

Integrating Postural and Physiological Features for High-Altitude Acclimatization Assessment: A Machine Learning Framework

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Abstract

Background and Objective

: Field-deployable objective screening tools for high-altitude acclimatization remain scarce. Existing assessments rely heavily on single physiological indicators—particularly hematological and cardiorespiratory parameters—and lack effective behavioral functional measures. This study introduces video-derived postural behavioral indicators to complement blood-based physiological indicators, establishing a multimodal assessment framework for evaluating acclimatization status in populations exposed to high-altitude hypoxic environments.

Methods

Healthy lowland-origin participants residing at high altitude were recruited under an approved ethics protocol. Multi-view video recordings were acquired during eyes-open and eyes-closed single-leg stance tasks, and hematocrit (HCT) was measured as the physiological reference. OpenPose was used to extract body keypoints from video frames, and a temporal convolutional network (TCN) was applied to model frame-wise postural time-series and generate composite balance features. These behavioral features were fused with HCT, and a support vector machine (SVM) with radial basis function kernel was constructed for acclimatization-status classification. Model performance was evaluated using ten-fold cross-validation with accuracy, F1-score, and area under the receiver operating characteristic curve (AUC), alongside feature-importance and learning-curve analyses.

Results

Fusion of postural behavioral features with HCT outperformed HCT-only models across all evaluation metrics, demonstrating that behavioral postural information provides incremental discriminative value beyond conventional physiological indicators. Feature-importance analysis confirmed that HCT remained the dominant predictor, while TCN-derived balance features—especially those from the eyes-closed condition—contributed supplementary predictive power. Learning curves indicated stable model performance with the current sample size.

Conclusions

Integrating video-based postural behavioral signals with hematological physiological indicators improves high-altitude acclimatization discrimination. This multimodal strategy offers a non-invasive, low-cost, and field-compatible auxiliary screening approach for high-altitude-exposed populations. Future work should validate the model in larger independent cohorts and deploy it as a real-world clinical decision-support tool.

1. Introduction

Hypoxia is one of the most fundamental characteristics of high-altitude environments (Cai et al., 2026). As altitude increases, atmospheric pressure and oxygen partial pressure continue to decrease, placing the human body in a state of chronic oxygen deprivation (Basnyat, 2014; Bian et al., 2013; Zhang et al., 2019). Under these conditions, the body employs physiological compensatory mechanisms to enhance oxygen uptake and utilization efficiency (Liu & Ma, 2016), for example, by increasing the number and volume of red blood cells to enhance oxygen-carrying capacity (Villafuerte et al., 2022), while regulating blood oxygen saturation to adapt to hypoxic metabolic demands and maintain tissue oxygen balance (Villafuerte et al., 2022).

In clinical health assessments conducted in extreme environments such as high-altitude regions, a long-standing challenge is how to achieve objective, quantitative, and field-deployable monitoring of the body's complex adaptive status. High-altitude acclimatization is an adaptive process by which individuals from lowland areas, upon entering high-altitude regions, gradually optimize oxygen utilization efficiency through multisystem, multilevel physiological compensation in a low-pressure, hypoxic environment (Gao et al., 2001). Objective, precise, and quantifiable assessment of high-altitude acclimatization levels can effectively determine the degree of human adaptation to high-altitude hypoxia and identify the risk of poor acclimatization, which holds significant theoretical and practical value in high-altitude medical research, health protection of workers in high-altitude environments, and rapid on-site screening.

To address this clinical assessment need, extensive research has evaluated high-altitude acclimatization based on physiological indicators, particularly those reflecting respiratory, circulatory, and hematological function. Jefferson et al. (2004) found that excessive erythrocytosis is a core feature of chronic mountain sickness, whereas well-acclimatized individuals exhibited only moderate erythrocytosis, suggesting that abnormally elevated red blood cell counts serve as an indicator of poor acclimatization. Gao et al. (2001) classified acclimatization into three stages—preliminary, basic, and complete—based on baseline physiological indicators, including respiration, pulse rate, blood pressure, red blood cell count, and hemoglobin. Wu and Li (2023) further linked the onset of high-altitude polycythemia to hypoxia-induced erythropoietin abnormalities, genetic polymorphisms, and elevated inflammatory factors. Building on this, Li et al. (2024) validated, through a retrospective study of 2,347 cases, that the SpO_2/HCT ratio (AAI) effectively distinguishes good from poor acclimatization with stable diagnostic performance. Collectively, these studies confirm that HCT and SpO_2 effectively reflect cardiorespiratory compensation and remain the most widely used physiological indicators in acclimatization assessment. However, a common limitation is the single-dimensional nature of these metrics—whether the three-tier system or the AAI composite index, their core components are confined to physiological parameters—raising the question of whether other categories of biological signals could serve as complementary information sources for evaluating acclimatization status.

Substantial physiological and neuroscientific evidence supports the association between postural behavior and human stress states. Dempsey and Morgan (2015) pointed out that the core characteristic of high-altitude hypoxic adaptation is “multisystem coordination”—the human body requires close functional integration and coordination among multiple systems, including the respiratory, circulatory, hematological, and neuroendocrine systems, to maintain homeostasis under hypoxic conditions, and this multisystem coordination often comes at the cost of functional impairment in certain systems. Taking the central nervous system as an example, Wilson et al. (2014) noted that acute hypoxic exposure can lead to elevated intracranial pressure, which is closely associated with the pathophysiological processes underlying neurological syndromes such as high-altitude headache, acute mountain sickness, and even high-altitude cerebral edema. Wen and Long (2024) further summarized the multifaceted effects of high-altitude hypoxic environments on the nervous system, including reduced attention, memory decline, impaired visual working memory, and balance dysfunction, with the underlying mechanisms involving reduced cerebral blood supply, impaired neural signal transmission, and abnormal cerebrovascular regulation. Neural function damage manifests most intuitively in postural control and balance: Debenham et al. (2021) conducted a systematic review confirming that under normobaric hypoxic conditions, standing balance parameters decline by approximately 2–10%, whereas in high-altitude hypobaric hypoxic environments, balance deterioration can reach up to 83%, and when altitude exceeds 1,524 meters, this impairment becomes persistent.

Building on this evidence, the present study considers whether postural behavior can be quantified as a complementary signal source. The postural time series generated during standing and walking contain rich information regarding neuromuscular control and motor coordination (Michalak & Przekoracka, 2022; Porto et al., 2019). These time-varying parameters—quantifiable through center-of-mass trajectory, joint angles, and stability—essentially constitute a behavioral time-series signal (Trabelsi et al., 2025), providing different dimensional information compared to traditional physiological signals such as heart rate and blood pressure. Therefore, balance function is not only a comprehensive reflection of neural integration capacity, but may also serve as a sensitive and easily measurable behavioral indicator for assessing high-altitude acclimatization status.

Machine-learning-driven assessment tools have been reported for altitude-related conditions using clinical and physiological predictors (Gesang et al., 2025). Despite evidence that high-altitude hypoxia impairs balance function (Debenham et al., 2021; Wilson et al., 2014), no study has systematically integrated temporal postural features with hematological indicators for acclimatization assessment. Physiological and behavioral signals reflect complementary dimensions—circulatory/respiratory compensation versus neural response to hypoxia—suggesting that their fusion may offer a more comprehensive evaluation. To this end, we propose a multimodal framework that combines video-based postural signals with hematocrit (HCT) using OpenPose for keypoint extraction, a temporal convolutional network (TCN) for balance feature modeling, and a support vector machine (SVM) for acclimatization status prediction. This study aims to verify whether postural signals can serve as effective supplementary information to physiological indicators and to evaluate the feasibility of this fusion strategy for field-based health monitoring at high altitudes.

2. Related Work

In recent years, computer-vision-driven human pose estimation and deep-learning-based temporal modeling have facilitated detailed quantitative assessment of human balance function. Relevant technical work can be grouped into two categories: human pose estimation and temporal-feature modeling.

Early pose estimation relied on traditional visual and model-driven pipelines, including sliding-window detection (Viola & Jones, 2001) and particle-filter-based kinematic-chain tracking under Bayesian motion priors (Sidenbladh et al., 2000). Nevertheless, high computational cost, initialization sensitivity and limited generalization hinder robust pose extraction under real-world dynamic conditions.

Deep-learning-based convolutional-neural-network pose estimation has become the dominant alternative for its strong robustness. As a widely adopted open-source bottom-up 2D pose estimator, OpenPose utilizes part-affinity fields to detect human body keypoints with per-joint confidence outputs (Cao et al., 2021). It supports real-time inference independent of subject count and offers dependable keypoint sources for frame-wise dynamic-balance analysis.

For temporal-feature modeling in balance evaluation, it is essential to characterize sequential variations such as center-of-mass sway and joint jitter beyond isolated single-frame poses. Classical approaches including Hidden Markov Models (Kuehne et al., 2014; Kuehne et al., 2016) lack sensitivity to subtle long-sequence postural fluctuations and cannot satisfy fine-grained balance assessment demands. Recurrent neural networks and long short-term memory networks (Elman, 1990; Hochreiter & Schmidhuber, 1997) were once widely used for temporal dependency learning, yet sequential computation overhead and long-sequence gradient-vanishing restrict their performance for full-duration single-leg-stance recordings.

Temporal convolutional networks (TCN) mitigate these bottlenecks via causal dilated convolutions, enlarging receptive-field size while preserving temporal ordering to capture both global dynamics and local subtle variations within long sequences (Lea et al., 2017). Benefiting from parallel computation, TCN achieves high inference efficiency and is well-suited for modeling long-range temporal relationships derived from pose sequences in balance-related tasks.

While these pose-estimation and temporal-modeling tools are widely available for human balance analysis, few studies have leveraged such vision-based behavioral measurements to build multimodal assessment tools targeting high-altitude acclimatization, which motivates the present study.

3. Experiment: Development of an Assessment Model for High-Altitude Acclimatization

Figure 1. Workflow of the multimodal modeling framework for evaluating high-altitude acclimatization. This framework consists of three layers: (1) Data layer: Raw video data from 321 participants were

screened, retaining 133 valid samples that included complete HCT, SpO₂, and video records; the video data underwent preprocessing, including valid segment extraction and resolution normalization. (2) Feature layer: Human keypoints were extracted from the preprocessed video using OpenPose; balance features were generated via TCN temporal modeling and fused with HCT physiological indicators. (3) Model evaluation layer: The fused features were input into an RBF kernel SVM classifier, using a 3:7 training-to-test split and 10-fold cross-validation; model performance was evaluated using ACC, AUC, and F1-score, supplemented by learning curves and feature importance analysis.

3.1. Participants and Experimental Procedure

3.1.1. Participants

This study recruited 321 participants from several universities in the Tibet Autonomous Region, including 219 non-Tibetan participants from outside the region and 102 Tibetan participants from within the region; 182 participants were male and 139 were female. After screening, 133 participants were included in the subsequent high-altitude acclimatization assessment study. The inclusion criteria were as follows: (1) Han Chinese or Tibetan residents of Tibet and (2) participants aged 18 years or older, regardless of sex.

3.1.2. Experimental Procedure and Data Collection

Prior to the experiment, venous blood samples were collected from participants to measure blood oxygen saturation and HCT. All participants completed a single-leg balance test. Using their dominant leg as the support leg and lifting the non-dominant leg with the knee bent, they sequentially performed single-leg standing tasks with eyes open and closed. The experiment was recorded simultaneously using three camera positions (front, left, and right) to document the entire standing process. An example of a single-leg standing posture is shown in Fig. 2.

3.2. Data Processing and Feature Engineering

3.2.1. Data Preprocessing

The data preprocessing in this study primarily focused on selecting valid segments from single-leg standing videos, with the core objective of ensuring the accuracy of subsequent posture feature extraction. Specifically, for the single-leg standing videos of the participants, we retained the valid single-leg standing segments from the completion of leg lift to just before leg placement, while excluding video content from the leg-lifting and leg-placement processes (see Fig. 3 for a schematic diagram of the single-leg standing video preprocessing workflow). These movements cause significant fluctuations in the body's center of gravity and abnormal joint angles. If included in the analysis, they would interfere with the extraction of core features such as center-of-gravity shifts and joint tremors, thereby affecting the accuracy of balance ability assessment. Additionally, noise reduction was applied to the selected valid video segments to ensure the stability of subsequent human keypoint detection and balance

feature extraction, thereby providing high-quality raw data for subsequent model training and feature analysis.

3.2.2. Human Pose Extraction

This study employed the open-source pose estimation algorithm OpenPose to extract human keypoint coordinates (Cao et al., 2021). Each participant completed both the eyes-open and eyes-closed single-leg standing tasks, and the experiment utilized synchronized recordings from three camera positions—frontal, left, and right—yielding six video samples per participant, all requiring pose extraction processing. After extracting keypoints frame-by-frame from all videos, low-confidence detection results were filtered out to ensure the accuracy and stability of the subsequent balanced feature calculations.

3.2.3. Calculation of Balance Characteristics

In quantitative assessments of balance function, center-of-mass sway parameters (including root-mean-square sway, maximum displacement, and total sway energy) are widely used to quantify postural stability (LaRoche et al., 2010; Li et al., 2016; Yan et al., 2025): larger root-mean-square sway indicates poorer postural control; maximum displacement reflects limits of control over the center of gravity within the base of support; and total sway energy reflects the overall metabolic cost and neuromuscular load of postural control. Additionally, angular jitter in key joints of the trunk and limbs also constitutes an important dimension of balance assessment (Yamamoto et al., 2015). The single-leg standing duration is a comprehensive balance indicator widely used in clinical settings (Iwata et al., 2025; Springer et al., 2007) that effectively reflects an individual's postural control reserve during dynamic tasks. These indicators characterize multiple dimensions of postural control in the time, frequency, and angular domains and have been validated by numerous domestic and international studies as effective quantitative features for assessing balance function.

Based on the above rationale, after screening valid video clips, we utilized human keypoints extracted via OpenPose to calculate feature metrics representing dynamic balance ability. The body's center of mass (COM) coordinates were calculated using hip keypoints to analyze the root mean square (RMS) of COM sway, maximum displacement, and total sway energy, while key joint angles of the trunk and limbs were used to derive joint angular jitter. Finally, single-leg standing duration, RMS of COM sway, maximum COM displacement, total sway energy, and joint angle jitter were extracted as quantitative features for balance assessment.

3.2.4. A TCN-Based Temporal Score for Balance Ability

After extracting balance features from single-leg standing, the balance features of each frame (RMS of the center-of-mass sway, maximum COM displacement, total sway energy, and joint angle jitter) were concatenated in chronological order to construct a continuous time-series feature sequence, which served as the input to the TCN. The core objective was to leverage the structural advantages of the TCN to simulate human visual perception of dynamic balance posture, thereby achieving objective,

quantitative assessment of balance ability and eliminating the subjective bias inherent in traditional manual scoring.

The model uses duration as the base weight and frame-level jitter features as dynamic correction terms. Through automatic aggregation and nonlinear mapping of temporal features, it outputs a unified TCN balance score. A higher score indicates that the subject maintained a single-leg stance for a longer duration, exhibited minimal postural jitter, and demonstrated stronger balance control, while a lower score indicates a shorter stance duration, severe swaying, and poorer balance stability. Thus, the model enables automated balance scoring from raw video data by integrating duration and jitter features, providing an objective, quantifiable basis for balance assessment that can be used in subsequent construction of high-altitude acclimatization evaluation models in conjunction with physiological indicators.

3.2.5. Multi-view Feature Fusion

After completing the TCN-based temporal balance scoring, feature fusion was performed on the multicamera video scores under the same task conditions. In this study, the TCN balance scores from three camera angles for the same subject under the same condition (eyes open/eyes closed) were averaged to obtain mean balance scores for eyes open and eyes closed. Multi-camera fusion not only eliminates systematic errors caused by the limited perspective of a single camera angle but also effectively captures lateral body sway and three-dimensional postural changes that are difficult to observe from a single viewpoint, thereby providing a more comprehensive assessment of the subject's overall balance control ability.

3.2.6. Calculation of Physiological Metrics and Feature Engineering

After constructing the behavioral balance features, supervised labels for evaluating high-altitude acclimatization were developed by integrating physiological blood parameters. In this study, HCT was used as the core physiological indicator for model input, while the high-altitude acclimatization assessment index ($AAI = SpO_2 / HCT$), constructed based on HCT and SpO_2 , served as the criterion for label classification. The index was constructed following Li et al. (2024). Based on a predefined threshold, subjects were classified into two groups, poorly and well-acclimatized, to create a binary label that served as a supervised signal for subsequent model training.

3.2.7. Feature Normalization

Because physiological metrics and video balance features have different units and numerical ranges, all input features were normalized using Z-score standardization to prevent feature scale from interfering with model training. This method maps the features to a standard normal distribution with a mean of zero and a variance of one.

3.2.8. Ethics Statement

This study was conducted in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki declaration and its later amendments. The research protocol was reviewed and approved by the Institutional Ethics Committee of Xizang University (approval reference number: ZDYXLL2024003). All participants provided written informed consent prior to data collection.

3.3. Results

3.3.1. Sample Size Notes

Using G*Power 3.1 software, we performed a priori sample size calculations for an independent samples t-test, setting a two-tailed α of 0.05, a power of $1-\beta = 0.80$, and an effect size of Cohen's $d = 0.5$ (moderate effect). Given an expected sample ratio of 1.15:1 (good acclimatization group to poor acclimatization group), the calculated minimum sample size required to achieve the desired power was 130 participants, comprising 69 in the good acclimatization group and 61 in the poor acclimatization group. This study enrolled 71 and 62 participants in the good and poor acclimatization groups, respectively. The actual power was 0.81, which was higher than the prespecified value of 0.80, indicating that the sample size met the statistical requirements.

3.3.2. Distribution Characteristics of Balance Scores in the Single-Leg Standing Task

This study utilized preprocessed video data of single-leg standing with three viewpoints (left, front, and right) for the eyes-closed condition and the eyes-open condition. Balance scores were calculated using a TCN. The distribution characteristics of the eyes-closed single-leg standing task are shown in Fig. 4, and those of the eyes-open single-leg standing task are shown in Fig. 5.

In the eyes-closed single-leg standing task, the balance scores across different camera angles exhibited a unimodal distribution, with most participants' scores concentrated in the low-to-mid range; the score distribution was most concentrated in the front-view perspective, while the left- and right-view perspectives showed greater dispersion.

In the one-leg standing task with eyes open, the balance scores from the frontal camera view exhibited a unimodal distribution, with the peak located in the mid-to-high range; the scores from the left camera view also exhibited a unimodal distribution, with the peak similarly located in the mid-to-high range; and the scores from the right camera view exhibited a bimodal distribution, with two high-frequency score ranges.

3.3.3. Prediction Performance Evaluation of High Altitude Acclimatization

This study employed a support vector machine (with a radial basis function kernel) to construct a predictive model for high-altitude acclimatization. As shown in Table 1, under the optimal classification

threshold, the model achieved an accuracy of 0.883, an F1 score of 0.906, and an AUC of 0.924, while under the default threshold of 0.5, the model achieved an accuracy of 0.851 and an F1 score of 0.875. The model’s ROC curve is shown in Fig. 6, demonstrating an AUC of 0.924. The model’s learning curve is shown in Fig. 7, as the number of training samples increased, the AUCs for both the training set and the 10-fold cross-validation set gradually stabilized, and the difference between the two was small.

Table 1
Model Performance Metrics

Metric	Value
Accuracy (Threshold = 0.5)	0.851
Accuracy (Optimal Threshold = 0.6473)	0.883
AUC	0.924
F1-score (Threshold = 0.5)	0.875
F1-score (Optimal Threshold = 0.6473)	0.906

3.3.4. Contribution of Features from Each Dimension to Predictive Performance

The results of the Gini importance analysis based on the random forest model are shown in Fig. 8. Physiological indicators accounted for 63.8% of the predictive power for high-altitude acclimatization, whereas behavioral indicators accounted for 36.2%.

4. Discussion

4.1. Discussion of the Distribution Characteristics of Balance Scores in the Single-Leg Standing Task

This study analyzed balance-score distributions obtained from multi-camera single-leg-stance tests under eyes-open and eyes-closed conditions, revealing interactions between visual feedback, camera perspective, and human balance control under high-altitude hypoxia.

Balance performance generally declined when visual input was removed (eyes-closed condition), consistent with known physiological effects of high-altitude hypoxia on peripheral-nerve and vestibular function. The frontal-view camera yielded more concentrated balance-score distributions, whereas lateral views showed greater dispersion, which may be attributed to coronal-plane sway and limb-occlusion artifacts. In the eyes-open condition, visual compensation improved overall balance performance. The bimodal distribution observed from the right-side camera may stem from individual differences in sway patterns or partial occlusion during recording, and requires further investigation with larger posture-sequence datasets.

Collectively, these observations highlight the importance of multi-camera acquisition to capture multi-dimensional balance information, and indicate that side-view recordings should be interpreted cautiously to mitigate perspective-derived bias. These empirical distribution findings inform parameter selection for our video-based balance assessment pipeline.

4.2. Discussion on the Selection of True Labels for High-Altitude Acclimatization

This study adopted the high-altitude acclimatization/adaptation index (AAI) as the ground-truth criterion for binary acclimatization classification. The AAI correlates with chronic mountain-sickness phenotypes and exhibits satisfactory stability for identifying early-phase acclimatization status among newly arrived high-altitude migrants. Compared with single physiological markers, the composite AAI better reflects integrated oxygen-transport and blood-compensatory responses, reducing bias inherent to one-dimensional indicators and supporting reliable label construction for our multimodal assessment model.

Only hematocrit (HCT) was retained as the physiological input feature in the present model, while SpO_2 was excluded from model training. This design avoids feeding components of the label-building index directly into the classifier, preventing trivial input-to-label mapping and enabling an unbiased evaluation of the incremental value added by behavioral postural features. Furthermore, SpO_2 measurements are susceptible to motion artifacts and environmental interference in field high-altitude settings. HCT, by contrast, follows standardized laboratory assays and delivers more stable read-outs, making it a pragmatic physiological feature for our assessment framework. This approach mitigates multicollinearity and measurement-noise confounders, strengthening the robustness of model outputs.

4.3. Discussion on the Evaluation of the Predictive Performance of High-Altitude Acclimatization

In this work, we constructed a multimodal predictive model for high-altitude acclimatization that fuses hematological physiological indices and video-derived postural features. Predictive performance was assessed under two classification thresholds (default 0.5 and F1-optimized 0.6473) to support objective quantitative evaluation of acclimatization status.

At the default threshold of 0.5, the model achieved accuracy = 0.851 and F1-score = 0.875 on held-out test data. Using the F1-optimized threshold of 0.6473, accuracy reached 0.883, F1-score reached 0.906, and AUC was 0.924. All key metrics remained high across both threshold settings. The performance gain obtained by threshold adjustment illustrates that careful threshold tuning can help balance sensitivity and specificity, an important practical consideration for clinical-oriented screening applications.

The step-shaped ROC curve is typical for small-sample high-dimensional classification tasks. The model maintained a very low false-positive rate while steadily raising true-positive rates, showing good specificity and adequate sensitivity for distinguishing well-acclimatized versus poorly-acclimatized

participants. An AUC of 0.924 demonstrates strong overall discriminatory capacity for acclimatization status.

Learning-curve analysis revealed gradual stabilization of both training-set and cross-validation-set AUC values with increasing sample size, with only a small gap (0.0295) between curves, indicating no substantial over-fitting or under-fitting. Even under complex high-altitude field conditions, the multimodal fusion strategy combining physiological and postural-behavioral features improved assessment reliability compared with single-parameter physiological evaluation. Feature-importance results confirmed that physiological indices occupy the dominant predictive weight, while behavioral features deliver meaningful supplementary information to boost overall model performance.

Compared with purely physiology-driven evaluation workflows, our model incorporates dynamic functional behavioral signals, enabling multi-perspective characterization of high-altitude acclimatization. The model keeps false-positive rates low across medium-to-high-sensitivity operating ranges, which aligns with general best-practice requirements for medical prediction tools, where suitable threshold tuning can achieve a practical trade-off between sensitivity and specificity.

4.4. Discussion of the Contribution of Features Across Dimensions to Predictive Performance

Gini-based feature-importance analysis from the random-forest model yielded a physiological-to-behavioral contribution ratio of 1.762 (0.638 : 0.362). Both feature classes jointly shape model outputs, yet physiological indicators exerted dominant predictive influence.

Physiological hematological markers directly reflect homeostatic adaptive responses under hypoxic high-altitude exposure and constitute the core predictive foundation of this assessment framework. Even so, postural-behavioral features captured from single-leg-stance tasks provide non-redundant functional information reflecting neuromuscular and balance-regulation efficiency that cannot be obtained from blood assays alone. Joint utilization of both signal categories therefore enables multidimensional evaluation of high-altitude acclimatization.

These feature-weight observations carry practical implications for developing future acclimatization-screening tools: physiological measurements remain primary predictors, but complementary postural-behavioral inputs can enrich model interpretability and predictive robustness. Subsequent work should further refine behavioral-feature specifications to explore their full potential for field-oriented high-altitude health-assessment systems.

4.5. Limitations

This study has several notable limitations. First, constrained by field-research conditions on the plateau, the sample size is relatively moderate. Environmental confounding factors including high-altitude hypoxia, ambient temperature, and individual physical activity levels may interfere with pose-estimation outputs and feature stability, potentially increasing misclassification under certain conditions. Second,

participant recruitment was conducted at a single site among university populations in the Xizang Autonomous Region; therefore, our findings lack external validation across independent cohorts from different altitude-geographic settings, which limits generalizability to broader populations. Third, the current multimodal framework exists only as an offline analytical pipeline and has not been engineered into practical, deployable software for on-site high-altitude field screening. Further multi-center studies with enlarged sample sizes, multi-altitude-gradient cohorts, and long-term follow-up data are required to optimize feature selection and model parameters, reduce false-positive interference at high-sensitivity operating points, and advance the real-world application of such assessment tools for high-altitude acclimatization monitoring and risk warning.

5. Conclusion

This study developed a multimodal assessment model for high-altitude acclimatization that integrates physiological indicators with the temporal features of postural balance, demonstrating that a system that combines physiological and behavioral features can effectively evaluate high-altitude acclimatization. At a default threshold of 0.5, the model achieved an accuracy of 0.851 and an F1 score of 0.875. At the optimal F1 threshold of 0.6473, the accuracy reached 0.883 and the F1 score reached 0.906, with an AUC of 0.924, demonstrating excellent discriminatory ability and generalization performance. The contribution ratios of physiological and behavioral indicators were 0.638 and 0.362, respectively, with physiological indicators playing a dominant role, while postural balance features provided an effective supplement.

Existing high-altitude acclimatization assessments mostly rely on blood-derived physiological markers. This work introduces video-captured postural-behavioural signals as complementary functional evidence, offering a non-invasive, low-cost auxiliary screening option for field-based high-altitude population monitoring. Our results confirm that behavioural balance information carries additional predictive value beyond hematological measurements. This multimodal assessment idea provides new methodological insights for high-altitude medicine, and may support the future development of practical on-site screening tools for evaluating acclimatization status among high-altitude-exposed populations.

Abbreviations

AAI

Altitude acclimatization/adaptation index

AUC

Area under the receiver operating characteristic curve

F1-score

F1-score

HCT

Hematocrit

ROC

Receiver operating characteristic
SVM
Support vector machine
TCN
Temporal convolutional network
SpO₂
Peripheral blood oxygen saturation

Declarations

7.1 Ethics approval and consent to participate

This research was reviewed and approved by the Institutional Ethics Committee of Xizang University, approval reference number: ZDYXLL2024003. All participants provided written informed consent prior to data collection, and all experimental procedures complied with the ethical principles outlined in the Declaration of Helsinki.

7.2 Consent for publication

Not applicable. No identifiable individual participant data, images or videos are included within this manuscript.

7.4 Competing interests

The authors declare that they have no competing interests.

7.5 Funding

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Author Contribution

H.L. conceived and designed the study. X.L. performed statistical analysis, prediction model development, interpretation of the results, and drafted the manuscript. S.J., Y.Y., Y.L., J.Z., X.L., Q.H., and Y.J. participated in clinical data collection and organization, data verification, and interpretation of the results. H.L. supervised the study, provided methodological and clinical guidance, and critically revised the manuscript for important intellectual content. All authors read and approved the final manuscript.

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Data Availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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Figures

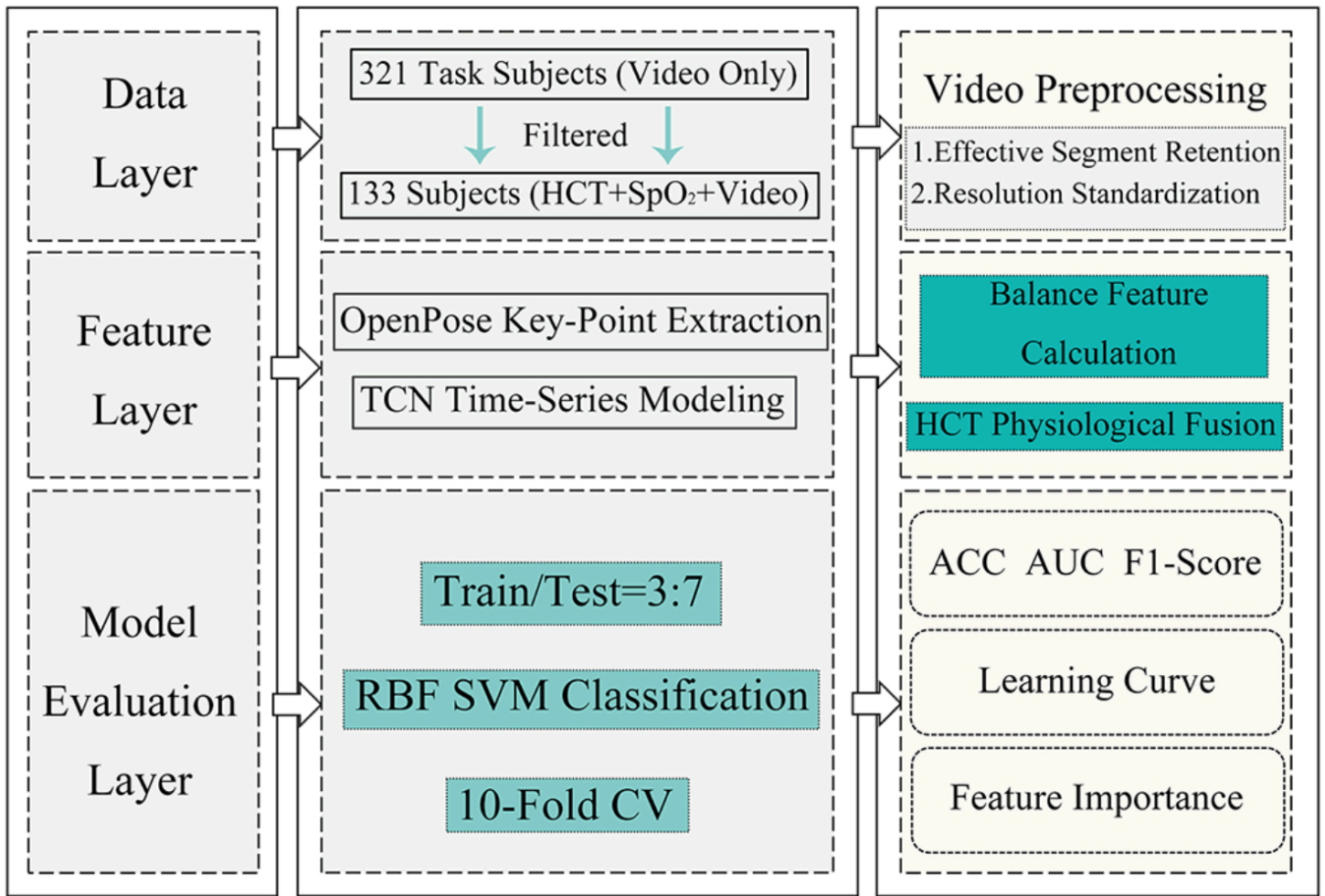


Figure 1

Workflow of the multimodal modeling framework for evaluating high-altitude acclimatization. This framework consists of three layers: (1) Data layer: Raw video data from 321 participants were screened, retaining 133 valid samples that included complete HCT, SpO₂, and video records; the video data underwent preprocessing, including valid segment extraction and resolution normalization. (2) Feature layer: Human keypoints were extracted from the preprocessed video using OpenPose; balance features were generated via TCN temporal modeling and fused with HCT physiological indicators. (3) Model evaluation layer: The fused features were input into an RBF kernel SVM classifier, using a 3:7 training-to-test split and 10-fold cross-validation; model performance was evaluated using ACC, AUC, and F1-score, supplemented by learning curves and feature importance analysis.

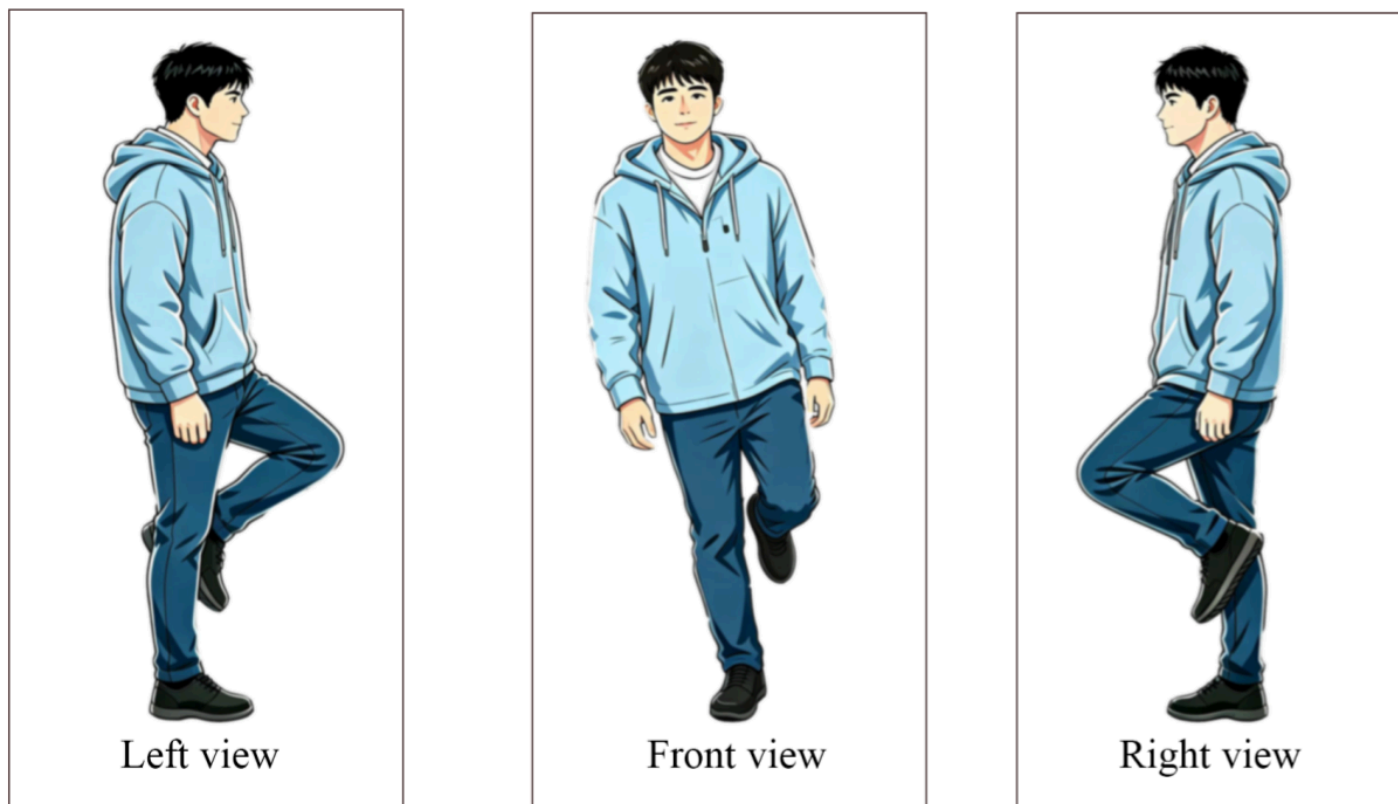


Figure 2

Schematic of multi-camera recording for the single-leg standing task. This figure shows the three synchronized camera angles used in the experiment: left-side view, front view, and right-side view. Recording the subject's posture from multiple angles during this task provides comprehensive kinematic data for subsequent keypoint extraction and balance analysis.

Effective Segment Selection for Single-Leg Standing Video Data

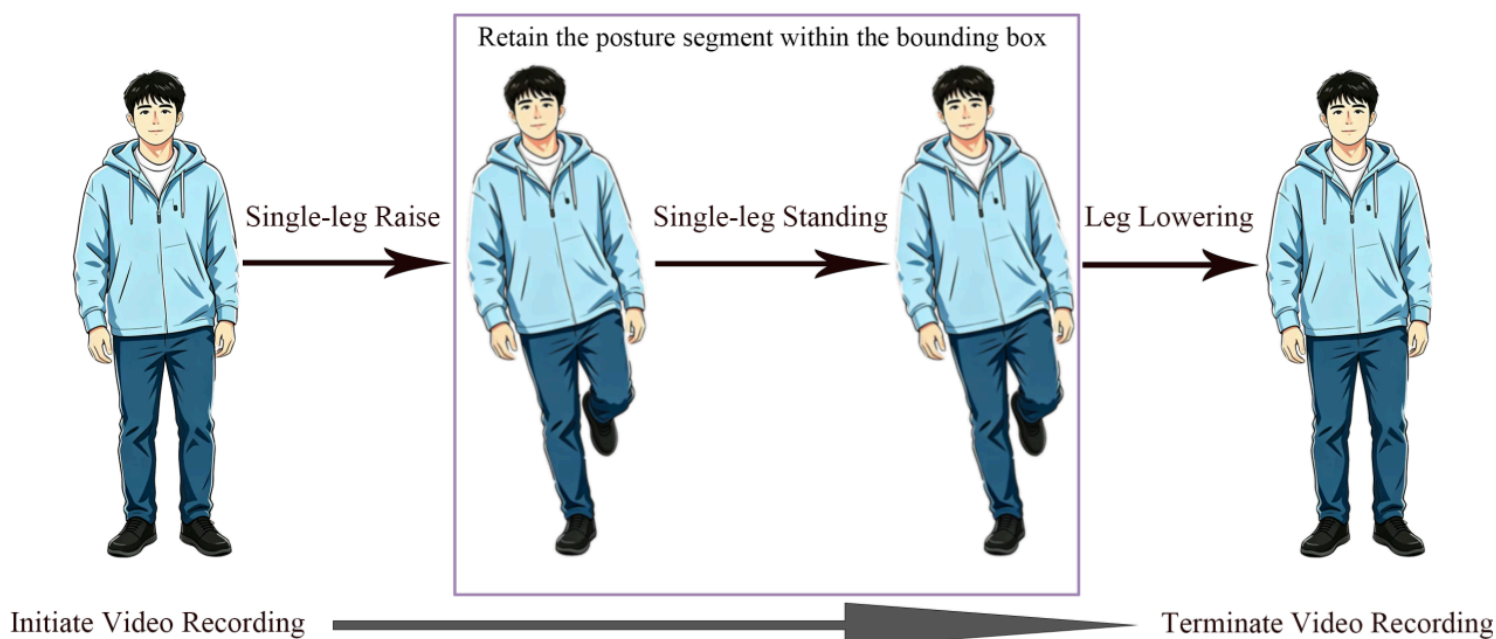


Figure 3

Schematic of the video preprocessing workflow for single-leg standing. This figure illustrates the video data processing workflow in this study: First, the entire single-leg standing task is recorded. Next, the valid single-leg standing segments—spanning from the completion of leg lift to just before leg placement—are segmented and extracted, while invalid movements characterized by significant fluctuations in the center of gravity during leg lift and placement are discarded. Finally, the selected segments undergo noise reduction to provide high-quality data support for subsequent keypoint detection and balance feature extraction.

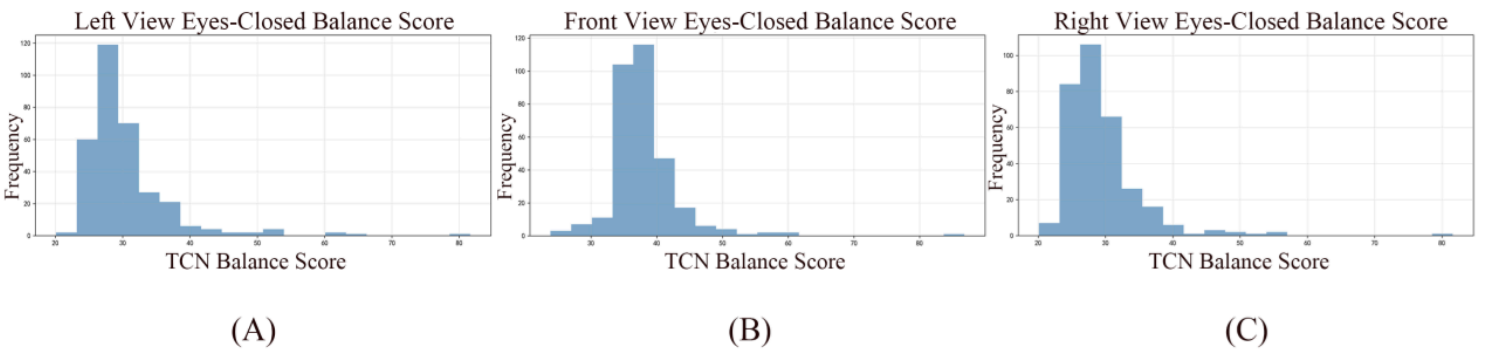


Figure 4

Histograms of the frequency distribution of balance scores in the eyes-opened condition, extracted using a TCN model. (A) shows the view from the left camera position, (B) the front camera position, and (C) the right camera position. The scores from all three camera positions exhibit a unimodal distribution, with most samples concentrated in the mid-score range and only a few individuals exhibiting extremely high scores, reflecting the overall balance ability characteristics of the participants.

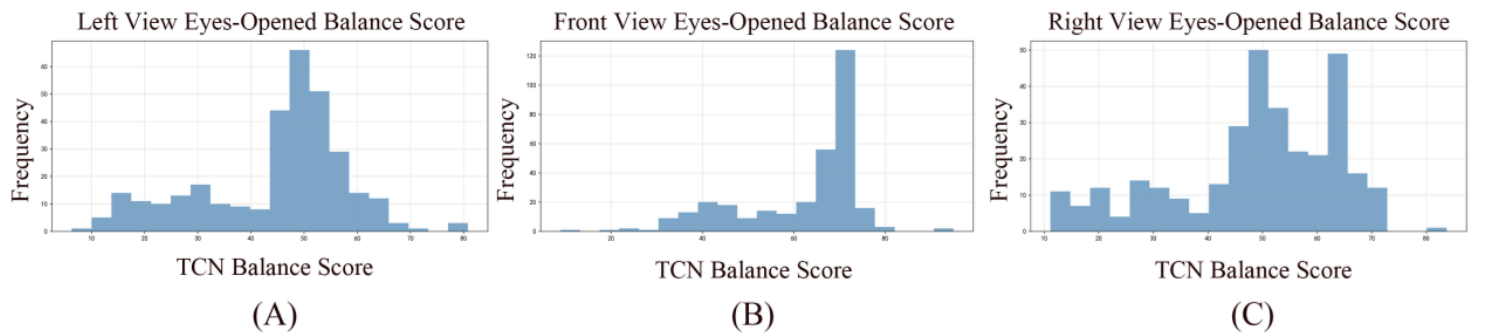


Figure 5

Histograms showing the frequency distributions of balance scores for the left (A), central (B), and right (C) camera positions, extracted using the TCN model while the subject’s eyes were open. Specifically, the scores for the left and front positions generally follow a unimodal distribution, with most samples

concentrated in the mid-to-high score range, whereas the scores for the right position exhibit a bimodal distribution, forming two distinct clusters, with only a few individuals showing extremely low scores. Overall, this reflects the balance ability characteristics of the participants in the eyes-open state.

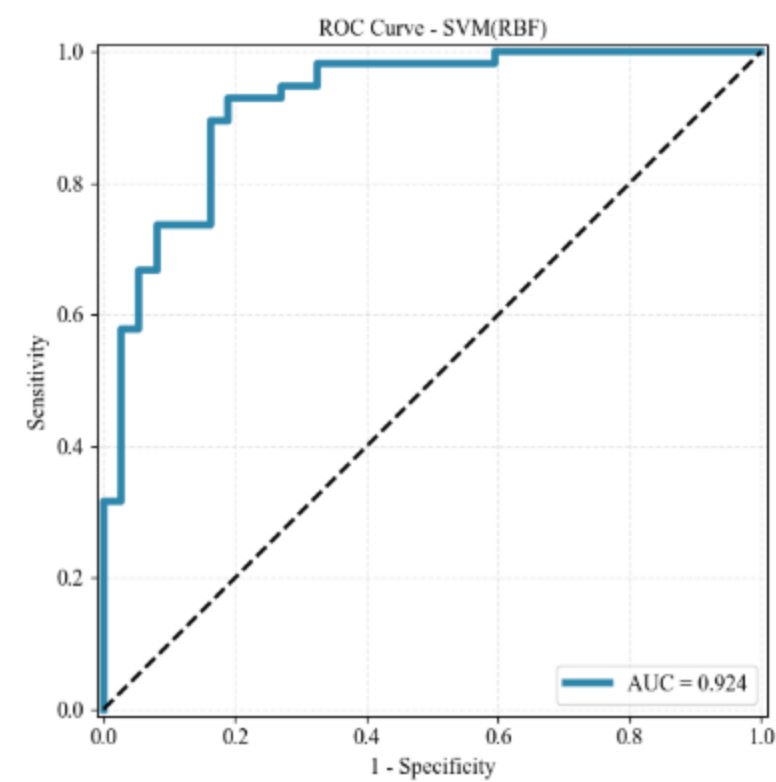


Figure 6

Receiver operating characteristic (ROC) curve of the high-altitude acclimatization prediction model based on radial basis function support vector machines (SVM-RBF). The area under the curve (AUC) is 0.924, which is significantly higher than random guessing performance (AUC = 0.5), indicating that the model has strong discriminatory ability and predictive performance for high-altitude acclimatization status.

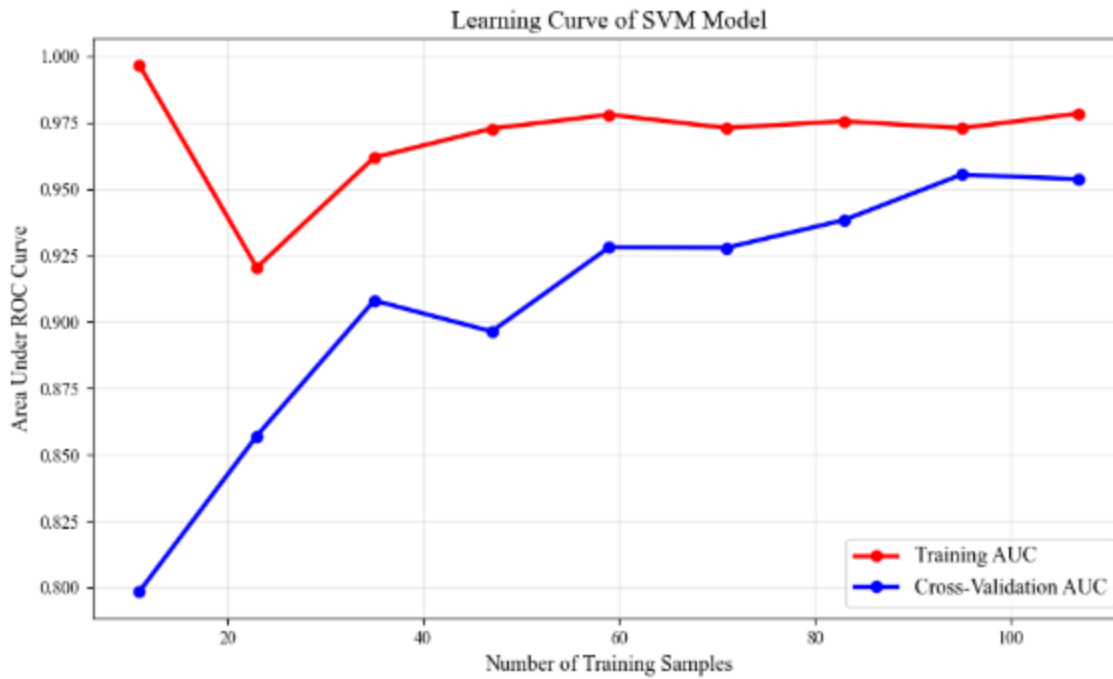


Figure 7

Learning curve of the SVM model. The horizontal axis represents the number of training samples, and the vertical axis represents the AUC value. As the number of training samples increases, both the AUC of the training set (red curve) and that of the cross-validation set (blue curve) gradually stabilize. The gap between the two remains small throughout, indicating that the model fits the data well, with no obvious signs of overfitting or underfitting, demonstrating good generalization ability.

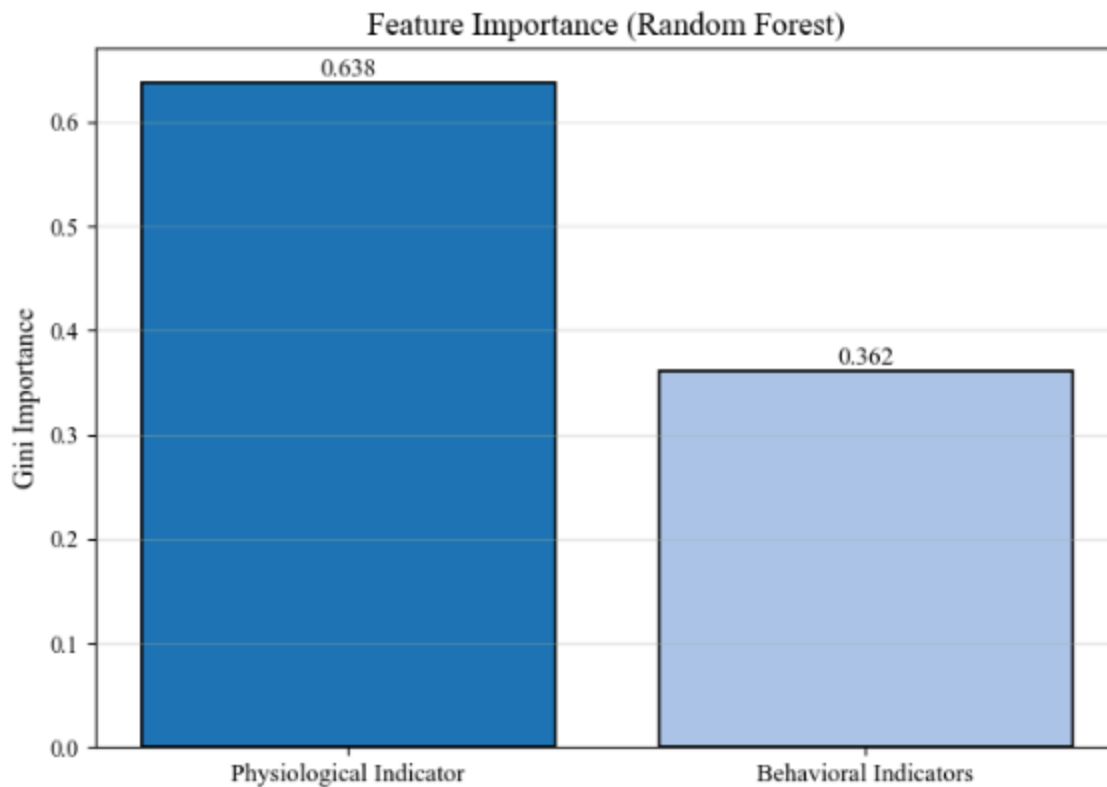


Figure 8

Distribution of feature importance as output by the random forest model. The Gini coefficient (Gini Importance) is used as the evaluation metric. The importance of physiological indicators is 0.638, while that of behavioral indicators is 0.362. This indicates that physiological indicators contribute significantly more to the high-altitude acclimatization prediction model than behavioral indicators, serving as the core influencing factors of the model's predictions.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [GA.jpg](#)