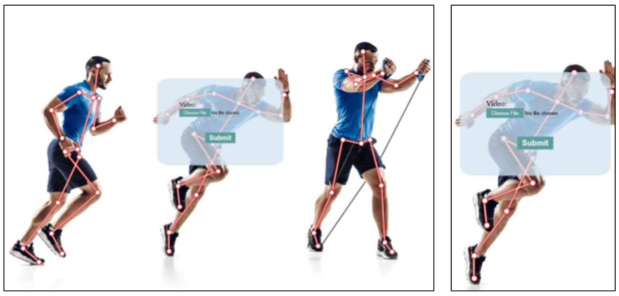


Fig. 3 – System architecture diagram for the EVGS gait analysis platform, highlighting the interaction between the modular Angular client interface and the single-instance AWS EC2 processing layer using Python and OpenPose.

CLIENT-SIDE INTERFACE (FRONTEND LAYER)

The client application is implemented as a single-page web interface using Angular and TypeScript, which provides a modular, component-based structure for presenting gait analysis functionality across desktop and mobile devices; both views are illustrated in Fig. 4.



(a) Web interface (b) Mobile application

Fig. 4 – Client-side interface: (a) web interface view, (b) mobile application view

The frontend exposes a dedicated video upload and recording module that allows clinicians to capture or select standardized gait recordings of the same subject and securely submit these files via HTTPS to the backend REST API.

A complementary data presentation module renders the processed results returned as JSON, displaying Edinburgh Visual Gait Score (EVGS) subscores for sagittal and coronal planes in an interactive, responsive layout.

HTTPS / REST API COMMUNICATION

Communication between the browser client and the server follows a stateless REST paradigm over HTTPS, where each video upload and result request is encapsulated as a JSON-based API call. This design decouples the user interface from the computational pipeline, facilitates integration with external systems, and simplifies horizontal scaling of the backend if higher throughput is required.

SCALABLE AWS EC2 DEPLOYMENT

The entire application stack is deployed on a single Amazon Web Services (AWS) Elastic Compute Cloud (EC2) instance, which provides configurable CPU and GPU resources for compute-intensive pose estimation while maintaining global network accessibility.

Persistent block storage is provisioned using Amazon Elastic Block Store (EBS), enabling reliable backup of intermediate JSON outputs and processed gait scores without impacting the runtime performance of the pose estimation pipeline.

On the server side, a standard Python web framework exposes a RESTful API that manages request routing, file handling, and orchestration of the downstream analysis pipeline. Upon receiving a video, this layer is responsible for persistent storage of the raw file, queuing of the processing task, and returning either intermediate job-status updates or the final EVGS report as structured JSON to the frontend.

MULTI-STAGE PREPROCESSING, KEYPOINT FILTERING, AND VALIDATION

Each video is decomposed into individual frames, which are then passed through a multi-stage preprocessing pipeline that performs resizing, normalization, and other basic enhancements to ensure stable performance of the pose estimator.

Given the sensitivity of EVGS to incomplete kinematic information, every frame is evaluated according to the availability of the essential OpenPose keypoints (9–24); only detections that contain the full set of required landmarks are retained, and frames without a complete detection are automatically discarded.

In frames where multiple persons are detected, the system selects the detection with the most complete and consistent keypoint set, thereby enforcing subject-specific tracking and minimizing contamination from background individuals.

To avoid scoring based on poor-quality data, a global video-level validation stage rejects any recording that yields fewer than 10 fully annotated frames after filtering, prompting acquisition of a new trial and preventing unreliable scores from entering the clinical workflow.

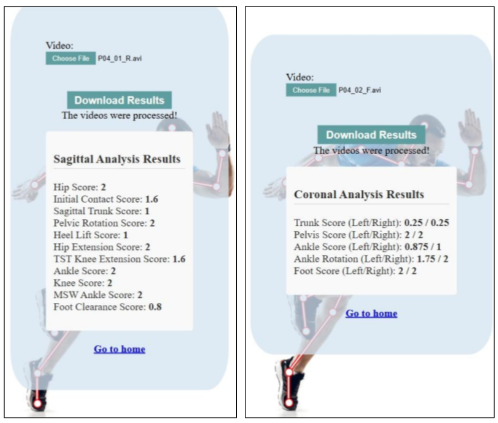
OPENPOSE CORE ENGINE AND EVGS COMPUTATION MODULE

For human pose estimation, the backend integrates the OpenPose solution, a real-time multi-person 2D keypoint detector that predicts body, limb, and foot landmarks.

The sequence of validated keypoints produced by OpenPose is then processed by a dedicated Python worker that reconstructs joint trajectories in the sagittal and coronal planes and automatically maps the observed deviations to the 17-item EVGS scoring scheme for each limb.

This module aggregates frame-level observations into clinically interpretable subscores (*e.g.*, hip, knee, ankle, trunk, and foot items) and computes total EVGS values that are directly comparable to those obtained through conventional visual scoring by trained observers.

JSON REPORT GENERATION AND NOSQL STORAGE



(a) Sagittal view results (b) Coronal view results

Fig. 5 – Rendered results for EVGS score computation: (a) sagittal and (b) coronal views

After EVGS computation, the backend serializes all intermediate and final outputs: validated keypoints, per-frame observations, segment-level subscores, and total EVGS into structured JSON documents.

These JSON records are stored in a lightweight NoSQL database with EBS-backed persistence, which supports efficient retrieval of longitudinal gait assessments for the same patient and facilitates downstream statistical analysis or integration with external electronic health record systems.

The same JSON documents are transmitted to the Angular frontend, where they are rendered into human-readable reports and downloadable result files, closing the loop between automated video processing and clinical interpretation at the point of care.

4. RESULTS AND DISCUSSIONS

In this section, we present the empirical evaluation of the proposed cloud-based EVGS pipeline, focusing on both computational performance and clinical interpretability of the automatically generated gait scores. The analysis is based on representative gait recordings acquired in frontal and sagittal planes, for which end-to-end processing times, per-frame pose-estimation costs, and resulting EVGS subscores were quantified. In addition to reporting numerical results, we discuss how video quality and the multi-stage keypoint filtering strategy influence the robustness of the scores, and we highlight current limitations, most notably CPU-bound OpenPose inference and directions for improving execution speed and clinical applicability in future iterations of the system.

Table 3

Processing performance of two analyzed videos.

Metric	P04_02_F.avi (coronal – front)	P04_01_R.avi (sagittal – right)
Number of frames	128	209
Upload time (s)	0.894	0.918
Server-side processing time (s)*	549.539	893.298
Mean OpenPose time per frame (s)	4.292	4.273
EVGS computation time (s)	0.0111	0.0061

*Server-side processing time includes filtering, OpenPose inference, and EVGS computation.

Table 3 summarizes the execution times measured for two analyzed videos. The results show that video upload contributes negligibly to the total delay, whereas the dominant computational cost is associated with server-side preprocessing and, in particular, OpenPose inference. The EVGS computation itself requires only a few milliseconds per video, indicating that the scoring stage is lightweight compared with the pose-estimation stage.

For the frontal-plane recording, the total end-to-end time was approximately 1471 s, while the sagittal-plane recording required about 894 s. Although the second video contained more frames, both recordings exhibited a similar average OpenPose runtime of about 4.27–4.29 s per frame, confirming that the main bottleneck is the pose estimation process executed on the current infrastructure. These findings indicate that the proposed pipeline is functionally valid for automated gait assessment and suggest that GPU acceleration would be necessary to improve the system's efficiency for practical clinical deployment.

Table 4

Coronal-plane EVGS subscores for P04_02_F video.

Metric	Value (left)	Value (right)	Interpretation
Trunk score	0.25	0.25	Near-normal alignment
Pelvis score	2	2	Marked deviation
Ankle score	0.875	1	Minor–moderate deviation
Ankle rotation	1.75	2	Marked deviation
Foot score	2	2	Marked deviation

* Interpretation scale: 0 = normal, 1 = minor deviation, 2 = marked deviation.

The generated EVGS outputs demonstrate that the system can produce detailed gait-related parameters for both coronal and sagittal views. In the frontal-plane recording, the model yielded bilateral subscores for trunk, pelvis, ankle, ankle rotation, and foot components, as shown in Table 4. The values indicate substantial deviations at the pelvis, ankle rotation, and foot level, while trunk deviations remained limited.

Table 5

Processing performance of two analyzed videos

Metric	Score	Interpretation
Hip score	2	Marked deviation
Initial contact score	1.6	Between minor and marked
Sagittal trunk score	1	Minor deviation
Pelvic rotation score	2	Marked deviation
Heel lift score	1	Minor deviation
Hip extension score	2	Marked deviation
TST knee extension score	1.6	Between minor and marked
Ankle score	2	Marked deviation
Knee score	2	Marked deviation
MSW ankle score	2	Marked deviation
Foot clearance score	0.8	Near-normal

For the sagittal-plane recording, the system generated scores for hip, initial contact, sagittal trunk, pelvic rotation, heel lift, hip extension, terminal stance knee extension, ankle, knee, mid-swing ankle, and foot clearance, as summarized in Table 5. Several parameters reached the maximum abnormality score of 2, especially those related to hip, ankle, and knee function, suggesting pronounced gait deviations in this view. By contrast, foot clearance showed a lower score, indicating a less severe abnormality for that specific parameter.

According to the EVGS interpretation framework, a score of 0 corresponds to normal gait, 1 to a minor deviation, and 2 to a marked deviation. The global EVGS is obtained by summing all parameters from the coronal and sagittal analyses, making the final score suitable for longitudinal monitoring and comparison with conventional observational clinical assessment.

DISCUSSIONS

The obtained results show that the proposed architecture is capable of automatically extracting clinically interpretable gait information from uploaded videos and transforming it into structured EVGS outputs. At the same time, the experiments confirm that the reliability of the analysis depends strongly on the quality of the recorded data, which justifies the inclusion of the multi-stage frame filtering and validation pipeline. By rejecting frames that do not contain all required keypoints and invalidating videos with fewer than 10 fully annotated frames, the system reduces the risk of generating misleading clinical scores from incomplete or noisy pose information.

A second important observation concerns computational efficiency. The results clearly show that OpenPose inference dominates the total execution time, whereas score computation is almost instantaneous once valid keypoints are available. This suggests that future optimization efforts should focus primarily on accelerating the pose-estimation stage, for example through GPU-enabled AWS instances and better hardware allocation.

Finally, the present evaluation should be interpreted as a proof of concept rather than a large-scale validation study. The system was tested on a limited number of recordings, and the quality of the experimental videos still leaves room for improvement in terms of camera stability, illumination, and resolution. Future work should therefore include testing on a larger cohort, acquisition of standardized videos, and direct comparison between automatically generated scores and expert clinical ratings to assess agreement, repeatability, and practical usefulness in rehabilitation settings.

5. **CONCLUSIONS**

The proposed cloud-based framework is a modern technical solution for automated gait analysis, combining a lightweight web client with a centralized cloud-based processing backend deployed on Amazon Web Services (AWS). The Angular/TypeScript frontend is responsible for video acquisition, upload, and visualization of the generated results, while the main computational workload is executed on the server side. Within the AWS EC2-hosted backend, the Python processing pipeline performs frame extraction, multi-stage validation, OpenPose-based keypoint detection, and computation of the Edinburgh Visual Gait Score (EVGS), thereby transforming raw visual data into clinically interpretable gait metrics.

After processing is completed, the backend generates structured JSON outputs that can be rendered in the client interface as detailed gait-analysis results, including sagittal and coronal EVGS components, summary indicators, and downloadable reports. In this way, the platform extends beyond a simple video-upload application and moves toward a digital clinical support framework capable of assisting remote, objective, and repeatable gait evaluation.

This architecture provides a practical foundation for an integrated solution for automatic EVGS computation and cloud-based gait assessment, with the potential to reduce evaluation time, improve consistency, and facilitate future adoption in rehabilitation practice. However, the current implementation should still be regarded as a prototype and requires additional validation before clinical use. Its performance may be affected by factors such as video quality, camera viewpoint, illumination, clothing, occlusions, and the variability of pathological gait patterns, while the final EVGS accuracy depends directly on the reliability of the detected anatomical keypoints and the robustness of the gait-event segmentation process.

Future work will focus on improving execution speed through hardware acceleration, expanding validation on larger patient cohorts, and extending the platform toward a more comprehensive clinical decision-support environment with stronger reporting, longitudinal monitoring, and secure multi-user access control.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

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RAMONA LUCA: methodology, visualization, writing original draft, review & editing.
FLORIN ROTARU: simulation, formal analysis, validation.
HARITON COSTIN: conceptualization, supervision, resources, writing original draft, results curation, corresponding author.

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