Gait-Recognition of Neurological Patients Using GHQ Labels

Abstract

*Accurate and early classification of neurological conditions remains a clinical challenge. In this work, we propose a novel gait recognition system to classify patients into General Health Questionnaire (GHQ) labels, linking biomechanical gait patterns with psychological well-being. Our method extracts spatial features from gait videos using pose estimation, processes them through Extreme Gradient Boosting (XGboost), and outputs GHQ categories. Experiments on a dataset of 312 patients demonstrate an overall accuracy of **76%**.*

1 Introduction

Neurological disorders often manifest through altered gait patterns. Early detection of such conditions can significantly improve patient outcomes through timely intervention. Psychological health, as measured by the General Health Questionnaire (GHQ), plays a crucial role in overall well-being. By bridging gait biomechanics with GHQ-based psychological assessment, this work introduces a hybrid diagnostic framework that is non-invasive, cost-effective, and scalable.

Our contributions are:

- We introduce the first gait-based classifier for GHQ labels, linking physical gait features to psychological categories.
- We design a XGBoost architecture. It's a super powerful and efficient implementation of gradient boosting for supervised learning problems. It uses decision trees and is known for its speed and performance, especially in structured/tabular data.
- We are using only spatial feature of individual frame and not how it is evolving with time because it has no need for modeling long sequence, which reduces both computation and data requirements and it is immune to variable frame rates of the training video.

2 Proposed Method

2.1 Data Collection and Preprocessing

Datasets on the patients were downloaded from a pre existing source, which contained information on various psychological traits, including GHQ labels. The data consisted of three types: videos converted into arrays in the form of SMPL features (.npz), skeleton data (.json), and frame-wise grayscale silhouette images. GHQ labels were already provided for the patients and categorized into three labels: Typical, Minor Distress, and Major Distress. We employed SMPL features for 2D pose estimation, which included 72 keypoints per frame. The keypoint sequences were normalized and stored frame-wise in the same .npz file for each video.

2.2 Model Architecture

Our Model consists of:

1. **Feature Extraction**: A top-down pipeline for 3D human pose and shape estimation, which enables decoupled optimization of detection and pose inference. However, conventional top-down approaches rely on cropped human regions, thereby discarding critical spatial information relative to the original camera coordinate system.This limitation significantly affects accurate

prediction of the global orientation and translation of the subject. To address this,we integrate the CLIFF (Carrying Location Information in Full Frames)framework into our methodology.

We made significant modifications to the original CLIFF implementation to ensure compatibility with our dataset and hardware configuration. The official CLIFF codebase was designed for execution on CUDA-enabled GPUs, but due to the absence of GPU drivers on our systems, we adapted the codebase for CPU-only. Additionally, the original implementation relied on SMPL parameters, which presented compatibility issues on Windows platforms. To address this, we replaced SMPL with SMPL-X, which offered better cross-platform support and richer body modeling. Furthermore, we customized the main Python script to handle our specific input video formats. This involved integrating the torchgeometry library to manage video frame processing and geometric transformations more effectively.

2. **Structure of .npz file**:

   - `imgname`: Image name
   - `center`: Bounding box center
   - `scale`: Bounding box scale
   - `part`: 2D keypoint annotation, shape
   - `annot_id`: Annotation ID (available only for the COCO dataset)
   - `pose`: SMPL pose parameters in axis-angle format, shape `(72,)`
   - `shape`: SMPL shape parameters, shape `(10,)`
   - `has_smpl`: Indicates whether SMPL parameters are available (true for all samples)
   - `global_t`: Pelvis translation in the camera coordinate system w.r.t. the original full-frame image
   - `focal_l`: Estimated focal length for the original image, calculated as `np.sqrt(img_w ** 2 + img_h ** 2)`

Figure 1: Regenerated mesh using extracted features

   - `S`: 3D joints with pelvis aligned at `(0, 0, 0)`, shape `(24, 4)`, format: `[x, y, z, conf]`, same keypoint order as `part`

3. **Spatial Aggregation**:We leverage sequential SMPL keypoint features extracted frame-wise and structured into gait cycles.

4. **Classification Head**: Instead of a traditional neural network-based classification head, we utilize XGBoost—a tree-based ensemble method—for multi-class classification of GHQ labels

3 Experiments and Results

3.1 Dataset and Evaluation Metrics

We evaluate on $N = 312$ patients (35-Major distress, 68-Minor distress, 209-Typical) with an 80/20 train/test split. Metrics include accuracy, precision, recall, f1-score. We also tried identifying GHQ label for some random videos from internet,which gave us satisfactory results.

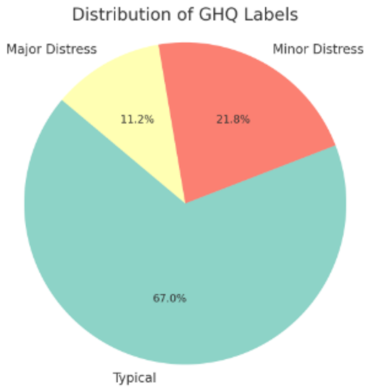

Figure 2: Distribution of GHQ labels among patients

Evaluation Metrics

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where:

- TP = True Positive
- FP = False Positive
- FN = False Negative

3.2 Comparison for Skeleton

Table 1: Random Forest on Skeleton

Class	Precision	Recall	F1-Score
Major Distress	0.94	0.08	0.14
Minor Distress	0.81	0.26	0.39
Typical	0.72	0.99	0.84

Table 2: XGBoost on Skeleton

Class	Precision	Recall	F1-Score
Major Distress	0.79	0.04	0.07
Minor Distress	0.64	0.13	0.21
Typical	0.70	0.98	0.82

One of the primary challenges we encountered when working with the Skeleton dataset was the presence of a large number of video samples corresponding to the same individual under varying conditions—such as different clothing, carrying accessories like bags, etc. This variability significantly increased the computational time required for identity association and merging multiple video samples of the same person into a unified label file. Due to these reasons, we decided to avoid using this dataset in our Model.

3.3 Comparison for Silhouettes

Table 3: XGBoost on Silhouettes

Class	Precision	Recall	F1-Score
Major Distress	0.98	0.25	0.39
Minor Distress	0.84	0.31	0.45
Typical	0.74	0.99	0.84

Table 4: KNN on Silhouettes

Class	Precision	Recall	F1-Score
Major Distress	0.76	0.61	0.68
Minor Distress	0.77	0.68	0.73
Typical	0.86	0.92	0.89

3.4 Comparison for SMPL Features

Table 5: XGBoost on SMPL Features

Class	Precision	Recall	F1-Score
Major Distress	0.00	0.00	0.00
Minor Distress	1.00	0.18	0.31
Typical	0.77	0.98	0.86

Table 6: KNN on SMPL Features

Class	Precision	Recall	F1-Score
Major Distress	0.00	0.00	0.00
Minor Distress	0.43	0.27	0.33
Typical	0.76	0.89	0.82

3.5 Comparison for different features

Table 7: Accuracy from Different Feature Types

Feature Type	Accuracy
Skeleton	0.73
Silhouettes	0.72
SMPL	0.76

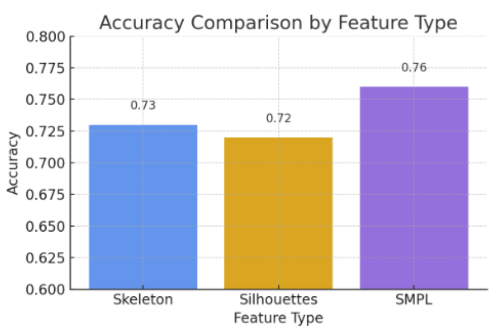

Figure 3: Accuracy from Different Feature Types

4 Conclusion

We presented a novel gait-based classification framework that maps gait dynamics to GHQ labels, achieving 76% accuracy on neurological patients. This demonstrates the potential of combining biomechanical and psychological assessments for non-invasive diagnostics.

5 Study materials

1. **What is Gait recognition**: https://recfaces.com/articles/what-is-gait-recognition
2. **Survey on Gait recognition**: https://dl.acm.org/doi/pdf/10.1145/3230633
3. **Biometric Gait recognition**: https://www.researchgate.net/publication/221621870_Biometric_Gait_Recognition

A Appendix: Code and Dataset Links

- **Feature Extractor**: https://github.com/huawei-noah/noah-research/tree/master
- **Dataset Access**: https://drive.google.com/drive/folders/1Ldo3Yzh1Oo_dOByFjaWVdh5K_1pfxPkV
- **Source code**: https://github.com/Code-Breach/GAIT_Recognition-for-Patients

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